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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, earnings, or the employment rate. 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 \$67 per capita per year. Private insurance-related transfers over the same time period average only \$2.4 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 from natural disasters to rise (Board on Natural Disasters, 1999). World insured losses have exceeded \$11

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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 22 percent higher in the eleven years following the hurricane while overall transfer payments are 2.1 percent higher. Correspondingly, there is no change in population, the employment rate, or wages. 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

¹Unless 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.

\$67 per capita per year or about \$640 per capita in present discounted value. Transfers from businesses to individuals (mostly insurance payments) increase temporarily as well, but add only an estimated \$23 to per capita transfers over the eleven years. Together, the transfers represent a large fraction of the immediate damages, which FEMA estimates to be \$1,278 per capita for the major hurricanes during my study period.² This suggests that non-disaster policy, in addition to disaster aid and wealth, may be an important factor in explaining the relative resilience to natural disasters in the United States.

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, employment shrinks three to eight years after the hurricane. Nine to ten years later, there is a sign of an upward movement in employment, suggesting that the decline in the construction sector may be temporary. The decline corresponds to a decrease in new single family home construction. I 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. In particular, there is 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 increases in per capita unemployment payments and overall transfers are substantially higher in low-housing value counties than in high-housing value counties. 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, there are differences in their post-hurricane paths.

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

²Minor hurricanes, which are in my data but not in FEMA's estimates, are generally less damaging.

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 background information on hurricanes and US federal disaster aid. Section 4 describes the setting, data and empirical strategy. Sections 5 and 6 present and discuss the results, respectively. Section 7 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.³

³For a simple formal model and simulation results, see the online "Model Appendix": <http://econ-www.mit.edu/files/6350>

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 choose to take transfers and remain in the area instead of moving away.⁴ This implies that the net effect on total labor supply is ambiguous: 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

⁴Transfer 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.

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.⁵

For hurricane data, I use the Best Tracks (HURDAT) dataset from the National Oceanic and Atmospheric Administration (NOAA).⁶ It contains the location of the storm center and wind speed (in six hour intervals)

⁵ Author calculations using data from Nordhaus (2006). I use 2008 dollars throughout the paper.

⁶ Available from <http://www.nhc.noaa.gov/pastall.shtml#hurdat>

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.⁷ 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". Between 1980 and 1996, there were on average 5.6 North Atlantic hurricanes per year, with at least two hurricanes each year and 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 1 shows the geographic distribution of hurricane hits that occurred between 1980 and 1996, as well as the control counties used in subsequent analysis (selected using propensity score matching). Out of the hurricane region counties, 127 experience one or more hurricanes between 1980 and 1996 (119 experience only one hurricane). Only 19 counties outside the hurricane region experience any hurricanes during this time and virtually all the major hurricanes occur within the 9 states listed above. I therefore limit my analysis to this region. Although it may be preferable to focus on the major hurricanes, they are relatively rare (there are only 8 between 1980 and 1996). For this reason, I focus on the 21 minor and major hurricanes that affected the hurricane region during that time.

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.⁸ 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

⁷See Appendix A for a discussion of the distribution of eye diameters.

⁸Available by request from <http://www.fema.gov/plan/prevent/hazus/index.shtml>

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 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:

$$D_{ct} = a_c + a_t + \beta_1 Major_hurricane_{ct} + \beta_2 Minor_hurricane_{ct} \\ + \gamma_1 Flood_{ct} + \gamma_2 Tornado_{ct} + \gamma_3 Severe_storm_{ct} + \varepsilon_{ct}$$

and

$$D_{ct} = a_c + a_t + \sum_{k=1}^5 \beta_k \mathbf{1}[Category_{ct} = k] + \gamma_1 Flood_{ct} \\ + \gamma_2 Tornado_{ct} + \gamma_3 Severe_storm_{ct} + \varepsilon_{ct}$$

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

D_{ct} is log of property damages, property damages per capita or the log of flood insurance payments in that county.⁹ 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. $\mathbf{1}[Category_{ct} = k]$ 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.¹⁰ The results are shown in 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

⁹Data 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).

¹⁰The results for all US counties are similar.

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.¹¹ 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.

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

¹¹The 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.

