The Dynamic Effects of Hurricanes in the US: The Role of Non-Disaster Transfer Payments

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Abstract

We know little about the dynamic economic impacts of natural disasters. I examine the effect of hurricanes on US counties' economies 0-10 years after landfall. Overall, I find no substantial changes in county population or earnings. The employment rate is 0.17 percentage points lower ten years after the hurricane. The largest empirical effect of a hurricane is observed in large increases in government transfer payments to individuals, such as unemployment insurance. The estimated magnitude of the extra transfer payments is large. While per capita disaster aid averages \$356 per hurricane in current dollars, I estimate that in the eleven years following a hurricane an affected county receives additional non-disaster government transfers of \$70 per capita per year. Private insurance-related transfers over the same time period average only \$3.6 per capita per year. These results suggest that a non-trivial portion of the negative impact of hurricanes is absorbed by existing social safety net programs. The fiscal costs of natural disasters are thus much larger than the cost of disaster aid alone. Because of the deadweight loss of taxation and moral hazard concerns, the benefits of policies that reduce disaster vulnerability, such as climate change mitigation and removal of insurance subsidies, are larger than previously thought. Finally, the substantial increase in non-disaster transfers suggests that the relative resilience of the United States to natural disasters may be in part due to various social safety nets.

1 Introduction

Extreme weather events are a large and growing source of negative economic shocks. Larger population densities, ecosystem alteration, and population movements to hazardous areas are causing real damages

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from natural disasters to rise (Board on Natural Disasters, 1999). World insured losses have exceeded $11 billion per year every year since 1987, reaching $53 billion in 2004 (Kunreuther and Michel-Kerjan, 2007).[1] Economic losses between 1992 and 2001 averaged $49 billion a year (Freeman et al., 2003). Damages are likely to continue growing as climate change is expected to increase the number and intensity of extreme events and to change their spatial distribution (Meehl et al., 2007; Schneider et al., 2007). One estimate is that damages will reach $367 billion a year by 2050, a 750 percent increase in real terms (Freeman et al., 2003). However, the economic impacts of extreme weather are neither predetermined nor random: they depend not only on the meteorological strength of the event, but also on the policies and infrastructure in place (e.g. Zeckhauser, 1996). The exogenous cause of a natural catastrophe is weather, but the difference between an extreme weather event and a disaster is partly man-made. To date, we know very little about the economic impacts of natural disasters over time or the role of institutions and policy in mitigating them.

Governments spend billions of dollars annually on disaster relief and mitigation programs. And, although this is rarely discussed in relation to disaster policy, they also fund transfer programs designed for general economic downturns, such as unemployment insurance, welfare, and food stamps. These may in fact act as a buffer when an extreme weather event occurs, even in absence of direct disaster aid. Ignoring traditional transfer programs would then attribute too much of the resilience of a developed economy to its wealth or disaster-specific response policies. In addition, the fiscal cost of disasters will appear smaller than it actually is.

I study the county-level empirical economic effects of hurricanes, which are one of the most damaging weather events in the US. Specifically, I look at the effects of hurricanes in the 1980's and 1990's from zero to ten years after landfall. I use a simple difference-in-differences framework and focus on changes in population, earnings, employment, and various transfer payments. In addition, I semi-parametrically estimate the post-hurricane economic dynamics, which paints a richer picture of how a county adjusts to this negative shock. My goal is to identify the economic margins along which adjustment takes place (e.g., population movements versus labor market changes) and to understand the role of government spending in post-disaster economics within US counties. I interpret my estimates using a simple spatial equilibrium framework, which suggests that transfers prevent relocation and generally act as a buffer against both disaster and non-disaster negative capital shocks. Some of the results in this paper may apply to capital shocks more generally. The main advantages to using hurricane incidence as an indicator for a capital shock are that hurricanes are exogenous and their onset is known precisely. This is typically not the case with other types of capital shocks.

My results suggest that the potential negative economic consequences of the hurricane may be substantially mitigated through non-disaster social safety net programs. I find that per capita unemployment insurance payments are on average 21 percent higher in the eleven years following the hurricane while overall transfer payments are 2.1 percent higher. Correspondingly, there is a continuous decline in the employment rate of about 0.18 percentage points, but no change in population or wages. This suggests that non-disaster policy, in addition to disaster aid and wealth, may be an important factor in explaining the relative resilience

[1] Unless stated otherwise, all monetary amounts have been converted to 2008 dollars using the Consumer Price Index. Uninsured losses are difficult to estimate, but a rule of thumb is that they are at least as large as the insured losses in developed countries and at least ten times larger in developing ones.

to natural disasters in the United States.

In addition to the funds provided through an official disaster declaration, which average $356 (2008 dollars) per capita per hurricane during my study period, I estimate that in the eleven years following a hurricane, an affected area receives transfers from the government to individuals averaging $70 per capita per year or about $670 per capita in present discounted value. Transfers from businesses to individuals (mostly insurance payments) increase temporarily as well, but add only an estimated $34 to per capita transfers over the eleven years. Together, the transfers total almost as much as the estimated total immediate damages, which FEMA estimates to be $1,278 per capita for the major hurricanes during my study period. Minor hurricanes, which are in my data but not in FEMA's estimates, are generally less damaging. Thus, disaster and non-disaster transfers together replace all or nearly all the immediate hurricane damages.

My estimates imply that the fiscal impact of natural disasters is nearly twice as large if non-disaster transfers are also considered. Although in the simplest public finance framework transfers are welfare-neutral, in practice the deadweight loss of taxation is estimated to be 12-30% of revenue (Ballard et al., 1985; Feldstein, 1999). Finally, because transfers are not paid for by the people receiving them, they may create moral hazard problems, leading individuals to live in riskier places than they would with actuarially fair insurance. Transfers may be welfare-improving once the hurricane has occurred but their welfare implications are much less clear in the long run.

I consider the effects of hurricanes on the construction sector because it is a proxy for how post-hurricane capital adjustment takes place. Although I do find positive effects on construction wages immediately after the hurricane, the sector as a whole shrinks three to eight years after the hurricane. Nine to ten years later, there is a sign of an upward movement in employment, number of firms, and total payroll, suggesting that the decline in the construction sector may be temporary. This decline may occur because construction goods are durables and their destruction causes individuals to substitute intertemporally, lowering demand in the years following rebuilding. I also find suggestive evidence that over time part of the construction sector activity moves to the neighboring unaffected counties. These results suggest that longer-run effects should be an important point of focus when studying the effects of idiosyncratic regional shocks.

I also find evidence of changes in the age structure of the county, but no change in its racial composition. Ten years after the hurricane, the mean age is estimated to be 0.26 years lower than before the hurricane. This is driven by an increase in the fraction of population under 20 years of age and a decrease in the fraction of population 65 and older. However, the pattern of these changes is inconsistent with the transfer increases, implying that the change in transfers is not being driven by changes in the age structure.

Finally, I look at heterogeneity in the impact of hurricanes by the pre-hurricane median income and housing value of a county. I find quantitative as well as qualitative differences between counties in the top and bottom quartiles. Ten years after a hurricane, the employment rate in low-housing value counties is substantially lower that the top quartile counties, while per capita unemployment payments are substantially higher. In addition, trend break and mean shift tests reveal that, although ten years after a hurricane there is no significant difference in per capita earnings changes between the bottom and top quartiles, the post-hurricane paths are qualitatively different.

I contribute to two main strands of the natural disaster literature. The first focuses on the economic impacts of natural disasters, typically considering a single outcome or single event (Leiter et al., 2008; Brown et al., 2006) and looking at effects from one to four quarters (Strobl and Walsh, 2008) to three to four years after the event (Murphy and Strobl, 2009). In one of the few studies to consider long-run effects, Hornbeck (2009) finds that the US Dustbowl had persistent effects on land values and land use practices. Belasen and Polachek (2008) estimate that earnings in Florida counties affected by a hurricane increase sharply and remain higher two years after the hurricane. Brown, Mason, and Tiller (2006) estimate that hurricane Katrina had a negative but temporary effect on local employment zero to six months after. Strobl (2008) estimates that coastal counties affected by major hurricanes subsequently experience lower per capita income growth. I add to this literature by looking at a comprehensive set of outcomes for a large sample of disasters over a longer time period and connecting the outcomes together in a cohesive framework.

The second related strand of literature examines the importance of area characteristics, institutions and wealth in determining disaster-related losses and deaths (Kahn, 2005; Skidmore and Toya, 2005; Nordhaus, 2006). Skidmore and Toya (2002) find that a higher frequency of climatic disasters is correlated with higher rates of human capital accumulation. Kahn (2005) finds that a country's institutional quality is inversely related to the number of disaster-related deaths. I contribute to this literature by looking at the economic effects of disasters rather than the damages they cause and by considering the role of transfer payments and within-country heterogeneity.

In the most closely related study, Yang (2008) estimates the effect of hurricanes on international financial flows and finds that four-fifths of the estimated damages are replaced in poorer countries by both international aid and remittances. In richer countries, the increase in lending by multilateral institutions is offset by similar declines in private financial flows. I contribute to this strand of literature by focusing on the role of non-disaster transfer programs in post-disaster economics. Like Yang, I consider the impact of hurricanes on monetary transfers but focus on within-country flows related to social and private insurance.

In addition, there is a literature considering the short-run economic effects of temperature fluctuations (e.g. Dell et al., 2009; Deschenes and Greenstone, 2007a and 2007b; Jones and Olken, 2010) and relating these to climate change. Climate change is forecast to increase the intensity of hurricanes, which, all else equal, will raise the damages they cause by more than one-for-one. In this paper, I underscore the additional fiscal and long-term economic impacts which are currently not incorporated by simple measures of initial damages. My results suggest that climate-induced hurricane intensification may have larger negative consequences than previously thought. This in turn implies that the benefits of mitigation, including policies that diminish the effect of climate change and removal of insurance subsidies, are larger.

The rest of the paper is organized as follows. Section 2 presents the conceptual framework. Section 3 provides some background information on hurricanes and US federal disaster aid. Section 4 describes the setting and data and discusses the empirical strategy. Section 5 presents and discusses the results. Section 6 tests for demographic changes in the county. Section 7 presents suggestive evidence on within-country heterogeneity of hurricane impacts. Section 8 concludes and contains suggestions for further research.

2 Conceptual Framework

Hurricanes in the US can be thought of as negative capital shocks; except for Hurricane Katrina, they do not cause substantial loss of life in the modern US. Thus, I use a simple production function framework to guide the discussion of the results. I describe how economic outcomes evolve following a capital shock under various assumptions about moving costs, capital adjustment costs and the ability of individuals to receive transfer payments instead of working.[2]

Suppose that there are many identical locations, so that changes in one location will not have substantive effects on other locations. Representative firms in each location produce a homogenous good with some standard production function $F(K, L)$, where K is capital and L is labor. Capital and labor are complements. Now suppose that one location experiences a negative capital shock. Generally, what happens to population, labor supply, and wages depends on capital and individual mobility costs, as well as the presence of unemployment insurance or other transfer programs. If capital is perfectly mobile, a capital shock will have no effect on the equilibrium population or any other economic indicators because adjustment will be immediate. This is regardless of whether there are individual moving costs or transfer programs.

If capital is not perfectly mobile, there will be observed changes in the local economy. If individuals face zero moving costs, there will be no change in the wage, but a decline in the population. This is intuitive: without moving costs, individuals will only stay in the area if they are at least as well off as before. Because the destruction of capital lowers the wage rate, all else equal, individuals will respond by decreasing their labor supply until the wage rate is equal to the pre-shock wage. Because of zero moving costs, decreasing labor supply will be equivalent to moving, as individuals who were choosing to work before will simply costlessly switch to another location. Thus, in the case where capital is not perfectly mobile but individuals are, transfers will play no role in the post-hurricane dynamics. The degree to which population falls depends on how immobile or slow-adjusting capital is.

When both capital and individuals are not perfectly mobile, we expect to see a decline in the wage rate. As long as some of the individuals have negligible moving costs, the population will also fall. Unlike in the previous case, individuals may also decrease their labor supply without moving away, so there may be a decline in the employment rate. The relative decline of population and labor supply depends on the relationship between moving costs and disutility of labor supply. For example, if both moving costs and disutility of labor supply are high, the fall in the employment rate relative to the fall in population will be larger than if moving costs are low.

If, in addition to imperfectly mobile capital and imperfectly mobile individuals, there are transfer payments, the population decline will be weakly smaller than without transfers, while the change in total labor supply and the wage rate relative to the no transfer case is ambiguous. Per capita labor supply should fall more as some individuals take the outside option of transfers instead of working. This will counteract the decrease in wages due to the lower capital. Likewise, some individuals will chose to take transfers and remain in the area instead of moving away.[3] This implies that the net effect on total labor supply is ambiguous:

[2] For a simple formal model and simulation results, see the online "Model Appendix": http://econ-www.mit.edu/files/6350

[3] Transfer payments can be either a decreasing function of the wage (i.e., compensate individuals living in an area for lower wages, as in Notowidigdo, 2010) or unemployment insurance payments that the individual can choose instead of working.

although labor supply per capita is lower than in the no transfer case, there are more people remaining in the area relative to the no transfer case.

In Table 1, I summarize the predictions of this framework following a negative capital shock under various assumptions about the mobility of capital and individuals, as well as the availability of transfer payments. If capital is perfectly mobile (Columns 1 and 2), a negative capital shock will have no effect on any economic indicators, regardless of individuals' mobility costs and transfer availability. If capital is not perfectly mobile, there are no transfers, and moving is costless (first row of Column 3) wages will remain unchanged, but population will fall. In the presence of moving costs but no transfer payments (first row of Column 4), the fall in the population will be smaller, while the decline in wages will be larger. When there are employment-related transfer payments but no moving costs (second row of Column 3), the fall in capital will have the exact same effect as in the no transfer case and the total amount of transfers going to an area will remain unchanged. Finally, when there are both transfer payments and moving costs (second row of Column 4), the fall in utility resulting from a negative capital shock will be buffered by transfers. The presence of transfers will lead some individuals to cease working while remaining in the area, lowering the number of people who leave and causing the drop in labor supply to be larger than the drop in population. The fall in wages will be smaller than in the no-transfer case.

To summarize, if capital is perfectly mobile (or close to it), I expect to find no change in the economy following a hurricane. If capital is somewhat immobile but individual mobility costs are negligible, I expect to find decreases in population but no changes in transfer payments. Finally, if capital adjustment costs and individual moving costs are both non-trivial, transfer payments flowing into the area should increase. The degree to which population falls will reflect both the magnitude of the moving costs and the capital adjustment costs.

The presence of transfer payments weakly increases welfare for individuals living in the area relative to the no transfer case. However, as I discuss later, whether transfer payments increase social welfare is unclear.

3 Hurricanes and Federal Disaster Aid

3.1 Hurricanes in the United States

Hurricanes that affect the US form in the Atlantic Ocean. The Atlantic hurricane season lasts from June through November, with most hurricanes forming in August and September. Warm humid air over the ocean creates storms known as "tropical disturbances". If circulating winds develop, the disturbance becomes a tropical cyclone. Prevailing winds and currents move the cyclone across the ocean, where it gains and loses strength based on the favorability of conditions. When cyclones encounter cold water or land, they lose strength quickly and dissipate. Sometimes a circular area with low internal wind speeds, called the "eye", develops in the system's center. Although the entire storm system can span a few hundred miles, the perimeter of the eye (the "eyewall") is where the strongest winds are found. Wind intensity declines quickly as one moves away from the eyewall (or the center of the storm, if there is no eye). The outer parts of the hurricane are called "spiral bands"; these are characterized by heavy rains but typically do not have hurricane-force winds. Hurricanes that make it to land create widespread wind and flood damage: physical damages from hurricanes in the US have averaged \$4.4 billion per hurricane (2008 dollars) or \$7.4 billion per year between 1970 and 2005 and \$2.2 billion per hurricane or \$3.7 billion per year if 2005 is excluded.[4]

For hurricane data, I use the Best Tracks (HURDAT) dataset from the National Oceanic and Atmospheric Administration (NOAA).[5] It contains the location of the storm center and wind speed (in six hour intervals) for each North Atlantic cyclone since 1851. To determine which counties the storm passed through, I assume that the storm path is linear between the given points. Data on storm width are unfortunately not collected; this adds some measurement error. But because the eye of the hurricane is typically not very large, and counties through which the eye passes suffer much more extensive damage (as I show later), this should not be a problem for the estimation.[6] Although the hurricane data span a long time period, annual county-level economic data are only available for 1970-2006. Because the main econometric specification has ten balanced leads and lags (i.e. each lead and lag is estimated using the same set of hurricanes), I estimate the economic effects of hurricanes that occurred between 1980 and 1996.

North Atlantic cyclones are classified by maximum 1-minute sustained wind speeds using the Saffir-Simpson Hurricane Scale. A storm is considered a hurricane if maximum 1-minute sustained wind speeds exceed 74 miles per hour. Category 3 and higher hurricanes have wind speeds greater than 111 mph and are called ”major hurricanes”. Category 1 and 2 hurricanes are ”minor hurricanes”, characterized by maximum wind speeds of $74 - 110$ mph. A tropical storm is a cyclone with wind speeds of 39 - 73 miles per hour. Cyclones with lower wind speeds are called ”tropical depressions”. Figure 1 shows the distribution of all hurricanes and major hurricanes (Category 3 and higher) as well as landfalling minor and major hurricanes between 1980 and 1996. Over this time period, there were on average 5.6 North Atlantic hurricanes per year. There are at least two hurricanes each year and there are three years with ten or more hurricanes. About a third (1.9 out of 5.6) of hurricanes are major hurricanes. Less than a third (1.5 out of 5.6) of all hurricanes that form make landfall, and about half of the landfalling hurricanes (0.7 out of 1.5) are major hurricanes.