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.¹² 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 – 1996.¹³ 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 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

¹²Data on spending are from the PERI Presidential Disaster Declarations database (Sylves and Racca, 2010).

¹³Summary statistics for other times periods are similar, with the caveat that real spending on hurricane-related declarations is rising over time.

programs.

4 Empirical Strategy

4.1 Sample of Analysis

Ideally, one would estimate the effect of hurricanes by looking at 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 characteristics and trends of counties that do not experience any hurricanes between 1980 and 1996 with counties that experience one hurricane.¹⁴

Columns 1 and 2 of Panel A show the 1970 characteristics of hurricane region counties that experience a hurricane between 1980 and 1996 and the difference from counties with no hurricanes. Nearly fifty percent of 119 counties that experience one hurricane are coastal, compared to forty-one percent of 811 counties that have not had hurricanes over this period. Counties that experience hurricanes are about fifty percent more populous than non-hurricane counties and have lower population densities. These differences are statistically significant (as shown in Column 3). Counties with hurricanes also have larger per unemployment insurance payments, but smaller per capita transfers from the federal government. However, differences in levels are not problematic because county fixed effects are included in every specification. However, differences in levels may be indicative of differences in trends. In Panel A, I test for differential trends between 1970 and 1979 (before any hurricanes in the sample occur) for the time-varying characteristics. In this case, Columns 1 and 2 show the trend in the hurricane counties and their difference from the trend in non-hurricane counties. Only two variables show differential trends for these two groups of counties: per capita transfers from government and per capita family assistance, both significant at the 5% level.

Another way to construct the control group is by requiring balance in pre-hurricane covariates and hurricane risk.¹⁵ I construct a hurricane risk variable using historic (1981-1970) hurricane data. I predict counties' propensity to be hit by hurricanes by spatially smoothing observed hurricane hits. I then use two-nearest neighbor propensity score matching to select a control group from the no-hurricane sample.¹⁶ Column 4 shows the difference between the hurricane counties and the propensity matched control group, while Column 5 shows the p-value of this difference. In general, propensity score matching eliminates differences in levels and trends for all variables except population, whose trend and level differences continue to be significant at the 5% level. 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.

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

¹⁴I 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.

¹⁵Matching is based on all outcome variables, although some are not shown due to space constraints.

¹⁶Using two-nearest neighbor rather than nearest neighbor matching ensures that the number of counties in the control group is approximately equal to the number of counties in the treatment group. When nearest neighbor matching is used, some non-hurricane counties are assigned as nearest neighbors multiple times, resulting in a control group that's much smaller than the treatment group.

by relying on mean shift and trend break tests.

4.2 Economic and Demographic Data

Annual county-level outcomes such as unemployment payments, population, and earnings come from either the Regional Economic Information System (REIS), while sector-specific employment, wages and number of establishments come from County Business Patterns (CBP). County-level population by race and age are from Surveillance Epidemiology and End Results (SEER) population database. Data on single family housing starts are from McGraw-Hill. All four series span the years 1970-2006.

I define the employment rate as the ratio of total employment to the number of people aged fifteen and older.¹⁷ An establishment is defined as a single *physical* location of a firm with paid employees. Net earnings by place of residence (which I later refer to as simply "net earnings") 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. 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. Total transfers from government to individuals include unemployment insurance. In addition, the category includes income maintenance (e.g., Supplemental Security Income or SSI), family assistance, 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 net insurance settlements and personal injury liability payments to non-employees.

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 coastal-by-year fixed effects. 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

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

¹⁸If 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.

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:

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

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

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. $\{\beta_{ct}^{-11}, \beta_{ct}^{11}\}$ are indicators for hurricanes outside the estimation window. α_c and α_t are county and year fixed effects.

$1 [\textit{coastal}] \alpha_t$ is a set of year fixed effects for coastal counties, as defined by the NOAA's Strategic Environmental Assessments Division. 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.

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.