US hurricanes are geographically concentrated. Most of the landfalling hurricanes over this time period occur in Alabama, Georgia, Florida, Louisiana, Mississippi, North Carolina, South Carolina, Texas, and Virginia (hereafter the ”hurricane region”). Figure 2 shows the distribution of the cumulative number of hurricanes and major hurricanes by county. A county is considered affected by a hurricane if the hurricane’s center passed through it. Most counties in the US (95%) do not experience a hurricane by this measure. Out of 838 counties in the hurricane region, 127 experience one or more hurricanes (115 of those experience only one hurricane). Only 19 counties outside the hurricane region experience any hurricanes during this time. Virtually all the major hurricanes occur within the hurricane region. For this reason, I limit my sample to counties in these states. Although it would be preferable to focus on the major hurricanes, they are relatively rare (there are only 8 affecting the hurricane region between 1980 and 1996). For this reason, I focus on the 21 minor and major hurricanes that affected the hurricane region during that time.

[4] Author calculations using data from Nordhaus (2006). I use 2008 dollars throughout the paper.

[5] Available from http://www.nhc.noaa.gov/pastall.shtml#hurdat

[6] See Appendix A for a discussion of the distribution of eye diameters.

3.2 Destructiveness of Hurricanes

In order to gauge the potential economic impact of hurricanes, it is helpful to look at the damages they cause in absolute terms and relative to other US disasters.

To provide evidence on the absolute level of damages caused by hurricanes, I use estimates of direct damages from HAZUS-MH, published by FEMA.[7] Table 2 shows the summary statistics of the effects of the eight major hurricanes that affected the hurricane region between 1980 and 1996. HAZUS-MH is software meant to help state, local, and Federal government officials prepare for disasters and to help the private sector estimate risk exposure. The software combines scientific and engineering knowledge with detailed historic data to produce damage estimates that are likely to be more accurate than those made using simpler estimates or reports. In addition to simulating hypothetical damages, HAZUS contains highly detailed damage estimates of past major hurricanes. These damage estimates are shown in Table 2.

Panel A summarizes the estimated effects in the counties which, according to the Best Tracks data, were in the path of the hurricane's center (I refer to these as "centrally affected" counties). On average, these counties suffered $\$406$ million in damages to buildings (with a standard deviation of about $\$2$ billion) or about 1.46% (with a standard deviation of 3.85%) of the total building value. The maximum county-level building damage was $\$20$ billion while the maximum loss as a percent of total building value was 23.6%.

HAZUS-MH also provides estimates of non-structural losses, such as building content and inventory losses, as well as estimates of the number of households displaced by the disaster**.** Total losses (including building damages) average $\$571$ million per county with a standard deviation of $\$3.7$ billion. The largest total loss on a county level over this period was $\$35.4$ billion. On average, about 1,500 households (with a standard deviation of 10,700) are displaced as a result of a central hit by a major hurricane and 450 people require temporary shelter. Per capita total damages average $\$1,280$ with a standard deviation of about $\$3,340$.

Panel B shows the estimated effects of the hurricane on counties that are listed as affected in the FEMA simulations but do not have the center of the storm passing through them ("peripherally affected" counties). The damage estimates are much smaller. For example, the average damage to buildings is only $\$8.6$ million or about 65 times smaller than the average damage in a centrally affected county. The *maximum* damage in peripherally affected counties is $\$390$ million, which is smaller than the *mean* damage in centrally affected counties. The average loss ratio is 0.15%, which is about 10 times smaller than the loss ratio in centrally affected counties. Per capita total losses are also about 10 times smaller, averaging $113 per capita, and total losses are about 50 times smaller. Only 12 households are estimated to be displaced, on average, and only 3 people require temporary shelter. Thus, although the omission of these counties from the analysis may introduce some measurement error, it should not affect the estimates much.

The above estimates provide evidence both on the level of a hurricane's damage and on the likely importance of including counties not directly in the storm's path. It should be noted that the damage estimates are an upper bound on the average destructiveness of the hurricanes in my sample because my sample includes minor as well as major hurricanes. Unfortunately, FEMA does not provide detailed damage estimates for minor hurricanes. A theoretical result is that the energy carried by the wind increases with the third power of

[7] Available by request from http://www.fema.gov/plan/prevent/hazus/index.shtm

wind speed. The average maximum wind speed in a county that was centrally affected by a major hurricane between 1980 and 1996 is 124 miles per hour, while the average maximum wind speed in a county centrally affected by a minor hurricane is 86 miles per hour. If the power carried by the wind translates directly into destructiveness, a back of the envelope calculation implies that a 124 miles per hour hurricane would cause about three times more damage than an 86 miles per hour hurricane. This, in turn, would imply that the average minor hurricane in my sample caused about $190 million in total damages per centrally affected county. Although this is not as large as the damage caused by major hurricanes, it is a non-trivial amount for a local economy and may affect subsequent economic outcomes.

I now address the relative damages caused by hurricanes. I regress three different damage statistics on measures of hurricane strength and other natural event indicators. The regression specifications are as follows:

$$
\begin{aligned}
D_{ct} &= a_c + a_t + \beta_1 Major\_hurricane_{ct} + \beta_2 Minor\_hurricane_{ct} \\
&\quad + \gamma_1 Flood_{ct} + \gamma_2 Tornado_{ct} + \gamma_3 Severe\_storm_{ct} + \varepsilon_{ct}
\end{aligned}
$$

and

$$
\begin{aligned}
D_{ct} &= a_c + a_t + \sum_{k=1}^{5} \beta_k \mathbf{1}\left[Category_{ct} = k\right] + \gamma_1 Flood_{ct} \\
&\quad + \gamma_2 Tornado_{ct} + \gamma_3 Severe\_storm_{ct} + \varepsilon_{ct}
\end{aligned}
$$

$$c = \text{ county; } t = \text{ year}$$

D_{ct} is log of property damages, property damages per capita or the log of flood insurance payments in that county. [8] All damage measures are in 2008 dollars. $Major\_hurricane_{ct}$ is an indicator for Category 3, 4, and 5 storms, while $Minor\_hurricane_{ct}$ is an indicator for Category 1 and 2 storms. $\mathbf{1}\left[Category_{ct} = k\right]$ is an indicator variable equal to 1 if the hurricane is classified as a Category k hurricane. Because there are very few Category 4 and 5 hurricanes, I combine them in the second equation. The $Flood$, $Tornado$, and $Severe\_storm$ indicators are equal to 1 if the county was reported as having at least one of these events over the year. These, along with hurricanes, are the most common and damaging meteorological events in the US. Other rarer events in the region include droughts, wildfires, and heat. Thus, the reference category is a combination of these extreme events and no reported extreme events. Finally, a_c and a_t are county and year fixed effects.

I estimate these two equations for the nine states in the hurricane region.[9] The results are shown in

[8] Data on damages and extreme weather events other than hurricanes are from the Hazards & Vulnerability Research Institute (2009) and are based on weather service reports by local government officials. Data on flood claims and liabilities are from the Consolidated Federal Funds Report (CFFR).

[9] The results for all US counties are similar.

Table 3. Column 1 compares the log of damages for different disasters. A major hurricane increases the reported property damages by 4.2 log points or over 400%. In levels, this implies that a major hurricane increases the total damages in a county by about $\$760,000$ (2008 dollars). The next most damaging event is a minor hurricane, which increases property damages by 2.4 log points or about $\$110,000$. In contrast, tornadoes, floods, and severe storms increase property damages by $2.1\ (\$76,000)$, $0.9\ (\$15,000)$, and $1.0\ (\$18,000)$ log points (dollars), respectively. A similar pattern holds when the dependent variable is property damages per capita, although some of the point estimates become statistically insignificant. This is possibly because hurricane-prone counties are more populous. Column 4 shows the effect of hurricanes broken down by category. As expected, Category 1 hurricanes are the least damaging, causing an extra 2.2 log points of damage ($\$84,000$), while Category 4 and 5 storms are the most damaging, increasing property damages by 4.6 log points ($\$1,100,000$). The least damaging hurricane is about as damaging as a tornado, and more damaging than a flood or severe storm.

An important caveat is that the damage measures are estimates made by local officials soon after the occurrence of the event. Using hurricane-level damage data from Nordhaus (2006), I estimate the direct damages from hurricanes to be about $3.7 billion per year between 1970 and 2004, in 2008 dollars. Given that there are on average 1.5 landfalling hurricanes per year, the estimates in this section appear to understate the per-county damage of hurricanes (and possibly of other disasters as well) by at least a factor of ten. However, as long as the damage measurements do not exhibit differential bias for hurricanes, floods, storms, and tornadoes, these numbers are valid for comparing the *relative* magnitudes of the different events.

Column 3 shows the effect of various extreme weather events on flood payments. Major hurricanes increase flood claims by about 3.1 log points or about $1.1 million, while minor hurricanes increase them by 1.5 log points or about $\$190,000$. The mean insurance liability in the sample is $\$538$ million. Tornadoes have no significant impact on flood claims and the estimated effect of a severe storm is significantly negative.[10] Floods increase claims by only about 0.5 percentage points.

When the effect of a hurricane is broken down further, Category 3 storms are estimated to have the largest effect, raising flood insurance payments by about 3.1 log points. Category 1 and 2 hurricanes raise flood-related insurance payments by 1.1 and 2.8 log points, respectively. Category 4 and 5 storms increase them by 3 log points.

The flood insurance payments are likely to be a lower bound on total insurance payments for two reasons. First, in addition to flood damage, the wind associated with hurricanes creates massive damage, which is covered by homeowner's insurance. Second, the fiscal year of the US government ends on September 30th. Some flood insurance claims originating in August and September (the peak hurricane time) may be settled in the same fiscal year, while some may not appear until the following year. Despite all the caveats, these estimates imply that hurricanes are the most destructive of the common US disasters, which makes them an important phenomenon to study.

[10]The comparison category is not "no extreme weather event", but a combination of this indicator and other, rarer, weather events. Some of these, such as heat waves, may be more damaging than the average severe storm.

3.3 Federal Disaster Aid

This section summarizes US federal disaster spending between 1980 and 1996. Federal disaster aid is given to a county if the state's governor files a request and provides evidence that the state cannot handle the disaster on its own. The final decision about whether to declare a disaster is made by the US President. If the request is approved, federal money can be used to repair public structures and to make individual and business grants and loans. Grants to individuals are made only up to the amount of uninsured damages. The Federal Emergency Management Agency (FEMA) also provides personnel, legal help, counseling, and special unemployment insurance for people unemployed due to the disaster. Although there is some long-term recovery spending in extreme cases, most of the transfers to individuals occur within six months of the declaration and most of the public infrastructure spending occurs within two-three years (FEMA, personal communication).

Between 1980 and 1996, the federal government spent $\$6.4$ billion (2008 dollars) on hurricane-related disaster aid and $\$23.1$ billion on other disasters.[11] The bulk of the non-hurricane disaster spending ($\$10.1$ billion) was due to the Northridge earthquake in 1994. Excluding the Northridge earthquake implies that hurricane-related spending accounts for about a third of all disaster aid. This number includes all declaration-related spending by FEMA, including assistance given for infrastructure repair, individual grants, as well as mitigation spending. The Small Business Administration also offers subsidized loans to affected individuals and businesses, which are not included here. Spending by the state and local governments is also excluded. By law, the state pays some of the cost of disaster aid, but its share cannot exceed 25%. Thus, state spending comprises at most a third of the federal spending. Unfortunately, annual county data on disaster spending over time is not available, so I cannot incorporate disaster spending into my main empirical framework. However, there are data that allow me to directly compute the county-by-hurricane amount of disaster transfers.

Table 4 shows the summary statistics for federal aid related to hurricanes between $1980 - 1996$.[12] Because data on federal disaster aid is provided on the level of a declaration, which includes multiple counties in a state, an assumption about how the money is divided among counties is necessary. As I show in the previous section, counties through which the center of the storm passes experience much more damage than peripherally affected counties. Therefore, a natural assumption is that the money is split among only those counties and the rest can be ignored. Another natural assumption is that the money is divided among the included counties in proportion to the population in each county. Panel A shows the total and per capita federal aid transfers assuming that only centrally affected counties are given aid. The average amount of aid given to counties experiencing hurricanes was $\$58.7$ million. Counties experiencing major hurricanes received about 2.5 times as much on average, $\$128 - 133$ million. The standard deviations of aid for counties that experienced hurricanes are all larger than the mean, ranging from $187 to over $460 million. Note that this period excludes Hurricane Katrina and the 2004 hurricane season, in which four hurricanes affected Florida. Thus, even "business as usual" hurricane seasons are associated with non-trivial amounts of federal

[11] Data on spending are from the PERI Presidential Disaster Declarations database (Sylves and Racca, 2010).

[12] Summary statistics for other times periods are similar, with the caveat that real spending on hurricane-related declarations is rising over time.

spending.

Per capita spending in 1980-1996 averaged $\$356$ per hurricane and $\$412$ per major hurricane (2008 dollars). An extreme assumption of a uniform split across counties (which is unlikely to be true) leads to a larger per-capita average of $\$1,137$ per hurricane and $\$2,018$ per major hurricane.

Panel B shows the same statistics assuming that the money is divided among all counties included in the declaration, not just centrally affected ones. This implies spending of $\$8.4 - 8.9$ million per county, $\$24.6 - 30.0$ million per centrally affected county, and $\$59.2 - 73.4$ million per county centrally affected by a major hurricane. Per capita spending estimates range from $\$52$ to $\$187$ in the proportional split case and from $\$160$ to $\$954$ in the uniform split case.

In the results section, I use the preferred number of $\$356$ per capita as a benchmark to compare spending by disaster relief agencies to the extra spending associated with the hurricane triggering other transfer programs.

4 Empirical Strategy

4.1 Sample of Analysis

Ideally, one would test for differences over time between counties in the hurricane region that do and do not experience a hurricane between 1980 and 1996. However, finding a valid control group is not straightforward. In Table 5, I compare counties that do not experience any hurricanes between 1980 and 1996 with counties that experience one hurricane.[13] I omit the few counties that experience more than one hurricane between 1980 and 1996. Results are similar if counties with more than one hurricane are included.

Columns 1 and 2 show the 1970 characteristics of hurricane region counties that do and do not experience a hurricane between 1980 and 1996. Nearly sixty percent of 119 counties that experience one hurricane are coastal, compared to forty-two percent of 845 counties that have not had hurricanes over this period. Counties that experience hurricanes are about one and a half times as populous as the non-hurricane counties and have slightly more land area, and these differences are statistically significant (as shown in Column 3). Counties with hurricanes have a smaller population density (as compared to counties within the hurricane region without hurricanes), larger per unemployment insurance payments, but smaller per capita transfers from businesses and from the federal government. Joint testing of all variables excluding population, the coastal indicator, and land area[14] reveals that these counties are substantially different from each other in the pre-period.

I attempt to find a better control group by restricting the no-hurricane counties in Column 2 to those that experienced at least one hurricane between 1900 and 1969, but had no hurricanes between 1980 and 1996 (the "experienced sample"). The summary statistics for this sample of 177 counties are shown in Column 4. These counties are much more similar to the treatment sample in Column 1: they are equally likely to be coastal and have about the same land area, population, population density and per capita earnings.

[13]The county data are discussed in more detail in the next section.

[14]These are excluded because the size of a county and whether it's coastal is mechanically related to its probability of being affected by a hurricane and thus does not raise as much concern about differential trends.

However, the employment rate in experienced counties is significantly lower, while unemployment insurance and government transfer payments per capita are significantly larger. Joint testing of variables excluding population, the coastal indicator, and land area reveals that there are still significant differences between counties with and without hurricanes between 1970 and 1996. Because the sample in Column 4 is more similar to the treatment group than the sample in Column 2, I use the former as my preferred control group.[15]

Differences in levels are not a concern in themselves, as all regression specifications include county fixed effects. But differences in levels may be indicative of differential trends. Because the affected group is defined by its 1980-1996 hurricane experience, I can check for differential trends in the pre-period, 1970-1979. None of the variables for which annual data are available (population, employment, unemployment payments, earnings, and transfers) exhibit differential trends for the preferred control group and most don't exhibit differential trends for the broader control group in Column 2. Thus, the assumption of parallel trends appears to hold for the treatment and the preferred control group.

I discuss results using other samples in the robustness section (including using only the counties that experience a hurricane between 1980 and 1996). I show that these do not affect the estimates qualitatively and have only a moderate quantitative effect. I also address the problem of potentially different time trends by relying on mean shift and trend break tests.

4.2 Economic Data

The main estimation sample consists of a 1970-2006 panel of 296 counties in the hurricane region states, as discussed in the previous section.[16] Of these counties, 119 experience one hurricane between 1980 and 1996, while the rest have experienced a hurricane sometime between 1900 and 1969. I estimate the effects of a hurricane using hurricanes that occur between 1980 and 1996. This allows each of the ten leads and ten lags to be estimated using the same set of hurricanes.

Annual county-level outcomes such as unemployment payments, population, earnings, and sector-specific wages and number of establishments come from either the Regional Economic Information System (REIS) or County Business Patterns (CBP). Both series span the years 1970-2006. County-level population for the same period are from Surveillance Epidemiology and End Results (SEER) population database.

Summary statistics of the key economic outcomes are shown in Table 6. The employment rate is defined as the ratio of workers to the overall population.[17] An establishment is defined as a single *physical* location of a firm with paid employees.

The employment rate seems low, partly because I define the employment rate as total employment divided by total population, rather than total employment divided by total civilian non-institutionalized population aged 16 and older. Because county-level population disaggregated by age is likely less accurate, especially in earlier years, I use this rate as my main employment measure. Another reason for the low

[15] Appendix Table A1 presents the same comparisons but restricts the sample to coastal counties, as defined by the NOAA's Strategic Environmental Assessments Division. For most of the variables the differences between the hurricane and no-hurricane counties persist; restricting the sample to be coastal merely shrinks it but does not make the control and treatment groups more similar.

[16] The hurricane region states are Alabama, Georgia, Florida, Louisiana, Mississippi, North Carolina, South Carolina, Texas, and Virginia.

[17] Annual county-level unemployment rates are not available until 1990.

employment rate is the exclusion of most government employees from the CBP data. The data also exclude employment in crop and animal production, rail transportation, insurance and employee benefit funds, and trusts, estates, and agency accounts. Finally, because the CBP employment estimates are for March, some seasonal workers may be missed as well.

Net earnings by place of residence include wage and salary disbursements, supplements to wages and salaries, and proprietors' income, less contributions for government social insurance. Earnings do *not* include transfer payments. Earnings by place of work are converted to earnings by residence by the Bureau of Economic Analysis (BEA) using a statistical adjustment. Note that, on average, the construction sector represents slightly over 10% of all establishments, employees, and wages.

Unemployment insurance compensation consists primarily of standard state-administered unemployment insurance schemes, but also includes unemployment compensation for federal employees, railroad workers, and veterans. Income maintenance is a separate category that includes supplementary social insurance (SSI), food stamps, Aid for Families with Dependent Children (AFDC), Temporary Assistance to Needy Families (TANF), Earned Income Tax Credit (EITC), energy assistance, and other income maintenance benefits. Transfers from government to individuals include both unemployment insurance and income maintenance. In addition, the category includes retirement and disability insurance benefits, medical benefits (Medicare and Medicaid), veterans' benefits, and federal education and training assistance. Transfers from businesses to individuals consist primarily of personal injury liability payments to non-employees and net insurance settlements.

Disaster-related transfers are technically included in the measure of total transfers from the government. However, these are computed by assuming that national estimates are distributed in proportion to population to all the counties in the US. Thus, these will not affect the estimation once year fixed effects are included.

4.3 Event Study Regression Framework

In this section, I outline the procedure used to estimate the economic effects of a hurricane. I first employ an event study framework. Specifically, I regress outcomes on hurricane indicators 10 years before and after a hurricane, controlling for county, year, and other extreme weather events. It would be ideal to estimate the effects of major and minor hurricanes separately, but there are too few major hurricanes for a precise estimation of their effect.[18] Thus, I focus on the effect of all hurricanes. The identifying assumption is that, conditional on the location and the year, the occurrence of a hurricane is uncorrelated with unobservables. This is reasonable because even forecasting the severity of the hurricane season as a whole is difficult, much less the paths those hurricanes will take. Although there is no cause to believe that hurricanes are endogenous when proper controls are included, I estimate the leads of a hurricane to test for the presence of differential trends.

The basic event study framework for estimating the year-by-year effect of a hurricane up to ten years after its occurrence is:

[18] If I restrict the sample to estimate ten leads and lags using the same county-hurricane-year observations, I end up with less than 30 counties that experience major hurricanes. In contrast, there are 119 counties that experience a major or minor hurricane when the same restrictions are imposed.

$$O_{ct} = \sum_{\tau=-10}^{10} \beta_\tau H_{c,t-\tau} + \beta_{ct}^{-11} + \beta_{ct}^{11} + \alpha_c + \alpha_t + 1\left[coastal\right]\alpha_t + \varepsilon_{ct} \quad (1)$$

$$c = \text{county};\ t = \text{ year};\ \tau = \text{ lag}$$

O_{ct} is some economic outcome, as described in the data section. H_{ct} is a hurricane indicator, equal to 1 if the county is reported to have experienced any hurricane in year t, according to the NOAA Best Tracks data. I normalize the effect the year before the hurricane, $\tau = -1$, to zero. $\left\{\beta_{ct}^{-11}, \beta_{ct}^{11}\right\}$ are indicators for hurricanes outside the estimation window. α_c and α_t are county and year fixed effects.

$1\left[coastal\right]\alpha_t$ is a set of year fixed effects for coastal counties. These fixed effects allow the time indicators of coastal counties to differ from the average. Including this interaction term is necessary because coastal counties are more likely to experience hurricanes *and* may experience different growth trajectories. For example, the population data show that the coastal population has grown disproportionately in the past 30 years. Coastal counties are defined by the NOAA's Strategic Environmental Assessments Division.

I combine hurricane indicators into two-year bins to increase the power of the estimation.[19] The combined lags are years 1 and 2, 3 and 4, 5 and 6, 7 and 8, 9 and 10. The combined leads are -1 and -2, -3 and -4, -5 and -6, -7 and -8, -9 and -10. The assumption needed for this estimation procedure to be valid is that the effects of a hurricane for the years that are grouped together have the same sign and distribution. Year 0, which is the year that the hurricane makes landfall in a county, is not combined because the assumption that the effects in year 0 and year 1 are similar may not hold.

$$\begin{aligned} O_{ct} &= \beta_0 H_{ct} + \sum_{\tau=-5}^{-1} \beta_{-2\tau} \max\left\{H_{c,t-2\tau}, H_{c,t-2\tau-1}\right\} \\ &\quad + \sum_{\tau=1}^{5} \beta_{-2\tau} \max\left\{H_{c,t-2\tau+1}, H_{c,t-2\tau}\right\} \\ &\quad + \beta_{ct}^{-11} + \beta_{ct}^{11} + \alpha_c + \alpha_t + 1\left[coastal\right]\alpha_t + \varepsilon_{ct} \end{aligned} \quad (2)$$

The coefficient β_0 corresponds to year 0, which is the year in which the hurricane makes landfall in the county. For example, 1989 is year 0 for Hurricane Hugo, one of the hurricanes in my sample, and 1992 is year 0 for Hurricane Andrew.

The notation for the hurricane bins is unconventional, but straightforward. $\max\left\{H_{c,t-2\tau+1}, H_{c,t-2\tau}\right\}$ takes the maximum of the county's hurricane indicators in subsequent years, grouping them as described above. The set $\sum_{\tau=1}^{5} \beta_{-2\tau} \max\left\{H_{c,t-2\tau+1}, H_{c,t-2\tau}\right\}$ thus represents the causal effects of a hurricane 1-10 years following its occurrence. It can be written out as $\beta_{-2} \max\left\{H_{c,t-1}, H_{c,t-2}\right\} + \beta_{-4} \max\left\{H_{c,t-3}, H_{c,t-4}\right\} + \ldots + \beta_{-10} \max\left\{H_{c,t-9}, H_{c,t-10}\right\}$. The reference category is "hurricane one or two years from now", corresponding to $\max\left\{H_{c,t+1}, H_{c,t+2}\right\}$. The coefficients of interest is the set of hurricane lags $\left\{\beta_{-2\tau}\right\}_{\tau=1}^{\tau=5}$

[19] Results using year-by-year hurricane indicators are qualitatively similar, but noisier. The full set of results is available upon request.

and the estimated immediate impact of a hurricane, β_0. The average effect of combined years -1 and -2 is assumed to be 0, so the estimated coefficients should be interpreted as the change relative to the two years before the hurricane.

I do not use damages estimates as the independent variable for several reasons. County-level property damage estimates between 1960 and 2009 are available from the Spatial Hazard Events and Losses Database (SHELDUS).[20] To my knowledge, this is the only database that contains county-level damage estimates for all hurricanes over this period of time. However, the data are estimates made by local emergency officials fairly close to the time of occurrence. At best, they appear to be very imprecise, as discussed in Section 3. Second, damage is not only a function of the hurricane's strength, but of local characteristics such as construction practices and population density, which may be correlated with economic trajectories. Finally, damages may be endogenous with respect to the variable of interests. For example, communities with lower chances of recovery may be damaged relatively more because of poor construction. The county with heavier damages, all else equal, may be in decline or may be less prepared to deal with the disaster overall. Alternatively, the county with larger absolute damages may be more affluent and able to recover more quickly (for example, because of better access to credit, coordination, or governance).

Because there may be unobserved heterogeneity across hurricanes, I also restrict the sample of hurricanes to those for which I can estimate the full set of leads and lags. In practice, this means I am estimating the effects using hurricanes that occurred between 1980 and 1996. To maximize my sample size, I create indicator variables for the county 10 years before and after it experienced a hurricane that was taken out of the sample (i.e., counties that were affected between 1960-1979 and 1997-2006). This allows me to exclude certain county-year observations from the estimation without excluding the county completely.

Many of the outcome variables are autocorrelated as well as correlated with each other. Appendix B shows the empirical auto- and cross-correlation in the outcome variables. The autocorrelation creates multicollinearity concerns, which is why it is useful to rely on joint tests of significance to determine whether there are significant effects.

4.4 Differences in Differences Regression Framework

The basic results suggest that hurricanes may have an effect on the mean of the economic variable, its trend, or both. In addition to estimating the effects over time, I also test for trend breaks and mean shifts in the outcome variable. The trend break specification tests for a change in the slope of the economic outcome after the hurricane, while the mean shift specification tests for a change in the mean, assuming that there is no change in trend. These specifications summarize the net effect of a hurricane more concisely and are more powerful when the assumption of linear trends holds. In addition, if the assumption of parallel trends does not hold, the trend break test is useful for determining whether the hurricane has a significant impact on the economy.

The regression equation for testing for a mean shift controlling for an overall time trend is:

[20] Hazards & Vulnerability Research Institute (2009). Available from http://webra.cas.sc.edu/hvri/products/sheldus.aspx

$$
\begin{aligned}
O_{ct} &= \theta_1 * \mathbf{1}[\text{Hurr in past 10 years}]_{ct} + \beta^{11} post11_{ct} + \beta^{-11} pre11_{ct} \\
&\quad + \gamma_1 \mathbf{1}[\text{Hurr within 10 years}]_{ct} t + \gamma_2 \mathbf{1}[\text{Hurr outside 10 years}]_{ct} t \\
&\quad + \alpha_c + \alpha_t + 1\left[coastal\right]\alpha_t + \varepsilon_{ct}
\end{aligned} \tag{3}
$$

O_{ct} is some economic outcome, such as population or the employment rate. $\mathbf{1}[\text{Hurr in past 10 years}]_{ct}$ is an indicator variable equal to 1 if county c has experienced a hurricane in the ten years prior to and including t. Thus, θ_1 is the variable of interest, representing the average change in the outcome in the eleven years after the hurricane (the year of the hurricane and ten subsequent years).

Because my data span a large time period, including a single linear trend variable may be overly restrictive. Thus, I separately control for the trend in the ten years before and eleven years following and including the hurricane year with the variable $\mathbf{1}[\text{Hurr within 10 years}]_{ct} t$. $\mathbf{1}[\text{Hurr within 10 years}]_{ct}$ is an indicator equal to 1 if county c experienced a hurricane in the ten years before or in the ten years after time t. γ_2, the coefficient on $\mathbf{1}[\text{Hurr outside 10 years}]_{ct}$, controls for the overall trend in hurricane counties outside of the twenty-one year window of interest.

I include indicator variables $post11_{ct}$ and $pre11_{ct}$ to ensure that I am comparing the eleven-year post-hurricane mean to the ten-year pre-hurricane mean. These are equal to 1 if county c in year t experienced a hurricane eleven or more years ago or will experience a hurricane eleven or more years in the future. As before, I control for county, year, and coastal-county-by-year fixed effects with α_c, α_t, and $1\left[coastal\right]\alpha_t$.

The growth rate in outcomes may also be affected by a hurricane. To test for a change in the linear trend following a hurricane (i.e., a trend break model), I add an additional variable to the equation above:

$$
\begin{aligned}
O_{ct} &= \theta_1 * \mathbf{1}[\text{Hurr in past 10 years}]_{ct} + \theta_2 * \mathbf{1}[\text{Hurr in past 10 years}]_{ct} t \\
&\quad + \gamma_1 \mathbf{1}[\text{Hurr within 10 years}]_{ct} t + \gamma_2 \mathbf{1}[\text{Hurr outside 10 years}]_{ct} t \\
&\quad + \beta^{11} post11_{ct} + \beta^{-11} pre11_{ct} + \alpha_c + \alpha_t + 1\left[coastal\right]\alpha_t + \varepsilon_{ct}
\end{aligned} \tag{4}
$$

$\mathbf{1}[\text{Hurr in past 10 years}]_{ct} t$ is the interaction of the eleven-year post-hurricane indicator with year. As above, $\mathbf{1}[\text{Hurr within 10 years}]_{ct} t$ controls for the average trend in the ten years before and ten years after the hurricane. Because I want to compare trends ten years before the hurricane to eleven years after, I include indicators for hurricanes ($post11_{ct}$ and $pre11_{ct}$) as well as linear hurricane-specific trends ($\mathbf{1}[\text{Hurr outside 10 years}]_{ct} t$) outside of this window of interest.

The test for a mean shift without a trend break amounts to testing $\theta_1 = 0$ in equation (3), while the test for a mean shift with a trend break amounts to testing $\theta_1 = 0$ and $\theta_2 = 0$ in equation (4). For the trend break test, I also calculate the hurricane-driven change in the outcome five years after the hurricane (the year of the hurricane and four subsequent years) and eleven years after the hurricane (the year of the hurricane and ten subsequent levels). This is equivalent to calculating $\theta_1 + 5 * \theta_2$ for the five-year change and $\theta_1 + 10 * \theta_2$ for the eleven-year change. Note that the mean shift test restricts the hurricane-driven change to be identical in each year following the hurricane.

5 Empirical Results

5.1 Dynamic Effects of Hurricanes

In this section, I graph the estimated effects of a hurricane from equation (2) in Section 4. Because the results suggest that hurricanes have lasting effects and that there may be some differential pre-trends, following each figure is a table with the results of the trend break and mean shift tests described in equations (3) and (4). All monetary figures are in 2008 dollars. Standard errors are clustered by county. Each regression includes year, county, and year-by-coastal fixed effects. The point estimates from the figures are shown in Appendix Tables A2-A5.

The disaggregated results and the trend break/mean shift estimates are complementary. The trend break and mean shift tests may pick up effects that are not detectable in a single year. However, they may miss non-monotonic dynamic effects. Thus, I view both as important in understanding post-hurricane economics.

Figure 3 shows the impact of a hurricane on the construction sector, measured in terms of employment, total payroll, wages, and the number of firm locations. The y-axis shows the estimated coefficient and the 95% confidence interval. The x-axis represents the number of years since the hurricane; thus, negative numbers refer to leads of the hurricane variable. Because the coefficients are estimated from two-year bin variables, they are plotted at the midpoint of the two years (e.g. the point estimate for 1 and 2 years post-hurricane is plotted at 1.5 years). The coefficient for the two-year bin grouping years -1 and -2 (one and two years before the hurricane) is assumed to be 0.

Looking at the effects of the hurricane on the construction sector is useful for determining whether there are any effects of a hurricane that are observable a year or more after the event. Overall, these estimates clearly show that there are significant effects of a hurricane years after its occurrence. There are no visible impacts on the sector in the year of the hurricane. Subsequently, employment falls to $8-24\%$ below pre-hurricane levels (implying $84-218$ fewer construction workers), total payroll declines by $13-23\%$ ($\$3.3-5.3$ million), and the number of establishments is about 9% (4.8 construction firm locations) lower.[21] Wages do increase in years $0-4$, by $4.6-7.7\%$ ($\$1,152-1,966$), suggesting there may be a change in the composition of labor demand (e.g., more demand for specialized workers) or lower labor supply. The overall decline indicates a drop in construction demand three to eight years later: either less housing is being built or existing housing is being repaired less. This is possibly due to repairs being moved up temporally because of the hurricane. However, it is not clear whether the decline is temporary; nine to ten years later, the construction sector employment, number of establishments, and wages are still significantly lower than they were the year before the hurricane, but appear to be slowly increasing.

Table 7 shows the mean shift and trend break test results corresponding to Figure 3. There is a significant trend break in construction establishments, total wages, and per worker wages, and the estimated coefficients follow the pattern seen in Figure 3. Specifically, the number of construction firm locations (establishments)

[21] I estimate this by computing $e^{(\beta_l+\mu)}-e^{(\mu)}$, where μ is the mean of the outcome and β_l is the estimated effect of the hurricane l years ago. This gives the approximate hurricane-driven change for logged variables.

declines by 1.5% each year while total construction payroll declines by 2.9%. Construction employment is on average 5.6% lower in the ten years following the hurricane, but does not show a change in trend. Wages increase by an average of 7.3%, but then fall by an additional 1% each year. From the trend break specification, I estimate that construction employment is 17% lower five years after the hurricane and 28% lower at the end of my estimation sample, ten years after landfall.

Figure 4 shows the estimated effect of a hurricane on basic economic measures: population, the employment rate, and total and per capita earnings of residents. Population, net earnings, and net earnings per capita do not change significantly in any given year and the effects of a hurricane zero to ten years after are not jointly significant for any of these outcomes. Employment is about 1 percentage point lower five to ten years after the hurricane and does not return to its pre-hurricane levels. The post estimates for the employment rate are jointly significant. Total and per capita net earnings by residents and the employment rate show a significant pre-hurricane trend, as evidenced by the significance of the joint test of hurricane leads.