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

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. $\max \{H_{c,t-2\tau+1}, H_{c,t-2\tau}\}$ takes the maximum of the county's hurricane indicators in subsequent years, grouping them as described above. The set $\sum_{\tau=1}^5 \beta_{-2\tau} \max \{H_{c,t-2\tau+1}, H_{c,t-2\tau}\}$ thus represents the causal effects of a hurricane 1-10

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

years following its occurrence. It can be written out as $\beta_{-2} \max \{H_{c,t-1}, H_{c,t-2}\} + \beta_{-4} \max \{H_{c,t-3}, H_{c,t-4}\} + \dots + \beta_{-10} \max \{H_{c,t-9}, H_{c,t-10}\}$. The reference category is "hurricane one or two years from now", corresponding to $\max \{H_{c,t+1}, H_{c,t+2}\}$. The coefficients of interest is the set of hurricane lags $\{\beta_{-2\tau}\}_{\tau=1}^{\tau=5}$ 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. I also restrict my sample to counties that have a continuous record for each outcome variable in order to avoid biasing my results.

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 effect for each time period, 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

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

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:

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

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 $\mathbf{1}[\text{coastal}] \alpha_t$.

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:

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

$\mathbf{1}[\text{Hurr in past 10 years}]_{ct}t$ 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.

4.5 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. 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.

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.

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:

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

O_{ct} is some economic outcome, as before. TOP_{1970}^c is an indicator equal to 1 if the county was in the top quartile in 1970 while BOT_{1970}^c 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:

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

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 ($\theta_1^{BOT} + 10 * \theta_2^{BOT}$). 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.

5 Empirical Results

5.1 Dynamic Effects of Hurricanes

In this section, I present the estimated effects of a hurricane. I graph the coefficients 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, as well as indicators for

hurricanes occurring outside of the estimation window of interest. The point estimates from the figures are shown in Appendix Tables A1-A4.

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 2 shows the impact of a hurricane on the construction sector, measured in terms of employment, wages, and the number of firm locations. In addition, I present estimates of changes in per capita single family home construction. 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. After remaining unchanged in the year of the hurricane, employment falls to 7 – 19% below pre-hurricane levels (implying 70 – 170 fewer construction workers).²¹ The number of establishments is about 3.2% higher in the year of the hurricane and 3.7% higher the subsequent year (implying 2 – 3 more construction establishments). They subsequently return to their pre-hurricane levels. Construction wages increase in years 1 – 4, by 5.4 – 7.7% (\$1,400 – 2,000), 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 is still significantly lower than the year before the hurricane, but appears to be slowly increasing. Per capita single family housing starts are 5.7% lower in the year of the hurricane and 9.7% lower 3-4 years later (implying 0.2 – 0.4 fewer housing units per 1,000 people), with no significant changes in other years. The hurricane lags are jointly significant at the 1% level for all the outcomes.

Table 6 shows the mean shift and trend break test results corresponding to Figure 2. There is a significant trend break in construction employment, establishments, and per worker wages, and the estimated coefficients follow the pattern seen in Figure 2. Specifically, the number of construction firm locations (establishments) declines by 1.3% each year. Construction employment is on average 9.0% lower in the ten years following the hurricane, and declines by 2.0% per year. Wages increase by an average of 7.0%, but then fall by an additional 1.1% each year. From the trend break specification, I estimate that construction employment is 19% lower five years after the hurricane and 29% lower at the end of my estimation sample, ten years after landfall.

²¹I 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.

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. However, I also estimate that per capita housing starts fall by about 7.6% on average, which indicates a substantial decrease in construction demand. Thus, the downturn in the local construction sector is not solely driven by spatial shifts in construction activity.

Figure 3 shows the estimated effect of a hurricane on population and demographics. Population does not change significantly in any given year and the effects of a hurricane zero to ten years after are not jointly significant. The fraction of black residents is significantly lower in the years after the hurricane, but pre-trends suggest that further testing is necessary. The fraction of residents who are 65 and older falls steadily following the hurricane, while the fraction of those under 20 years of age steadily grows.

Trend break and mean shift tests in Table 8 indicate that there are no significant changes in the mean or trend of population or the fraction of residents who are black. There is indeed evidence of a change in the age structure of the county. In particular, the fraction of population under 20 is 0.0036 higher 10 years after the hurricane, a 1% increase. The fraction over 65 is 0.0058 lower, a 4.7% decrease relative to the mean. These changes are significant at the 10% and 5% levels, respectively.

Figure 4 shows the effect of a hurricane on the employment rate, earnings, and transfers. There is no change in the employment rate. 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, but no change following the hurricane. Overall per capita transfers from the government to individuals increase by 1.2% in the year of the hurricane and are 1.8 – 2.5% larger in subsequent years. Per capita transfers to individuals from businesses immediately increase by 11.6% following a hurricane.