Trend break and mean shift tests in Table 8 indicate that there are no significant changes in the mean or trend of population, total or per capita earnings. The employment rate is estimated to decline by 0.18 percentage points annually following the hurricane and is 1.7% lower at the end of the estimation period.

Figure 5 shows the effect of a hurricane on what I call the "producer side": total employment, wages, and the number of individual business establishments. Employment appears to decline while per worker wages increase temporarily. However, there are also significant pre-trends which could be confounding the result. The mean shift and trend break tests are useful in this case.

Table 9 shows the trend break and mean shift test results for the outcomes in Figure 5. There is no significant trend change in any of the variables, but the number of establishments is on average 2.2% larger. With no estimated change in total employment, this implies that the average number of employees per establishment may have decreased. Overall, the producer side does not appear to be significantly impacted.

Figure 6 shows the effect of hurricanes on unemployment insurance and income maintenance payments, as well as transfers from businesses and governments to individuals. Per capita transfers to individuals from businesses immediately increase by 11.7% following a hurricane. Per capita income maintenance payments show no immediate change, but increase by $5.0 - 5.5\%$ three to eight years after a hurricane. Per capita unemployment insurance payments increase immediately by 12.3% and are $13 - 27\%$ higher in years one through ten after a hurricane. Similarly, overall per capita transfers from the government to individuals increase by 1.8% in the year of the hurricane and are $3.1 - 4.7\%$ larger in subsequent years.

There are also pre-trends in the transfer variables, as evidenced by the significance of the joint test of the lead variables. Thus, in Table 10, I show the results of the mean shift and trend break tests for the outcomes shown in Figure 6. The mean shift test indicates a 2.1% average increase in per capita government to individual transfers, equivalent to about \$70 per person per year, an insignificant 0.8% average increase in income maintenance, and a 21% average increase in per capita unemployment benefits, equivalent to about \$18 per person per year. Per capita business to individual transfers in the eleven years following the hurricane are estimated to be 4.4% higher than the pre-hurricane transfers, or about \$3.6 per year. There are no significant changes in the trends of any of these variables. Assuming a 3% discount rate, the present discounted value (PDV) of the unemployment payments is about $176 per capita. The PDV of all government transfers is about $670 per capita, and the PDV of transfers from businesses is $34 per capita. Thus, post-hurricane transfers from general social programs are larger than transfers from disaster-specific programs and much larger than insurance payments.

5.2 Robustness

Joint tests of the lead hurricane indicators in Appendix Tables A2-A5 suggest that there are pre-trends in most of the hurricane variables. One explanation for the significance of these lead coefficients is that hurricane-prone areas have a different time trend. Combined with the fact that outcomes are autocorrelated, this implies that leads of the hurricane variable are likely to be significant spuriously, due to the omitted variable bias. Unfortunately, the paucity of hurricanes does not allow me to estimate a county-specific trend and include year and county fixed effects at the same time. In Appendix C, I use a Monte Carlo simulation to demonstrate that the pre-trends are not likely to affect the validity of the post-hurricane estimates in this case. In addition, the overall time trend is estimated to be insignificant in all trend break tests except for per capita transfers from businesses and per capita unemployment payments (which are both estimated to be decreasing in counties affected by hurricanes).

One possible interpretation of the decline in the local construction sector is spatial; the construction activity may have simply shifted to nearby counties without any aggregate effect. The implications of spatial changes, while non-trivial for the local economy, are different than if there's a general downturn in the housing market. To address this question, I estimate the affected-county change in all housing starts and single family housing starts, using data provided by McGraw-Hill. I find that housing starts fall by 8.4% on average and housing starts per capita fall by 8.9%. These estimates are significant at the 5% level. The change in single family housing is estimated to be -5.7% to -6.1% on average, but the estimates are not statistically significant. The fall in housing starts indicates a substantial change in construction demand. Thus, the downturn in the local construction sector is not solely driven by spatial shifts in construction activity.

The violation of the parallel trends assumption is a potential threat to validity. This can occur if hurricane-prone counties have a different growth path than counties with lower hurricane risk. In this section, I perform various robustness checks to verify that the results in Section 5.1 hold and to examine the variation in the magnitude of estimated effects. Overall, the qualitative result of higher transfer payments with no corresponding change in other variables is robust across different samples, and the magnitude of the estimated increase is relatively stable.

In the first robustness test, I restrict the sample to only counties affected once by a hurricane between 1980 and 1996 (in other words, only the treated group). Although the sample is smaller, the basic results still hold and are stronger in some cases. The fall in the construction employment is significant and estimated to be about 9.6%, on average. The downward trend in the employment rate following a hurricane is estimated to be larger, about 0.26 percentage points per year compared to 0.18 percentage points before. Overall employment is 1.7 percentage points lower 5 years after the hurricane and 3.2 percentage points lower eleven years after.

As before, the overall economy is largely unaffected, except for a marginally higher number of establishments. The estimated amount of extra government transfers is somewhat larger, but comparable to the original estimates. Per capita unemployment payments on average increase by about \$20.6 per capita or \$196 in PDV, while total transfers increase by \$73 per year or about \$697 in PDV. Per capita transfers from businesses are higher by \$3.1 per year or \$29 in PDV and income maintenance payments are unaffected. In addition to the mean increase, unemployment payments show an upward trend of about 2.7% per year. They are estimated to be 39% higher five years after the hurricane (equivalent to \$38 per capita) and 56% or \$58 per capita higher eleven years after the hurricane.

Another way to construct the control group is by imposing initial balance in hurricane risk. I do this by constructing a hurricane risk variable, using historic (1981-1970) hurricane data and propensity score matching. However, this still does not balance the 1970 covariates. To address this, I construct another sample that imposes risk balance as well as 1970 covariate balance.

The simple risk-based matching yields results that are very similar to the main sample and in some cases produces more precise estimates. The average fall in single family housing construction is estimated to be 7.8% or 8.1% in per capita terms and is significant. The employment rate falls by 0.19 percentage points per year, while changes in population and wages are insignificant. Per capita transfers from the government increase by 2.2%, while unemployment insurance payments increase by 23.3% on average, with an increasing trend.

The more restrictive matching procedure that imposes 1970 covariate balance as well as hurricane risk balance yields very similar qualitative and quantitative results. Per capita transfers from the government increase by 2%, on average, while per capita unemployment payments increase by 22%. Total housing construction falls on average by 9.7% or 10.2% in per capita terms.

One other concern with the basic specification and sample is that there may be spatial effects. In other words, a neighbor of a centrally affected county may also be affected. This could be either due to unmeasured hurricane destruction, as discussed in Section 3, or because of spatial economic spillovers. The spillovers can be positive or negative, so the sign of the bias created by spatial effects is ambiguous. To see if spatial spillovers are a concern, I omit unaffected neighbors of counties that experience hurricanes for eleven years after the hurricane. The construction sector estimates are qualitatively similar to the original estimates, but the changes in the number of establishments and total wages paid are only marginally significant. As before, the average construction wage increases by an average of 8.6% following the hurricane but shows no downward trend in this sample. This suggests that some of the downturn in the county's construction sector is offset by an increase in the neighboring counties. These results suggest that hurricanes may permanently affect the business patterns in centrally affected and neighboring counties.

When neighboring counties are ignored, population is still estimated to remain unaffected, but total and per capita earnings are estimated to be on average 4% higher. The employment rate shows a downward trend of about 0.31 percentage points per year. The employment rate is not significantly different from the pre-hurricane rate five years after the hurricane, but is about 2.7 percentage points lower eleven years after, which is slightly larger than the original estimate. This higher earnings and slightly larger fall in employment rate suggest that spatial effects may be present and that they are positively correlated with the changes in the affected economy. In other words, per capita earnings also rose and the employment rate also declined slightly in neighboring counties.

Estimated transfers into the area are slightly smaller than before, with estimated per capita unemployment payments that are about 22% larger per year and growing at 5.5% per year, on average. Total transfers from the government increase by 2.2% on average and are estimated to grow by 0.45% each year. The point estimate is equivalent to an increase in total transfers of $\$59.7$ per year or $\$569$ in PDV. Per capita transfers from businesses are slightly larger than estimated before, about $\$40$ in PDV or $\$4.2$ per year. Thus, even when potential spatial effects are accounted for, the estimates do not change much. However, spatial effects have not been extensively studied and represent an important area for future research.

One other potential confounder is that those likely to receive government transfers may be moving into the counties affected by hurricanes from nearby counties so that there is no aggregate impact on transfers, only a compositional change. One way to test for this is to look at changes in transfers on the state level. Unfortunately, the affected population represents 11% of the state population on average. Thus, the power to detect an aggregate affect is low. Instead, I look at the changes in transfers in counties whose center is within 50 miles from the center of the affected county (including the affected county itself). This distance should be large enough to capture potential compositional changes, but not so large that the power to detect a change in transfers is reduced.

The results are generally very similar. In the ten years following a hurricane, employment in the 50-mile radius is estimated to fall by 0.24 percentage points per year. Per capita transfers from the government increase by 2.4% on average and show an increasing trend of 0.3% per year following the hurricane. Per capita unemployment insurance payments increase by 26.8% on average and show an increasing trend of 3% per year. The only substantive difference between this and the other samples is that per capita earnings are estimated to decline by an extra 0.51% per year following the hurricane.

In another robustness test, I include all the counties in the hurricane region as controls. The fall in the employment rate is estimated to be about 0.19 percentage points per year, per capita unemployment insurance payments are \$20 per year higher (\$193 in PDV) and are estimated to be rising by 2% each year. Per capita transfers from the government increase by \$68 per year or \$649 in PDV, while transfers from businesses are \$2.6 larger (\$25 in PDV).

Finally, I repeat my analysis using coastal counties only. Coastal counties tend to suffer more damage from hurricanes because of the additional threat of storm surge. There is no estimated change in construction employment or the number of establishments, although the point estimates are similar. Construction wages are still estimated to initially increase and subsequently fall. There is no significant fall in the employment rate. The estimated increases in transfers are slightly larger than the original estimates, with unemployment insurance payments rising by $\$197$ per capita in PDV and total per capita transfers increasing by $\$834$ in PDV. The change in per capita business transfers, although similar in magnitude to previous estimates, is only marginally significant. The magnitude of the estimated employment drop is also very small, implying that the insignificance of this result is not driven only by the smaller sample size. Possible explanations include better building practices, which mitigate the effect of the hurricane. Alternatively, the mix of residents and how they are affected by the hurricane may be different. Finally, rebuilding, which should increase labor demand, may take longer, increasing the demand for workers and delaying the fall in employment.

Adding state-by-year fixed effects to the basic specification generally makes the results insignificant. This is not surprising given the autocorrelation of the outcomes and relatively few counties in the sample. The trend break and mean shift tests show no change in trend for any of the outcome variables. Construction employment is on average 13% lower, but this is only marginally significant. Per capita unemployment payments are estimated to be 9.5% larger in each year following the hurricane. Transfers from businesses to individuals are no longer estimated to be significantly higher. As these represent insurance payment, which should increase following a hurricane, this suggests that including state-by-year fixed effects is overly conservative.

5.3 Interpretation and Discussion

The construction estimates show that hurricanes have non-monotonic medium-run effects on that sector, with an initial increase in earnings followed by a decline three to eight years after the hurricane. However, the effect on general economic variables, such as population, employment, and wages, is small or insignificant. Although the US has a developed disaster response system, my estimates suggest that traditional social safety nets, such as unemployment insurance, also play an important role in post-disaster economics. The largest empirical effect of a hurricane is on non-disaster transfer programs, the transfers from which increase substantially after a hurricane. For a county with the average population of $78,000$, the estimated increase of $\$500 - \$700$ per capita in non-disaster government transfers translates to a total of $\$39 - \$55$ million. This is much larger than the estimated disaster aid, which contributes \$356 per capita, and could have non-trivial fiscal implications in the future if climate change intensifies the strength of hurricanes. Together, disaster and non-disaster transfers replace all or nearly all the direct damages caused by the hurricane. These estimates also imply that the fiscal impact of natural disasters is more than twice as large if non-disaster transfers are also considered. Although in the simplest public finance framework transfers are welfare-neutral, in practice the deadweight loss of taxation is estimated to be $12-30\%$ of revenue (Ballard et al., 1985; Feldstein, 1999). Assuming a 15% deadweight loss implies a real cost of \$53 per capita per hurricane for disaster transfers (\$$4.1$ million for a county with a population of $78,000$) and $\$75-\$105$ ($\$5.9-\$15.8$ million) per capita per hurricane for non-disaster transfers. Taking the upper estimate of 30% doubles these estimates. Moreover, the marginal deadweight loss of taxation, which is the relevant cost if we're considering mitigating the effect of hurricanes, is thought to be much larger. Feldstein (1999) estimates it to be $\$1 - \$2$ per dollar of revenue. Thus, this additional cost of hurricanes to society is not trivial.

Of course, the estimate that non-disaster transfers are $1.5 - 2$ times larger than disaster transfers does not imply that they are $1.5 - 2$ times as important. The designs of the disaster and non-disaster government programs suggest that they may be complementary. Social insurance programs may fill an important gap left by current disaster policy and private insurance markets. Disaster transfers target individuals immediately impacted by the disaster and provide funds to restore public infrastructure. Disaster aid to individuals makes up only about 39% of total disaster aid; the rest is allocated to activities such as debris cleanup and restoration of public buildings and roads (FEMA, personal communication). Private insurance targets individuals who sustain disaster losses in the form of property damage. Non-disaster social insurance programs, such as unemployment insurance, are able to target individuals who are affected indirectly.

Although the US has a disaster-related unemployment insurance program (it is included in the figure for disaster-related transfers), it provides benefits only to those who can show that they lost their jobs directly as a result of the disaster. Individuals who lose their jobs as a result of an economic downturn months to years later would be unable to claim these benefits. If there are lasting economic effects (as seems to be the case with US hurricanes), people may be affected months to years following the disaster. In that case, disaster aid and property insurance are not helpful, but standard social safety net programs will be automatically triggered. The presence of these programs can thus serve as insurance against delayed effects of natural disasters. As discussed in the conceptual framework, non-disaster transfers may buffer the economic shock of a hurricane and also explain why there are no large changes in population or wages. According to the World Labour Report 2000, seventy-five percent of the world's unemployed are not receiving any benefit payments (International Labour Organization, 2000). In addition to making individuals vulnerable to economic shocks, my analysis suggests that a lack of social safety nets also has implications for the economic recovery of an area following a natural disaster.

Whether the presence of unemployment insurance for those living in disaster areas is welfare-improving on a societal level is not straightforward. On one hand, the presence of insurance against economic losses not covered by homeowner's and flood insurance is a benefit when individuals are risk averse or credit constrained. Theoretically, they may allow credit constrained individuals to avoid moving costs during rebuilding. However, disaster risk is not currently accounted for in unemployment insurance premiums. This subsidizes business activity in disaster-prone areas, which decreases social welfare. Thus, disaster and non-disaster transfers may be creating a moral hazard problem. In addition, there are many other distortions in insurance and aid policy that discourage insurance and encourage people to live in disaster-prone areas. This makes even a theoretical welfare analysis of unemployment insurance difficult.

6 Demographic Changes

One possible explanation for the increase in unemployment payments and overall government transfers is changes in the demographic composition of an area. To investigate this, I compute the fraction of population that is (a) under 20 years old, (b) between 20 and 64 years old, and (c) 65 and older, using age-specific population data from SEER. I also consider the logs of these three populations and the mean age in the county. As with the previous outcomes, I use the trend break and mean framework in equations (3) and (4) to look at the ten-year change. For seeing how demographics evolve over time, I use the disaggregated specification in equation (2).

The disaggregated results are shown graphically in Figure 7. The mean shift and trend break tests are shown in Table 11. There is indeed evidence of a change in the age structure of the county. In particular, the fraction of population under 20 is 0.0067 higher 10 years after the hurricane, a 2% increase over the pre-hurricane mean of 0.31. The fraction over 65 is 0.0049 lower, a 4% decrease relative to the mean. These changes are significant at the 1% and 5% levels, respectively. The mean age in the county is estimated to be 0.26 years lower ten years later.

A similar but less significant pattern holds for the log population in each of these three groups, as shown in Appendix Figure A1 and Appendix Table A6. In this case, only the increase in the number of young people is estimated to be significant. Specifically, ten years after the hurricane, the size of the young population is estimated to be 4% larger than before the hurricane. Population data by race, also from SEER, indicate that there is no change in the fraction of population that is black or the fraction that is white; the same is true for log white and log black populations.

This change in the age composition is inconsistent with the changes in non-disaster transfers. Total government transfers include social security and disability payments. There is no a priori reason to think that a larger number of young people and a decline in the number of elderly would increase the total transfers. Young people are more likely to be unemployed than the elderly, but most of the people in the "under 20 years old" category are unlikely to be receiving unemployment insurance payments. When I separate the category "20 to 64 years old" into ten-year age categories, I find that there is no change in the fraction or log of population that is between 20 and 29, 30 and 39, or 40 and 49 years old. There is a ten-year 0.003 increase in the fraction of population that is between 50 and 64, corresponding to an increase of 0.039 log points. The size of this increase is not large enough to explain the increases in transfers. This age group makes up about 14% of the total population. To explain a non-trivial part of the increase in government transfers, each person in this age group would have to be receiving an implausibly large amount of them.

This demographic change does raise concerns about other unobserved changes in the population. However, to the extent that the changes in unobservable characteristics are correlated with the changes in observable ones, this is not likely to be an issue. Disaggregated estimates indicate that the compositional change is gradual, while the increases in the unemployment insurance and overall transfers are immediate and, in the cases of unemployment insurance, non-monotonic. If the non-disaster transfers were driven by demographic changes, I would expect the change in the age profile to correspond to the change in transfers. As the two differ, it's likely that the demographic change is another effect of the hurricane that is unrelated to the change in transfers. One possible explanation for the demographic change is a change in the composition of job opportunities that makes the county a relatively less attractive place to retire and a relatively more attractive place to raise children. Another is different risk preferences across different ages combined with updated beliefs following the hurricane. If the elderly are more risk averse, they will be more reluctant to live in a hurricane-prone area. Population as a whole may not decrease if housing prices adjust to compensate for the increase in the perceived risk of living in the county.

7 Heterogeneity of Effects by Wealth

Understanding the determinants of the post-disaster economic trajectory is important for policy design. The wealth of an area, such as income and house values, is likely to be important in determining how its economics are affected by a hurricane.

Whether wealth is measured by house values or median income may matter for the estimated heterogeneity in post-hurricane economics because hurricanes destroy housing. The median home value may be a good proxy for the absolute level of the wealth shock experienced by an area's residents. Income could be an important predictor of post-disaster economics because it may proxy for borrowing constraints, among other things. The poor typically have lower access to credit. If they cannot borrow, their labor supply or mobility response following a capital shock may differ from richer individuals. Specifically, credit constraints can cause the poor to supply labor inefficiently or prevent them from moving, which exacerbates the negative welfare effect of the initial shock. Other factors can also be at play: for example, Masozera et al. (2007) find that poor neighborhoods are less likely to have flood insurance and vehicles, suggesting that they may have a harder time dealing with the disaster's aftermath.

To look at the effects of wealth on post-hurricane dynamics, I interact the county's quartile for (a) 1970 median housing value and (b) 1970 median income with the hurricane indicator ten years before and after its occurrence. The data on income and housing values are from the Census. As in the main trend break and mean shift specifications, I compare the means and trends of low and high-income counties before and after the hurricane. First, I estimate a mean shift model that allows for an overall time trend, but has no differential time trends after the hurricane:

$$\begin{aligned} O_{ct} \quad = \quad & \theta_1^{TOP} * \mathbf{1}[\text{Hurr in past 10 years}]_{ct} * TOP^c_{1970} \\ & + \theta_1^{BOT} * \mathbf{1}[\text{Hurr in past 10 years}]_{ct} * BOT^c_{1970} \\ & + Controls_{ct} + \varepsilon_{ct} \end{aligned} \tag{5}$$

O_{ct} is some economic outcome, as before. TOP^c_{1970} is an indicator equal to 1 if the county was in the top quartile in 1970 while BOT^c_{1970} is the corresponding indicator for being in the bottom quartile. Thus, the changes in the mean are relative to counties that are in the two middle quartiles. To test for a differential change in the mean, I compare the estimated mean shift for the counties in the upper quartile of income (θ_1^{TOP}) to the mean shift in the bottom quartile (θ_1^{BOT}). Specifically, I compute $\theta_1^{BOT} - \theta_1^{TOP}$ and whether this is statistically different from 0. $Controls_{ct}$ ensures that I am comparing the ten year pre-hurricane means to the eleven year post-hurricane means. It includes a quartile-specific trend variable for the 21-year window around the hurricane (minus ten years to plus ten years), as well as a set of year, county, and coastal-by-year fixed effects, indicators for hurricanes outside the time window of interest, and trends outside the window of interest.

In order to test for a trend break, it is necessary to add two more variables which capture post-hurricane changes in the trend by quartile:

$$\begin{aligned} O_{ct} \quad = \quad & \theta_1^{TOP} * \mathbf{1}[\text{Hurr in past 10 years}]_{ct} * TOP^c_{1970} \\ & + \theta_1^{BOT} * \mathbf{1}[\text{Hurr in past 10 years}]_{ct} * BOT^c_{1970} \\ & + \theta_2^{TOP} \mathbf{1}[\text{Hurr in past 10 years}]_{ct} * TOP^c_{1970} t \\ & + \theta_2^{BOT} \mathbf{1}[\text{Hurr in past 10 years}]_{ct} * BOT^c_{1970} t \\ & + Controls_{ct} + \varepsilon_{ct} \end{aligned} \tag{6}$$

To test for a differential change in the top and bottom quartile counties, I compare the 10-year change in the top quartile ($\theta_1^{TOP} + 10 * \theta_2^{TOP}$) to the 10-year change in the bottom quartile $\left(\theta_1^{BOT} + 10 * \theta_2^{BOT}\right)$. As in trend break equation (4), $Controls_{ct}$ ensures that I am estimating trend changes in the eleven years after the hurricane relative to the ten years before and includes the same set of fixed effects and quartile-specific trends. In addition to the variables included for equation (5), it includes quartile-specific post-hurricane indicators to allow for a mean shift.

Due to the small sample of hurricanes and affected counties, it is difficult to estimate the importance of these variables precisely, so these results should be taken as suggestive. Note that the quartile indicators also capture other differences between areas, such as race and other demographics. This means that the estimated coefficient should not be interpreted as the marginal effect of having more expensive housing, but as the effect on the average high housing value county in the hurricane region.

The average median family income in a county that experienced one hurricane between 1980 and 1996 is $\$40,000$ (2008 dollars), with a standard deviation of $\$9,595$. The bottom ten percent of counties has median incomes of $\$30,991$ and lower, while the top ten percent has median incomes of $\$51,954$ and higher. The variation in median housing values is similar, with a mean of $\$59,297$, a standard deviation of $\$17,585$, and tenth and ninetieth percentiles of $\$37,894$ and $\$82,580$, respectively. The distribution of median family income and housing values for the hurricane region as a whole is similar.

I focus on the differences in the post-hurricane employment rate, per capita earnings, population, and transfer payments. In Table 12, I show the results of the mean shift and trend break tests by the quartile of median housing value. There is no significant change in population. Per capita earnings increase on average in low housing value counties and subsequently decrease (relative to counties in the two middle quartiles). The reverse pattern holds in high housing values counties, so that ten years after the hurricane, per capita earnings changes are not estimated to be significantly different between high and low housing value counties. Concurrently, the employment rate in low housing value counties is also estimated to be falling following an insignificant increase in the mean. Again, the opposite pattern is observed in high housing value counties. Ten years after the hurricane, the employment rate in low housing value counties is substantially lower than in high housing value counties.

Estimate changes in per capita overall transfers from the government and per capita unemployment insurance are also qualitatively different from medium housing value counties. Per capita transfers from the government are substantially higher in low-value counties and subsequently decrease while in high-value counties they are substantially lower on average, but show a positive trend change. Per capita unemployment insurance increases by an average of 21% in low-value counties and shows an upward trend while remaining unchanged in high-value counties. These results highlight interesting qualitative differences between counties of different housing values and suggest that government transfers may play a larger role in low housing value counties in the aftermath of a hurricane.

Appendix Table A7 shows the corresponding estimates for high-income and low-income counties. Overall, the estimates follow the pattern in Table 12, but are somewhat less significant. Repeating the analysis using only the counties affected by the hurricane or ignoring unaffected neighbors leads to very similar results.

Overall, hurricanes appear to produce lasting differences in areas that differ in incomes and housing values, but the mechanism for how and why this occurs cannot be determined with the current data. The differential increase in per capita transfers reinforces the idea that these may also play an important role in absorbing the impact of the shock. Because heterogeneity in the post-hurricane economic dynamics should be an important factor for policy design, potential explanations such as differential credit constraints and moving costs deserve further detailed study.

8 Conclusion

If current demographic and economic trends continue, damages from natural disasters will increase, both in absolute terms and as a percentage of GDP. In addition, climate change is projected to increase the frequency and intensity of extreme weather events. Projections for future increase in disaster damages due to climate change are highly uncertain but thought to be large. A country's infrastructure and institutions have been identified as important determinants of the impact of extreme weather events, both theoretically and empirically. Thus, informed policy has the potential to reduce the damage caused by extreme weather and mitigate its economic impacts.

However, the economic impacts of extreme weather are understudied. Most of the literature to date has focused on studying damages or very short-run impacts on isolated variables; we still lack a comprehensive picture of post-disaster economic dynamics. The economic impact of a given damage level is not pre-determined. In particular, transfer programs designed for general economic downturns, such as unemployment insurance and food stamps, can act as buffers against adverse economic impacts following destruction. First, this has implications for the actual costs of a disaster: in addition to money spent on disaster relief, extreme weather has fiscal effects on other government transfer programs. Second, ignoring traditional transfer programs attributes too much of a developed economy's resilience to its wealth or disaster response policies and not enough to general social policies.

I estimate the dynamic economic effects of hurricanes on US counties, focusing on population, employment, wages, and transfers to individuals. Population and wages are largely unaffected in the ten years following the hurricane, while the employment rate declines steadily. The construction sector employment declines substantially.

I find that hurricanes have large and persistent effects on non-disaster transfer payments. Real transfers from traditional safety net programs over the eleven years following the hurricane (including the year of the hurricane) are estimated to total $\$500 - \$700$ per capita, which is much larger than the disaster-related transfers of $356 per capita. Insurance payments increase temporarily in the year of the hurricane but add only an estimated $\$30 - \$40$ per capita in present discounted value.

Most of the transfers from traditional safety net programs are estimated to occur later than government disaster transfers and insurance payments typically occur, suggesting that traditional safety net programs are filling in a gap in public and private disaster insurance. Private insurance in this case is best suited to targeting those who lose their homes, but traditional social insurance may target those who are affected by the dynamic economic effects of the disaster.

The fact that some of the negative economic impacts of hurricanes, such as a lower employment rate, do not show up until several years after the hurricane may be due to feedback effects that are amplified over time. Another possibility is that federal aid plays a significant role in early post-hurricane economics. Estimating the impact of federal disaster aid is thus an important area for future research.

My results also show gradual demographic changes in the affected county. Specifically, the mean age ten years after the hurricane is about 0.26 years lower. This is driven by an increase in the fraction of the population under 20 and a decrease in the fraction of the population 65 and older. These changes could be caused by differential economic opportunities for different demographic groups or by updated beliefs about risk and risk preferences that vary across groups. Finally, a county's wealth and housing stock value also seems to matter for employment and earnings trajectories. Whether this is because of different decisions or constraints of individuals or because of differential hurricane impacts is another area for future research.

My findings have several suggestive policy implications. First, policymakers should consider the potential role of non-disaster programs in recovery. Second, they may want to incorporate disaster-related unemployment risk into the design of social safety net programs to avoid moral hazard issues. Third, as the fiscal costs of disasters are larger than previously thought, implementing mitigation programs is correspondingly more beneficial. Admittedly, I cannot estimate what the effects of a US hurricane would be without social insurance programs using the current data. Given that much of the world's population does not have access to social or disaster insurance and is at an increasing risk of natural disasters, the causal effect of social insurance on disaster impacts and whether it creates moral hazard are two other areas that deserve further study.

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Appendix A. Distribution of Eye Diameters

Because eye diameters are related to the size of the affected area but the relevant data are not systematically collected, I have to consider how not observing the diameter might impact estimates of a hurricane's effect. The most comprehensive information on the characteristics of North Atlantic storms come from air reconnaissance data analyzed by Weatherford and Gray (1988). About 15% of cyclones in the data have eyes less than 18.6 miles in diameter, 25% have eyes $18.6 - 37.3$ miles in diameter (average is 27.3 miles), and 8% had larger eyes (the largest was 149 miles). Most (53%) had no discernible eye and very few had eyes larger than 49.7 miles in diameter. Thus, nearly 70% of all hurricane eyes appear to not be very large.

Appendix B. Cross- and Auto-correlation in Outcome Variables

In Appendix Tables A8-A10, I show some of the cross-correlation and autocorrelation coefficients of the variables used in the analysis (in logs), taking out year and county fixed effects.

Table A8 shows that total unemployment payments are significantly and positively correlated with total wages and employment, although the magnitudes are not large (8.6 and 6.3%, respectively), while unemployment payments per capita are negatively correlated with these variables (-23.1% and -32.9%, respectively). Earnings per capita are negatively correlated with income maintenance payments (the magnitude is -6.4%) while total earnings are positively correlated (21%). State and local tax receipts are highly positively correlated with both total earnings (82.3%) and earnings per capita (58.8%).

Table A9 shows the correlation between the construction sector variables and other economic outcomes. The number of construction firms, employees, wages, and payroll are heavily correlated with overall earnings and earnings per capita and the magnitudes are large. A 10% increase in earnings per capita is associated with a 7.3% increase in the number of construction firms, a 10.6% increase in the number of construction employees, and 12.6% and 2.3% increases in total construction payroll and wages, respectively.

Table A10 focuses on the autocorrelation between the outcome variables. The autocorrelation coefficients are all significant at the 1% level and range from 0.095 for construction wages per worker to 0.986 for overall business receipts. Total population and government transfers to individuals and non-profits are also heavily correlated, while earnings per capita, business transfers to individuals, and payroll wages per worker are among the least correlated (although the correlation coefficients are still between 0.275 and 0.693). This also leads to an R-squared that is nearly equal to 1.

These cross- and auto-correlations present some challenges for the estimation. In particular, it may be more difficult to estimate the effect of a hurricane in a given time period precisely. For this reason, I rely on both joint and individual significance testing when interpreting the results. Because I can identify the precise onset of a hurricane, I can still estimate its duration and net impact fairly accurately.

Appendix C. Risk-related Trends, Autocorrelation and Lead Significance: a Monte Carlo Analysis

The F-tests of hurricane lead indicators indicate that they are significant for many economic outcomes. In this section, I use a Monte Carlo simulation to show how this can arise when, in addition to autocorrelation, there is an unobserved time trend that is correlated with hurricane risk and discuss how this affects my estimates. Both heterogeneous time trends and autocorrelation appear to be present in my sample.

I generate a sample of 1000 ”counties” that are observed for 30 time periods. I randomly assign 5% of the observations to experience an ”event”. In addition, each county is assigned an unobserved risk variable which is correlated with the occurrence of the event. The outcome of interest is determined as follows:

$$Outcome_{ct} = \beta Event_{ct} + \gamma Outcome_{c,t-1} + \theta y * Risk_c + \varepsilon_{ct}$$

$Event_{ct}$ is the event indicator for county c in year t. $Risk_c$ is a uniform variable between zero and one, multiplied by the mean of the event indicator for the county (this implies that $Risk_c$ will be correlated with $E_c\left[Event\right]$). I assume that $\beta = 10$, $\gamma = 0.9$, and $\theta = 0.001$. ε_{cy} is standard normal and is identically and independently distributed across counties and time periods.

The risk variable captures the possibility that time trends are related to a county's propensity to be affected by hurricanes. This could be because the county is investing increasing amounts of mitigation over time, insurance is becoming more widely available and adopted or because people are slowly leaving the area as they realize the hazard they face. Alternatively, as the economy becomes wealthier, people may disproportionately prefer to live in hurricane-prone places if there is risk aversion or if wealthier people are more able to weather the shock of a hurricane. All of these factors could produce unobserved heterogeneity in the time trend.

Following the generation of the Monte Carlo sample, I estimate two regression specifications similar to those in the paper. One of them includes leads and the other considers lags only. These are specified as follows:

$$Outcome_{ct} = \sum_{\tau=-5}^{5} \beta_\tau Event_{c,t-\tau} + \beta_{ct}^{6} + \beta_{ct}^{-6} + \alpha_c + \varepsilon_{ct}$$

and

$$Outcome_{ct} = \sum_{\tau=0}^{5} \beta_\tau Event_{c,t-\tau} + \beta_{ct}^{6} + \alpha_c + \varepsilon_{ct}$$

$\left\{\beta_{ct}^{-6}, \beta_{ct}^{6}\right\}$ are indicator variables for the ”event” outside of the estimation window of interest. Thus, this estimation is analogous to the estimation of the effect of hurricanes on the US, with $\{\beta_\tau\}_{\tau=0}^{\tau=5}$ being the estimated effect of the event 0-5 years after relative to the pre-event outcome. Note that the estimated effect of the ”event” in years other than 0 is entirely due to the autocorrelation in the outcome variable and is also possibly affected by the unobserved time trend heterogeneity.

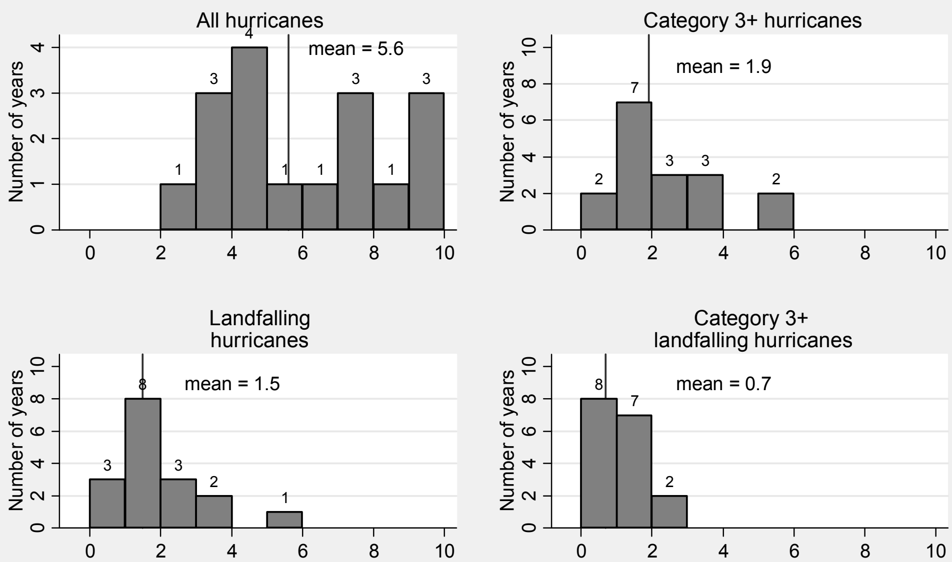
Appendix Table A11 shows the theoretical and estimated effects of the event 0 - 5 time periods after and 2 - 5 periods before its occurrence. Although the theoretical effects of lead variables are zero when no time trends are present, separate and joint tests indicate that all leads negatively affect the outcome. Including the lagged outcome variable does not change the significance of the leads. The inclusion of leads also appears to bias the estimated effect of an event down.

Despite the presence of risk-related time trends, the estimated coefficients of lags appear to be fairly close to the theoretical effect, although they are biased downwards. A priori, it is not clear whether the inclusion of leads will decrease or increase the bias; this depends on whether the time trend is positive or negative.

I do not include the lagged outcome variable in my analysis of hurricanes because the large number of variables combined with high autocorrelatioin makes the estimation ill-behaved. County and time fixed effects are likely to be more important to include. Moreover, I am interested in the overall effects of hurricanes, including through autocorrelation. The lagged hurricane indicators implicitly capture the autocorrelation *and* any non-standard dynamic that may occur following a hurricane (for example, the non-monotonicity of the construction sector response).

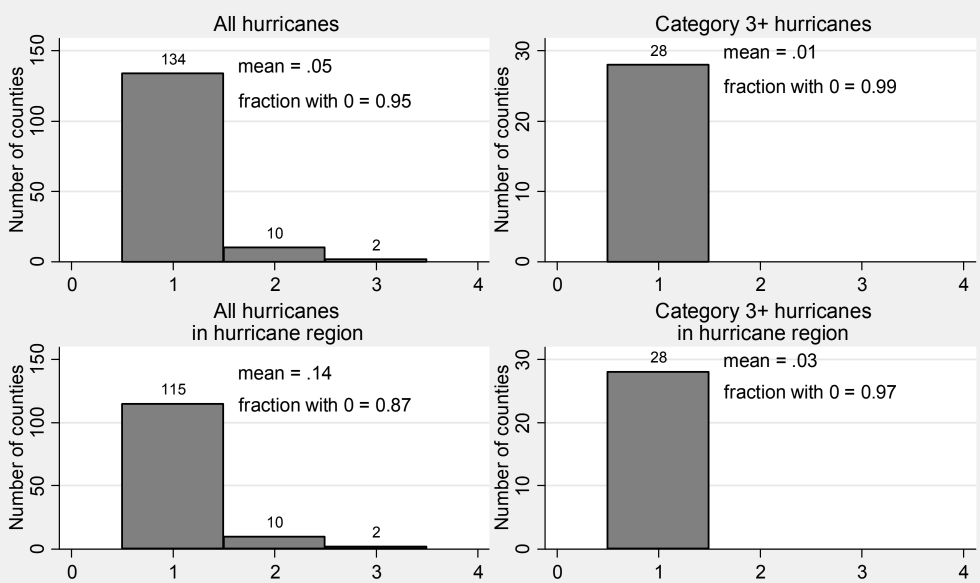
Tables and Figures

Figure 1. Distribution of US hurricanes by year, 1980-1996



In the 'All Hurricanes' panel, the highest category includes years with ten or more hurricanes.

Figure 2. Cumulative hurricanes by county, 1980-1996



Hurricane region is defined as the states of Alabama, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Texas, and Virginia.

Table 1: Predicted changes in the economy following a negative capital shock

<table>
<tr><th></th><th>(1)</th><th>(2)</th><th>(3)</th><th>(4)</th></tr>
<tr><th></th><th colspan="2">Perfectly mobile capital</th><th colspan="2">Imperfectly mobile capital</th></tr>
<tr><th></th><th>No individual moving costs</th><th>Individual moving costs</th><th>No individual moving costs</th><th>Individual moving costs</th></tr>
<tr><td>No transfers</td><td colspan="2" rowspan="2">No change</td><td>No fall in wages, decrease in population</td><td>Fall in wages, weakly decreasing population</td></tr>
<tr><td>Transfers</td><td>No fall in wages, weakly smaller population decrease than above</td><td>Weakly smaller population decrease than above, fall in wages may be smaller or larger</td></tr>
</table>

Table 2: Damages caused by major US hurricanes, 1980-1996

	(1) Mean	(2) Standard deviation	(3) Maximum	(4) Obs.
Panel A: centrally affected counties				
Total building value ($1000's)	10,704,091	32,552,770	268,081,632	99
Building damage ($1000's)	405,555	2,101,017	20,300,000	97
Loss ratio (percent)	1.46	3.85	23.62	97
Total losses ($1000's)	570,558	3,662,500	35,400,000	97
Total per capita loss ($)	1,278	3,336	16,238	97
Displaced households	1,546	10,702	104,559	99
People requiring shelter	449	3,078	29,945	99
Panel B: peripherally affected counties				
Total building value ($1000's)	7,464,867	26,808,163	464,355,684	400
Building damage ($1000's)	8,635	40,294	388,928	390
Loss ratio (percent)	0.15	0.51	5.20	390
Total losses ($1000's)	11,462	57,071	632,972	390
Total per capita loss ($)	113	430	4,816	385
Displaced households	12	85	1,193	403
People requiring shelter	3	23	331	403

Source: HAZUS-MH simulation software published by FEMA. All monetary figures are in 2008 dollars.

Table 3: Determinants of property damages in hurricane region[1]

	(1) Log damages	(2) Per capita damages	(3) Flood insurance payments (log)	(4) Log damages	(5) Per capita damages	(6) Flood insurance payments (log)
Major hurricane	4.236	678.279	3.090			
	(0.426)***	(309.795)*	(0.410)***			
Minor hurricane	2.417	65.184	1.515			
	(0.250)***	(46.066)	(0.247)***			
Category = 1				2.151	72.735	1.131
				(0.297)***	(57.567)	(0.263)***
Category = 2				3.253	39.028	2.769
				(0.411)***	(19.173)*	(0.492)***
Category = 3				4.049	710.213	3.100
				(0.311)***	(399.246)	(0.471)***
Category = 4 or 5				4.642	607.060	3.019
				(0.915)***	(316.198)*	(0.850)***
Tornado	2.061	12.507	-0.008	2.061	12.441	-0.011
	(0.197)***	(6.847)	(0.070)	(0.196)***	(7.174)	-0.070
Flood	0.862	0.380	0.762	0.864	0.299	0.758
	(0.102)***	(5.690)	(0.065)***	(0.102)***	(5.757)	(0.065)***
Severe storm	0.958	8.952	-0.205	0.956	9.075	-0.201
	(0.180)***	(3.915)*	(0.078)***	(0.181)***	(4.213)*	(0.079)**
Depvar mean (median)	9.31 (9.66)	11.00 (0.09)	10.87 (10.80)	9.31 (9.66)	11.00 (0.09)	10.87 (10.80)
Observations	18,592	24,331	7,029	18,592	24,331	7,029
R-squared	0.45	0.08	0.42	0.45	0.08	0.42

Standard errors (clustered by county) in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Damages and flood claims are in current dollars. Includes county and year fixed effects. Property damage data is from SHELDUS. Flood insurance payments data is from the Consolidated Federal Funds Report (CFFR). Time period is 1980-1996 for damages, 1983-1996 for flood claims.

[1] Alabama, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Texas, and Virginia.

Table 4: Descriptive statistics for hurricane aid, 1980 - 1996

	(1) Uniform split[1]	(2) Proportional split[2]	(3) Per capita - uniform split[1]	(4) Per capita - proportional split[2]
Panel A: centrally affected counties only				
Centrally affected, all hurricanes (N = 89)	58,700,000	58,700,000	1,137	356
	(187,000,000)	(260,000,000)	(3,193)	(307)
Centrally affected, major hurricanes (N = 27)	128,000,000	133,000,000	2,018	412
	(332,000,000)	(467,000,000)	(5,623)	(343)
Panel B: all counties listed in declaration				
All observations (N = 568)	8,982,356	8,417,279	160	52
	(48,400,000)	(65,200,000)	(631)	(91)
Centrally affected, all hurricanes (N = 89)	24,600,000	30,100,000	460	131
	(94,100,000)	(152,000,000)	(1,594)	(140)
Centrally affected, major hurricanes (N = 27)	59,200,000	73,400,000	954	187
	(167,000,000)	(273,000,000)	(2,824)	(184)

[1]Assumes aid money is split evenly among all counties in sample
[2]Assumes aid money is split in proportion to the population of counties in sample
Source: NOAA Best Tracks data, PERI disaster declarations. Standard errors in parentheses.
All amounts are in 2008 dollars.

Table 5: Comparison of hurricane region[1] 1970 characteristics by 1980-1996 hurricane experience.

	(1)	(2)	(3)	(4)	(5)
	One hurricane	No hurricanes	p-value of difference, (1) v. (2)	No hurricanes, experienced[2]	p-value of difference, (1) v. (4)
Coastal indicator	0.58 (0.50)	0.42 (0.49)	**0.005**	0.60 (0.49)	0.745
Land area, sq. mi	742 (415)	639 (483)	**0.015**	719 (312)	0.603
Population	65,805 (129,802)	40,633 (90,663)	**0.021**	57,398 (104,748)	0.556
Population density (person/sq. mile)	88 (110)	187 (973)	**0.005**	100 (290)	0.618
Log of net earnings per capita	9.37 (0.22)	9.37 (0.25)	0.310	9.35 0.22	0.409
Employment rate (fraction of population)	0.19 (0.09)	0.18 (0.10)	0.496	0.17 (0.06)	**0.040**
UI payments per capita	53 (31)	46 (35)	**0.041**	42 (33)	**0.004**
Per capita transfers from businesses	57.53 (3.28)	58.02 (2.69)	**0.047**	57.97 (1.83)	0.195
Per capita transfers from government	1,515 (370)	1,692 (485)	**0.000**	1,741 (513)	**0.000**
Median family income	36,197 (8,190)	37,078 (8,960)	0.277	35,794 (8,015)	0.675
Median housing value	58,778 (17,528)	57,719 (20,847)	0.547	58,973 (20,111)	0.930
Number of counties or F-test (p-value)	119	845	**0.000**	177	**0.000**

[1]Alabama, Georgia, Florida, Louisiana, Mississippi, North Carolina, South Carolina, Texas, Virginia.

[2]Defined as having had one or more hurricanes between 1900 and 1969 but no hurricanes between 1980 and 1996.

Source: 1970 REIS, 1970 CBP and 1970 Census. Standard errors in parentheses. Bold font indicates significance at the 5% level or less. F-test is for all variables excluding population, the coastal indicator and land area. Monetary values are in 2008 dollars.

Table 6: Descriptive statistics for the regression sample

	(1) Mean	(2) Standard deviation	(3) 5th percentile	(4) 95th percentile	(5) Obs.
Population[1]	78,120	130,539	8,505	307,100	8,337
Net earnings by residents ($ million)[2]	1,432	2,845	97	6,401	8,298
Per capita net earnings[1,2]	15,081	4,547	9,319	23,268	8,298
Employment rate[1,2]	0.23	0.10	0.10	0.43	7,868
Construction employees[3]	2,131	4,436	40	9,706	6,829
Construction establishments[3]	198	347	10	795	7,209
Construction payroll ($ million)[3]	72.7	174.0	0.6	344.0	6,811
Construction earnings per worker[3]	27,382	10,080	6,279	42,868	4,918
Total employees[3]	25,159	53,949	979	108,955	7,905
Total establishments[3]	1,757	3,454	112	7,548	8,108
Total wages and salaries ($ million)[3]	783	1,940	14	3,330	8,108
Total earnings per worker[3]	26,019	8,719	6,394	38,941	7,795
Per capita unemployment payments[1,2]	93	68	23	221	8,298
Per capita income maintenance[1,2]	486	265	137	970	8,298
Per capita gov't-->ind transfers[1,2]	3,738	1,563	1,580	6,641	8,298
Per capita business-->ind transfers[1,2]	91	148	37	151	7,977

[1]From SEER demographic and population data; [2]From Regional Economic Information System (REIS); [3]From County Business Patterns (CBP)

Note: Summary is for the regression sample for that variable. The county must have non-missing values for a variable in all years to be included in the estimation for that variable. All monetary figures are in 2008 dollars.

Figure 3. The effect of a hurricane on the construction sector

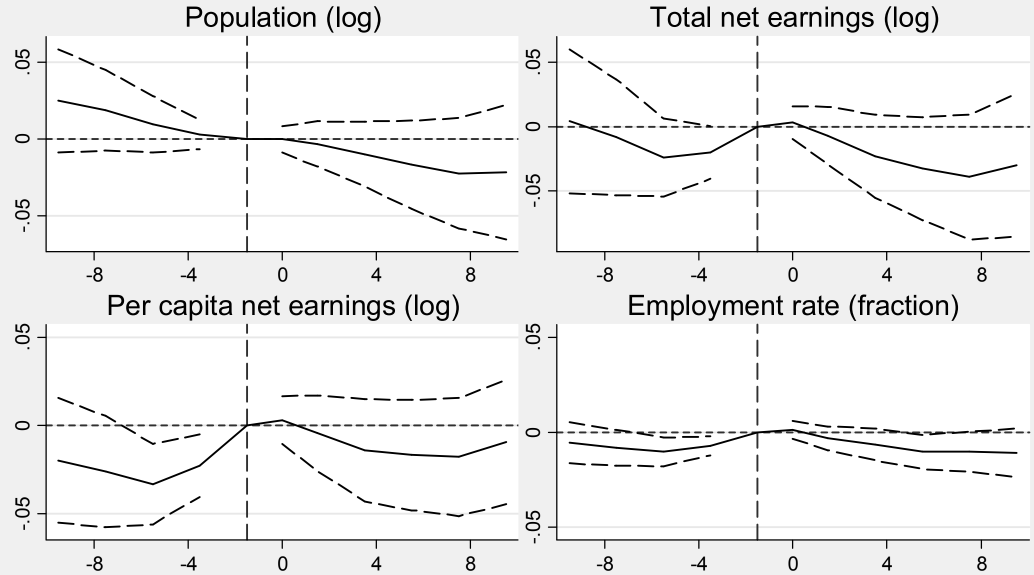
Sample: counties in Alabama, South Carolina, North Carolina, Florida, Georgia, Mississippi, Louisiana, Texas, and Virginia. 95% confidence intervals shown. Standard errors clustered by county. Controls include county, year, and coastal by year fixed effects.

Table 7: Mean shift and trend break tests for Figure 3

	Employment (log)		Number of establishments (log)		Total wages paid (log)		Wages paid per worker (log)	
Post hurricane	-0.0559	-0.0744	0.0202	0.0052	0.0145	-0.0142	0.0739	0.0637
	(0.0364)	(0.0425)*	(0.0233)	(0.0233)	(0.0339)	(0.0397)	(0.0265)***	(0.0278)**
Post hurricane time trend		-0.0188		-0.0151		-0.0290		-0.0103
		(0.0120)		(0.0068)**		(0.0143)**		(0.0052)*
Overall time trend	-0.0107	0.0000	-0.0083	0.0003	-0.0129	0.0037	-0.0030	0.0029
	(0.0048)**	(0.0093)	(0.0034)**	(0.0055)	(0.0055)**	(0.0114)	(0.0024)	(0.0044)
Observations	4,992	4,992	7,209	7,209	5,115	5,115	4,918	4,918
R-squared	0.94	0.94	0.96	0.96	0.95	0.95	0.84	0.84
Estimated 5-year change		-0.1684		-0.0701		-0.1593		0.0121
		(0.0926)*		(0.0439)		(0.0996)		(0.0443)
Estimated 10-year change		-0.2624		-0.1454		-0.3045		-0.0394
		(0.1506)*		(0.0751)*		(0.1692)*		(0.0675)

Standard errors (clustered by county) in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Includes indicators and time trends for hurricane events outside of the 21 year window of interest, year, county, and year-by-coastal fixed effects.

Figure 4. The effect of a hurricane on
population, employment and earnings



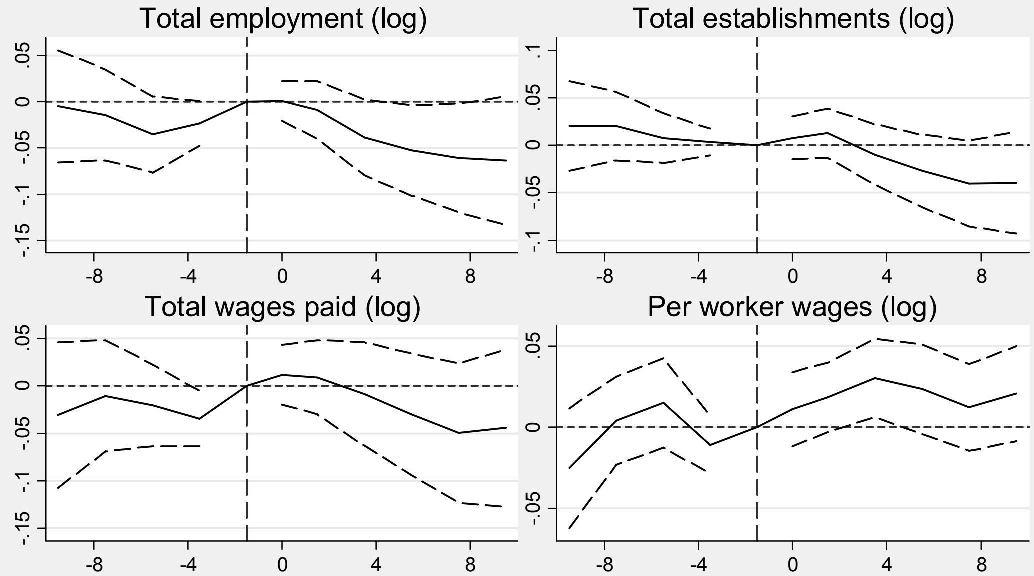
Sample: counties in Alabama, South Carolina, North Carolina, Florida, Georgia, Mississippi, Louisiana, Texas, and Virginia. 95% confidence intervals shown. Standard errors clustered by county. Controls include county, year, and coastal by year fixed effects.

Table 8: Mean shift and trend break tests for Figure 4

	Population (log)		Net earnings (log)		Employment rate (fraction)		Per capita earnings (log)	
Post hurricane	0.0047	0.0059	0.0124	0.0100	0.0028	0.0010	0.0074	0.0039
	(0.0048)	(0.0048)	(0.0126)	(0.0141)	(0.0035)	(0.0035)	(0.0136)	(0.0151)
Post hurricane time trend		0.0013		-0.0024		-0.0018		-0.0035
		(0.0015)		(0.0038)		(0.0009)**		(0.0031)
Overall time trend	-0.0028	-0.0035	-0.0025	-0.0012	-0.0004	0.0007	0.0002	0.0022
	(0.0020)	(0.0022)	(0.0024)	(0.0037)	(0.0005)	(0.0007)	(0.0012)	(0.0023)
Observations	8,337	8,337	8,298	8,298	7,868	7,868	8,298	8,298
R-squared	0.98	0.98	0.98	0.98	0.89	0.89	0.89	0.89
Estimated 5-year change		0.0122		-0.0018		-0.0081		-0.0136
		(0.0097)		(0.0289)		(0.0059)		(0.0274)
Estimated 10-year change		0.0185		-0.0136		-0.0172		-0.0311
		(0.0168)		(0.0472)		(0.0098)*		(0.0421)

Standard errors (clustered by county) in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Includes indicators and time trends for hurricane events outside of the 21 year window of interest, year, county, and year-by-coastal fixed effects.

Figure 5. The effect of a hurricane on the producer side



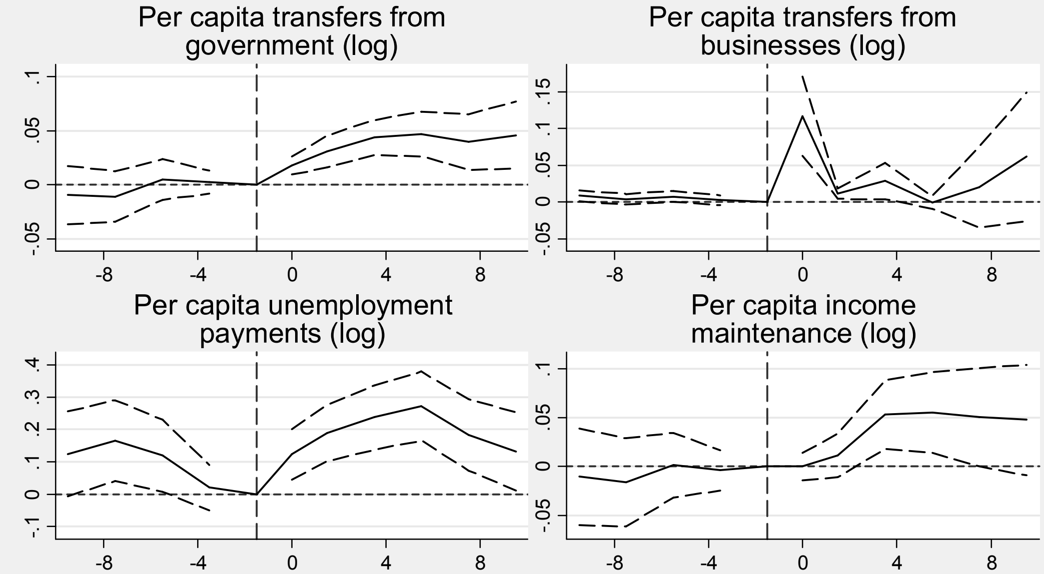
Sample: counties in Alabama, South Carolina, North Carolina, Florida, Georgia, Mississippi, Louisiana, Texas, and Virginia. 95% confidence intervals shown. Standard errors clustered by county. Controls include county, year, and coastal by year fixed effects.

Table 9: Mean shift and trend break tests for Figure 5

	Employment (log)		Number of establishments (log)		Total wages paid (log)		Wages paid per worker (log)	
Post hurricane	0.0154	0.0088	0.0223	0.0190	0.0319	0.0234	0.0159	0.0141
	(0.0154)	(0.0159)	(0.0108)**	(0.0105)*	(0.0219)	(0.0229)	(0.0105)	(0.0115)
Post hurricane time trend		-0.0066		-0.0033		-0.0086		-0.0018
		(0.0044)		(0.0027)		(0.0055)		(0.0026)
Overall time trend	-0.0039	-0.0002	-0.0048	-0.0029	-0.0033	0.0016	0.0007	0.0018
	(0.0027)	(0.0038)	(0.0023)**	(0.0030)	(0.0034)	(0.0048)	(0.0012)	(0.0022)
Observations	7,795	7,795	8,108	8,108	7,995	7,995	7,795	7,795
R-squared	0.98	0.98	0.98	0.98	0.97	0.97	0.94	0.94
Estimated 5-year change		-0.0239		0.0024		-0.0195		0.0052
		(0.0305)		(0.0178)		(0.0405)		(0.0205)
Estimated 10-year change		-0.0567		-0.0143		-0.0623		-0.0037
		(0.0513)		(0.0303)		(0.0656)		(0.0322)

Standard errors (clustered by county) in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Includes indicators and time trends for hurricane events outside of the 21 year window of interest, year, county, and year-by-coastal fixed effects.

Figure 6. The effect of a hurricane on public and private transfers



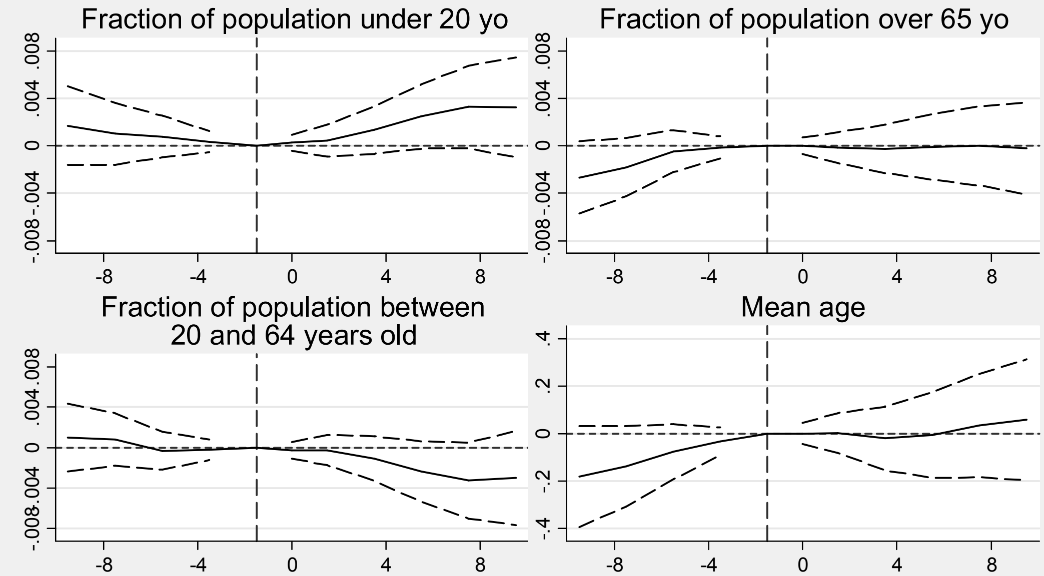
Sample: counties in Alabama, South Carolina, North Carolina, Florida, Georgia, Mississippi, Louisiana, Texas, and Virginia. 95% confidence intervals shown. Standard errors clustered by county. Controls include county, year, and coastal by year fixed effects.

Table 10: Mean shift and trend break tests for Figure 6

	Per capita transfers from government (log)		Per capita transfers from businesses (log)		Per capita income maintenance (log)		Per capita unemployment payments (log)	
Post hurricane	0.0214	0.0213	0.0443	0.0433	0.0083	0.0108	0.2104	0.2263
	(0.0071)***	(0.0068)***	(0.0162)***	(0.0130)***	(0.0149)	(0.0156)	(0.0562)***	(0.0582)***
Post hurricane time trend		0.0000		-0.0010		0.0024		0.0160
		(0.0024)		(0.0038)		(0.0046)		(0.0105)
Overall time trend	0.0020	0.0020	-0.0015	-0.0010	0.0036	0.0022	-0.0096	-0.0187
	(0.0012)	(0.0018)	(0.0022)	(0.0005)*	(0.0020)*	(0.0033)	(0.0048)**	(0.0086)**
Mean dep. var.	8.09	8.09	4.37	4.37	6.05	6.05	4.37	4.37
Estimated change	70.2	70.2	3.6	3.1	3.5	9.8	18.4	28.2
Observations	8,298	8,298	7,977	7,977	8,298	8,298	8,053	8,053
R-squared	0.95	0.95	0.80	0.80	0.91	0.91	0.66	0.66
Estimated 5-year change		0.0213		0.0381		0.0228		0.3061
		(0.0138)		(0.0113)***		(0.0313)		(0.0887)***
Estimated 10-year change		0.0213		0.0330		0.0348		0.3859
		(0.0248)		(0.0283)		(0.0524)		(0.1340)***

Standard errors (clustered by county) in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Includes indicators and time trends for hurricane events outside of the 21 year window of interest, year, county, and year-by-coastal fixed effects. Mean dependent variable in hurricane counties the year before the hurricane. Estimated change in levels is calculated from the "post hurricane" coefficient for the mean shift test and from the "estimated 5-year change" coefficient for the trend break test.

Figure 7. The effect of a hurricane on a county's age profile



Sample: counties in Alabama, South Carolina, North Carolina, Florida, Georgia, Mississippi, Louisiana, Texas, and Virginia. 95% confidence intervals shown. Standard errors clustered by county. Controls include county, year, and coastal by year fixed effects.

Table 11: The effect of a hurricane on the age composition in the population

	Fraction of population under age 20		Fraction of population between ages 20 and 64		Fraction of population over age 65		Mean age (years)	
Post hurricane	0.0000	0.0006	0.0007	0.0005	-0.0007	-0.0011	-0.0432	-0.0635
	(0.0005)	(0.0004)	(0.0007)	(0.0007)	(0.0006)	(0.0006)*	(0.0329)	(0.0309)**
Post hurricane time trend		0.0006		-0.0002		-0.0004		-0.0203
		(0.0002)***		(0.0003)		(0.0002)*		(0.0111)*
Overall time trend	0.0001	-0.0002	-0.0003	-0.0001	0.0001	0.0004	0.0136	0.0252
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)*	(0.0115)	(0.0137)*
Mean dep. var.	0.31	0.31	0.56	0.56	0.12	0.12	34.23	34.23
Observations	8,337	8,337	8,337	8,337	8,337	8,337	8,337	8,337
R-squared	0.94	0.94	0.91	0.91	0.94	0.94	0.94	0.94
Estimated 5-year change		0.0036		-0.0007		-0.0030		-0.1648
		(0.0012)***		(0.0018)		(0.0013)**		(0.0643)**
Estimated 10-year change		0.0067		-0.0018		-0.0049		-0.2661
		(0.0022)***		(0.0033)		(0.0023)**		(0.1168)**

Standard errors (clustered by county) in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Includes indicators and time trends for hurricane events outside of the 21 year window of interest, year, county, and year-by-coastal fixed effects.

Table 12: Post-hurricane mean shift and trend breaks by 1970 median housing value

	Population (log)		Per capita earnings (log)		Employment rate		Per capita government transfers (log)		Per capita unemployment payments (log)	
Mean change in bottom quartile	0.0053	0.0124	0.0418	0.0768	-0.0033	0.0045	0.0623	0.0649	0.2743	0.2663
	(0.0272)	(0.0265)	(0.0280)	(0.0355)**	(0.0073)	(0.0091)	(0.0234)***	(0.0309)**	(0.0916)***	(0.1155)**
Mean change in top quartile	0.0060	0.0004	-0.0489	-0.0937	0.0036	-0.0078	-0.0812	-0.0845	-0.0354	0.0669
	(0.0410)	(0.0390)	(0.0242)**	(0.0344)***	(0.0092)	(0.0120)	(0.0306)***	(0.0417)**	(0.0877)	(0.1295)
Trend change in bottom quartile		0.0006		-0.0120		-0.0037		-0.0011		0.0188
		(0.0022)		(0.0054)**		(0.0012)***		(0.0041)		(0.0153)
Trend change in top quartile		0.0011		0.0093		0.0024		0.0007		-0.0214
		(0.0026)		(0.0049)*		(0.0014)*		(0.0037)		(0.0164)
Estimated 10-year change in bottom quartile		0.0184		-0.0432		-0.0324		0.0542		0.4544
		(0.0359)		(0.0560)		(0.0126)**		(0.0322)*		(0.1697)***
Estimated 10-year change in top quartile		0.0116		-0.0012		0.0160		-0.0777		-0.1474
		(0.0467)		(0.0348)		(0.0110)		(0.0284)***		(0.1093)
Difference in means/10-year changes (bottom - top)	-0.0006	0.0069	0.0908	-0.0420	-0.0069	-0.0484	0.1435	0.1319	0.3097	0.6019
p-value of difference	0.992	0.937	0.072	0.489	0.656	**0.015**	**0.006**	**0.020**	0.060	**0.017**
Observations	8,337	8,337	8,298	8,298	7,868	7,868	8,298	8,298	8,053	8,053
R-squared	0.98	0.98	0.90	0.90	0.91	0.91	0.96	0.96	0.67	0.67

Bold denotes p-values less than 0.05. Standard errors (clustered by county) in parentheses. * significant at 5%; ** significant at 1%. Includes year, county, year-by-coastal fixed effects, as well as quartile-specific trends.

Appendix Tables

Table A1: Comparison of coastal hurricane region[1] 1970 characteristics by 1980-1996 hurricane experience.

	(1) One hurricane	(2) No hurricanes	(3) p-value of difference, (1) v. (2)	(4) No hurricanes, experienced[2]	(5) p-value of difference, (1) v. (4)
Coastal indicator	1	1	n/a	1	1
Land area, sq. mi	734 (362)	533 (341)	**0.000**	690 (335)	0.420
Population	91,214 (163,512)	48,658 (85,184)	**0.035**	75,613 (128,894)	0.505
Population density (person/sq. mile, 1970)	121 (132)	366 (1,494)	**0.003**	137 (367)	0.691
Log of net earnings per capita	9.45 (0.23)	9.42 (0.20)	0.351	9.42 (0.21)	0.447
Employment rate (fraction of population)	0.21 (0.10)	0.20 (0.20)	0.821	0.18 (0.07)	**0.038**
UI payments per capita	56 (28)	45 (36)	**0.007**	37 (32)	**0.000**
Per capita transfers from businesses	56.93 (4.19)	57.84 (2.38)	0.091	57.85 (1.68)	0.093
Per capita transfers from government	1,404 (354)	1,647 (526)	**0.000**	1,689 (586)	**0.000**
Median family income	38,805 (8,580)	39,967 (8,853)	0.304	38,620 (7,526)	0.884
Median housing value	64,044 (17,833)	65,813 (24,190)	0.478	65,249 (21,609)	0.689
Number of counties or F-test (p-value)	69	358	**0.000**	106	**0.000**

[1]Alabama, Georgia, Florida, Louisiana, Mississippi, North Carolina, South Carolina, Texas, Virginia.
[2]Defined as having had one or more hurricanes between 1900 and 1969 but no hurricanes between 1970 and 1996.
Source: 1970 REIS, 1970 CBP and 1970 Census. Standard errors in parentheses. Bold font indicates significance at the 5% level or less. F-test is for all variables excluding population, the coastal indicator and land area. Monetary values are in 2008 dollars.

Table A2: The effect of a hurricane on the construction sector

	Employment (log)	Establishments (log)	Payroll (log)	Per worker earnings (log)
T = - 9 or - 10	-0.003	0.003	-0.040	-0.031
	(0.074)	(0.045)	(0.090)	(0.037)
T = - 7 or - 8	-0.010	-0.004	-0.041	-0.030
	(0.057)	(0.035)	(0.071)	(0.030)
T = - 5 or - 6	-0.030	0.002	-0.027	0.004
	(0.044)	(0.027)	(0.050)	(0.027)
T = - 3 or - 4	-0.006	0.013	-0.020	-0.012
	(0.028)	(0.018)	(0.026)	(0.022)
T = 0	-0.028	0.014	0.003	0.031
	(0.028)	(0.013)	(0.027)	(0.027)
T = 1 or 2	-0.086	0.015	-0.011	0.077
	(0.034)**	(0.019)	(0.030)	(0.026)***
T = 3 or 4	-0.185	-0.062	-0.139	0.046
	(0.047)***	(0.026)**	(0.043)***	(0.026)*
T = 5 or 6	-0.241	-0.093	-0.207	0.032
	(0.055)***	(0.029)***	(0.057)***	(0.028)
T = 7 or 8	-0.226	-0.119	-0.233	-0.010
	(0.060)***	(0.034)***	(0.061)***	(0.025)
T = 9 or 10	-0.211	-0.099	-0.205	0.001
	(0.070)***	(0.039)**	(0.069)***	(0.027)
Mean of dep. var.	6.929	4.371	17.052	10.114
Observations	4,992	7,209	5,115	4,918
R-squared	0.94	0.96	0.95	0.84
p-value of all leads F-test	0.814	0.818	0.927	0.656
p-value of all lags F-test	**0.000**	**0.000**	**0.000**	**0.003**
p-value of T=0 to T=4 lags F-test	**0.000**	**0.000**	**0.000**	**0.013**

Standard errors (clustered by county) in parentheses. * significant at 5%; ** significant at 1%. Includes year, county, and year-by-coastal fixed effects.

Table A3: The effect of a hurricane on population, employment and earnings

	Population (log)	Net earnings by residents (log)	Per capita earnings by residents (log)	Employment rate (employees per capita)
T = - 9 or - 10	0.025	0.004	-0.020	-0.006
	(0.017)	(0.028)	(0.017)	(0.005)
T = - 7 or - 8	0.019	-0.008	-0.026	-0.008
	(0.013)	(0.022)	(0.015)	(0.004)*
T = - 5 or - 6	0.010	-0.024	-0.033	-0.010
	(0.009)	(0.015)	(0.011)***	(0.003)***
T = - 3 or - 4	0.003	-0.020	-0.023	-0.007
	(0.004)	(0.010)*	(0.008)**	(0.002)***
T = 0	0.000	0.003	0.003	0.001
	(0.004)	(0.006)	(0.006)	(0.002)
T = 1 or 2	-0.003	-0.007	-0.004	-0.003
	(0.007)	(0.011)	(0.010)	(0.003)
T = 3 or 4	-0.010	-0.023	-0.014	-0.006
	(0.010)	(0.016)	(0.014)	(0.004)
T = 5 or 6	-0.017	-0.033	-0.017	-0.010
	(0.014)	(0.020)	(0.015)	(0.004)**
T = 7 or 8	-0.022	-0.039	-0.018	-0.010
	(0.018)	(0.024)	(0.016)	(0.005)*
T = 9 or 10	-0.022	-0.030	-0.009	-0.011
	(0.022)	(0.028)	(0.017)	(0.006)*
Mean of dep. var.	10.539	27.031	9.581	0.233
Observations	8,337	8,298	8,298	7,868
R-squared	0.98	0.98	0.89	0.89
p-value of all leads F-test	0.410	0.075	0.050	**0.012**
p-value of all lags F-test	0.126	0.052	0.416	**0.008**
p-value of T=0 to T=4 lags F-test	0.075	0.128	0.395	0.268

Standard errors (clustered by county) in parentheses. * significant at 5%; ** significant at 1%. Includes year, county, and year-by-coastal fixed effects.

Table A4: The effect of a hurricane on the producer side

	Employment (log)	Establishments (log)	Payroll (log)	Per worker earnings (log)
T = - 9 or - 10	-0.005	0.020	-0.030	-0.025
	(0.030)	(0.023)	(0.038)	(0.018)
T = - 7 or - 8	-0.014	0.020	-0.010	0.004
	(0.024)	(0.018)	(0.029)	(0.013)
T = - 5 or - 6	-0.035	0.008	-0.021	0.015
	(0.020)*	(0.013)	(0.021)	(0.014)
T = - 3 or - 4	-0.024	0.004	-0.035	-0.011
	(0.012)*	(0.007)	(0.014)**	(0.008)
T = 0	0.001	0.008	0.012	0.011
	(0.010)	(0.011)	(0.015)	(0.011)
T = 1 or 2	-0.009	0.013	0.009	0.018
	(0.015)	(0.013)	(0.019)	(0.010)*
T = 3 or 4	-0.038	-0.010	-0.009	0.030
	(0.020)*	(0.016)	(0.027)	(0.012)**
T = 5 or 6	-0.053	-0.027	-0.030	0.023
	(0.024)**	(0.019)	(0.032)	(0.013)*
T = 7 or 8	-0.061	-0.040	-0.050	0.012
	(0.029)**	(0.022)*	(0.037)	(0.013)
T = 9 or 10	-0.064	-0.039	-0.044	0.021
	(0.035)*	(0.027)	(0.042)	(0.014)
Mean of dep. var.	9.025	6.534	19.121	10.082
Observations	7,795	8,108	7,995	7,795
R-squared	0.98	0.98	0.97	0.94
p-value of all leads F-test	0.060	0.468	0.052	0.050
p-value of all lags F-test	0.068	**0.000**	0.263	0.082
p-value of T=0 to T=4 lags F-test	**0.019**	**0.000**	0.355	**0.045**

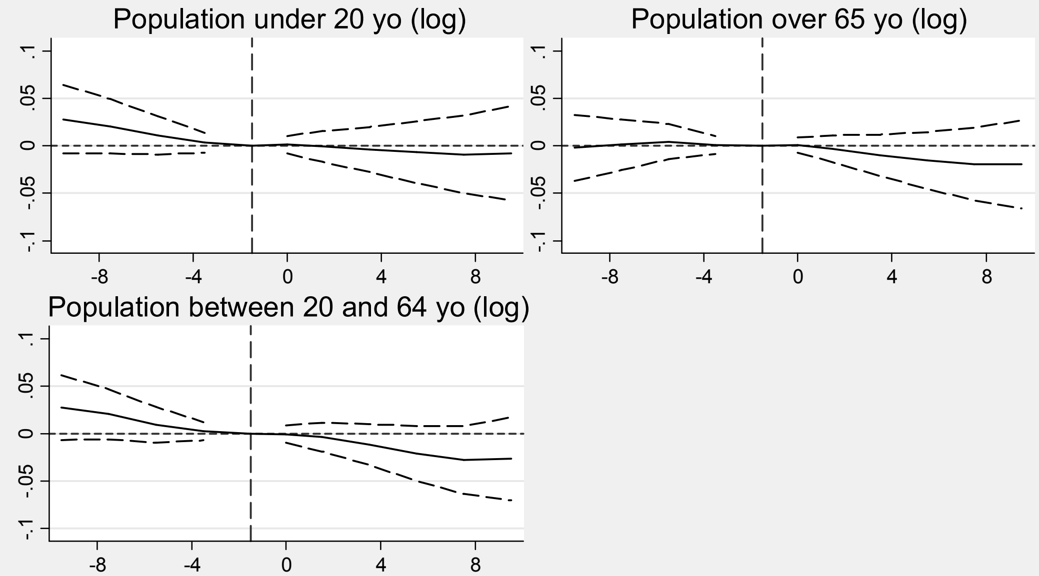
Standard errors (clustered by county) in parentheses. * significant at 5%; ** significant at 1%. Includes year, county, and year-by-coastal fixed effects.

Table A5: The effect of a hurricane on transfer payments

	Per capita unemployment payments (log)	Per capita income maintenance (log)	Per capita transfers from government (log)	Per capita transfers from businesses (log)
T = - 9 or - 10	0.124	-0.011	-0.010	0.009
	(0.066)*	(0.025)	(0.013)	(0.003)**
T = - 7 or - 8	0.165	-0.016	-0.011	0.004
	(0.063)***	(0.022)	(0.011)	(0.003)
T = - 5 or - 6	0.119	0.001	0.005	0.008
	(0.056)**	(0.016)	(0.009)	(0.003)**
T = - 3 or - 4	0.020	-0.004	0.002	0.003
	(0.035)	(0.010)	(0.005)	(0.003)
T = 0	0.123	0.000	0.018	0.117
	(0.039)***	(0.007)	(0.004)***	(0.027)***
T = 1 or 2	0.189	0.011	0.031	0.011
	(0.044)***	(0.011)	(0.007)***	(0.003)***
T = 3 or 4	0.237	0.053	0.044	0.029
	(0.050)***	(0.017)***	(0.008)***	(0.012)**
T = 5 or 6	0.272	0.055	0.047	-0.001
	(0.054)***	(0.020)***	(0.010)***	(0.004)
T = 7 or 8	0.183	0.050	0.040	0.021
	(0.055)***	(0.025)*	(0.013)***	(0.027)
T = 9 or 10	0.132	0.047	0.046	0.062
	(0.061)**	(0.028)	(0.015)***	(0.044)
Mean of dep. var.	4.331	6.025	8.135	4.393
PDV at 2% discount rate	165.3	162.9	1353.3	27.6
PDV at 3% discount rate	158.0	153.6	1285.0	26.5
Observations	8,053	8,298	8,298	7,977
R-squared	0.66	0.91	0.95	0.80
p-value of all leads F-test	**0.007**	0.634	**0.027**	0.058
p-value of all lags F-test	**0.000**	**0.000**	**0.000**	**0.000**
p-value of T=0 to T=4 lags F-test	**0.000**	**0.000**	**0.000**	**0.003**

Standard errors (clustered by county) in parentheses. * significant at 5%; ** significant at 1%. Includes year, county, and year-by-coastal fixed effects.

Figure A1. The effect of a hurricane on population by age



Sample: counties in Alabama, South Carolina, North Carolina, Florida, Georgia, Mississippi, Louisiana, Texas, and Virginia. 95% confidence intervals shown. Standard errors clustered by county. Controls include county, year, and coastal by year fixed effects.

Table A6: The effect of hurricane on the population by age

	Population under age 20 (log)		Population between ages 20 and 64 (log)		Population over age 65 (log)	
Post hurricane	0.0047	0.0079	0.0061	0.0071	-0.0011	-0.0033
	(0.0051)	(0.0052)	(0.0055)	(0.0055)	(0.0037)	(0.0038)
Post hurricane time trend		0.0032		0.0010		-0.0023
		(0.0016)**		(0.0017)		(0.0018)
Overall time trend	-0.0021	-0.0040	-0.0033	-0.0039	-0.0011	0.0001
	(0.0022)	(0.0024)*	(0.0020)*	(0.0022)*	(0.0020)	(0.0023)
Mean dep. var.	9.39	9.39	9.98	9.98	8.43	8.43
Observations	8,337	8,337	8,337	8,337	8,337	8,337
R-squared	0.98	0.98	0.98	0.98	0.98	0.98
Estimated 5-year change		0.0242		0.0121		-0.0146
		(0.0104)**		(0.0105)		(0.0109)
Estimated 10-year change		0.0404		0.0170		-0.0259
		(0.0178)**		(0.0183)		(0.0195)

Standard errors (clustered by county) in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Includes indicators and time trends for hurricane events outside of the 21 year window of interest, year, county, and year-by-coastal fixed effects.

Table A7: Post-hurricane mean shift and trend breaks by county income

	Population (log)		Per capita earnings (log)		Employment rate		Per capita government transfers (log)		Per capita unemployment payments (log)	
Mean change in bottom quartile	-0.0193	-0.0227	0.0440	0.0521	0.0097	0.0149	0.0591	0.0765	0.2266	0.2071
	(0.0195)	(0.0197)	(0.0225)*	(0.0284)*	(0.0073)	(0.0085)*	(0.0183)***	(0.023)***	(0.0903)**	(0.1023)**
Mean change in top quartile	0.0104	0.0155	-0.0336	-0.0503	0.0044	-0.0040	-0.0751	-0.1113	-0.0227	-0.0228
	(0.0335)	(0.0344)	(0.0222)	(0.0320)	(0.0100)	(0.0133)	(0.0259)***	(0.0335)***	(0.0992)	(0.1284)
Trend change in bottom quartile		0.0023		-0.0065		-0.0033		-0.0031		0.0269
		(0.0019)		(0.0049)		(0.0011)***		(0.0033)		(0.0141)*
Trend change in top quartile		-0.0011		0.0035		0.0018		0.0075		-0.0002
		(0.0024)		(0.0041)		(0.0013)		(0.0027)***		(0.0133)
Estimated 10-year change in bottom quartile		0.0008		-0.0130		-0.0179		0.0459		0.4757
		(0.0284)		(0.0509)		(0.0124)		(0.0296)		(0.1635)***
Estimated 10-year change in top quartile		0.0048		-0.0151		0.0136		-0.0365		-0.0248
		(0.0370)		(0.0285)		(0.0103)		(0.0244)		(0.1094)
Difference in means/10-year changes (bottom - top)	-0.0297	-0.0041	0.0776	0.0021	0.0053	-0.0316	0.1341	0.0824	0.2493	0.5005
p-value of difference	0.553	0.992	0.062	0.920	0.739	0.080	**0.002**	0.139	0.144	**0.039**
Observations	8,337	8,337	8,298	8,298	7,868	7,868	8,298	8,298	8,053	8,053
R-squared	0.98	0.98	0.90	0.90	0.90	0.90	0.96	0.96	0.67	0.67

Bold denotes p-values less than 0.05. Standard errors (clustered by county) in parentheses. * significant at 5%; ** significant at 1%. Includes year, county, year-by-coastal fixed effects, as well as quartile-specific trends.

Table A8: the co-movement of local economic indicators

	Total unemployment payments (log)		Per capita unemployment payments (log)		Earnings per capita (log)	Net earnings (log)	State receipts (log)	
Total employment (log)	0.063 (0.035)*		-0.329 (0.032)***					
Total wages paid (log)		0.086 (0.031)***		-0.231 (0.026)***				
Net earnings per capita (log)								0.588 (0.103)***
Net earnings (log)							0.823 (0.031)***	
Income maintenance (log)					-0.064 (0.008)***	0.210 (0.022)***		
Observations	33,844	34,767	33,822	34,745	36,809	36,809	12,168	12,168
R-squared	0.91	0.91	0.62	0.62	0.85	0.98	0.97	0.96

Standard errors (clustered by county) in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Includes county and year fixed effects.

Table A9: the co-movement of the local construction sector with earnings

	Total establishments (log)		Total employment (log)		Total pay (log)		Per worker pay (log)	
Net earnings per capita (log)		0.733 (0.056)***		1.058 (0.078)***		1.259 (0.089)***		0.229 (0.026)***
Net earnings (log)	0.899 (0.027)***		0.961 (0.036)***		1.137 (0.042)***		0.182 (0.013)***	
Observations	34,352	34,352	30,872	30,872	31,751	31,751	29,743	29,743
R-squared	0.97	0.96	0.95	0.94	0.95	0.94	0.78	0.78

Standard errors (clustered by county) in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Includes county and year fixed effects.

Table A10: autocorrelation in local economic indicators

				Panel A: general				
	Total population (log)	Gov't --> ind transfers	Business --> ind transfers	Income maintenance (log)	Earnings per capita (log)	UE compensation (log)	UE per capita compensation (log)	
Lagged variable	0.984	0.966	0.396	0.892	0.693	0.737	0.729	
	(0.002)***	(0.003)***	(0.029)***	(0.005)***	(0.021)***	(0.007)***	(0.007)***	
Observations	36,791	35,834	32,414	35,865	35,870	35,794	35,744	
R-squared	1.00	1.00	0.96	1.00	0.92	0.96	0.82	
				Panel B: producer-side				
	Construction employment (log)	Total employment (log)	Construction establishments (log)	Total establishments (log)	Construction total pay (log)	Total pay (log)	Construction per worker pay (log)	Total per worker pay (log)
Lagged variable	0.785	0.895	0.858	0.957	0.820	0.896	0.095	0.275
	(0.007)***	(0.008)***	(0.006)***	(0.003)***	(0.006)***	(0.007)***	(0.012)***	(0.023)***
Observations	30,730	34,844	35,233	36,002	31,630	35,828	29,871	34,799
R-squared	0.98	1.00	0.99	1.00	0.98	0.99	0.77	0.91

Standard errors (clustered by county) in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Includes county and year fixed effects.

Table A11: Monte Carlo simulation, heterogeneous trends with autocorrelation

Time relative to event	Theoretical effect of event[1]	Estimation without including lagged variable		Estimation including lagged variable	
T= - 5	0	-0.809 (0.067)***		-0.084 (0.036)**	
T= - 4	0	-0.793 (0.066)***		-0.081 (0.036)**	
T= - 3	0	-0.767 (0.066)***		-0.046 (0.036)	
T= - 2	0	-0.877 (0.066)***		-0.131 (0.036)***	
T= - 1	0	reference category		reference category	
T= 0	10.00	9.084 (0.067)***	9.423 (0.061)***	9.889 (0.036)***	9.947 (0.030)***
T= 1	9.00	8.074 (0.066)***	8.441 (0.061)***	0.698 (0.050)***	0.554 (0.041)***
T= 2	8.10	7.234 (0.067)***	7.632 (0.061)***	0.684 (0.047)***	0.538 (0.039)***
T= 3	7.29	6.372 (0.067)***	6.827 (0.062)***	0.557 (0.045)***	0.464 (0.038)***
T= 4	6.56	5.626 (0.067)***	6.083 (0.062)***	0.508 (0.043)***	0.403 (0.037)***
T= 5	5.90	4.943 (0.068)***	5.413 (0.062)***	0.398 (0.042)***	0.334 (0.035)***
Lagged outcome				0.82 (0.004)***	0.842 (0.003)***
Observations		20,000	25,000	20,000	25,000
R-squared		0.89	0.87	0.97	0.97
p-value of all leads F-test		**0.000**		**0.001**	
p-value of all lags F-test		**0.000**	**0.000**	**0.000**	**0.000**

[1]When lagged outcome is excluded from the estimation and time trends are appropriately controlled for.
Standard errors in parentheses. * significant at 5%; ** significant at 1%. Includes fixed effects for county and dummies for "event more than 5 years ago" and "event more than 5 years in the future".