In Table 8, I show the results of the mean shift and trend break tests for the outcomes shown in Figure 4. The mean shift test indicates a 2% average increase in per capita government to individual transfers, equivalent to about \$67 per person per year. Per capita business to individual transfers in the eleven years following the hurricane are estimated to be 3% higher than the pre-hurricane transfers, or about \$2.4 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 all government transfers is about \$640 per capita, and the PDV of transfers from businesses is \$23 per capita. Thus, post-hurricane transfers from general social programs are larger than transfers from disaster-specific programs and much larger than insurance payments.

Figure 6 looks at specific types of government transfers: namely, family assistance, public medical benefits (i.e., Medicaid and Medicare), SSI payments, and unemployment insurance. Per capita unemployment insurance payments increase immediately by 14.2% and are 18 – 30% higher in years one through ten after a hurricane. Family assistance payments are 2.9% lower in the year of the hurricane, but subsequently rise to 7 – 10% above their pre-hurricane average. SSI is estimated to fall, but the variable clearly exhibits a significant pre-trend. All of the increases appear to be temporary: per capita UI is the only variable that's significantly higher ten years later and appears to be coming back down to pre-hurricane levels.

Table 9 shows the corresponding mean shift and trend break tests. On average, per capita unemployment benefits increase by 22%, equivalent to about \$19 per person per year. Assuming a 3% discount rate,

the present discounted value (PDV) of the unemployment payments is about \$180 per capita. Per capita medical benefits increase by about 4.6% on average, but the dollar equivalent of the increase is very small. The overall increase in per capita family assistance payments is only marginally significant and the dollar equivalent of the increase is likewise small.

5.2 Heterogeneity of Effects by Wealth

In this section, I focus on the heterogeneity in the post-hurricane employment rate, per capita earnings, population, and transfer payments. In Table 10, I show the results of the mean shift and trend break tests by the quartile of median housing value. There are no significant differences in population or employment rate changes. 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.

Changes in per capita overall transfers from the government and per capita unemployment insurance are also qualitatively different for bottom and top quartiles of housing value (relative to counties in the two middle quartiles). Per capita transfers from the government are substantially higher in low-value counties while in high-value counties they are substantially lower on average. Per capita unemployment insurance increases by 0.21 log points more in low-value counties than in medium-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 A5 shows the corresponding estimates for high-income and low-income counties. The estimates generally follow the pattern in Table 10.

Overall, hurricanes appear to produce differences (some lasting and some temporary) 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.

5.3 Robustness

In this section, I report the results of various checks to verify that the results in the previous section are robust 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.

Joint tests of the lead hurricane indicators in Appendix Tables A1-A4 suggest that there are pre-trends in some 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 qualitative estimates in this case. In addition, the overall time trend is estimated to be insignificant in all trend break tests except for per capita unemployment and SSI payments and the fraction of population that is black (which are all estimated to be decreasing in the hurricane counties).

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. The estimated amount of extra government transfers is somewhat larger, but comparable to the original estimates. The only substantial difference is that, in addition to the mean increase, unemployment payments show an upward trend of about 2.7% per year. Per capita UI payments are estimated to be 39% higher five years after the hurricane and 53% higher eleven years after the hurricane.

Another robustness sample includes a control group that's constructed using only historic hurricane data and propensity score matching (recall that the main control group was also matched by 1970 covariates). The simple risk-based matching also yields results that are very similar to the main sample and in some cases produces more precise estimates.

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. There is no significant fall in construction employment but a 1.2% decline in the number of establishments. As before, the average construction wage increases by an average of 8.5% following the hurricane but shows no downward trend in this sample. This suggests that some of the hurricane county's construction activity moves to the neighboring counties, implying that hurricanes may permanently affect the business patterns in centrally affected and neighboring counties.

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 unaffected. Per capita transfers from the government increase by 2.2% on average and show an increasing trend of 0.4% per year following the hurricane. Per capita unemployment insurance payments

increase by 26.6% on average and show an increasing trend of 4% per year. The only substantive difference between this and the other samples is that per capita earnings are estimated to decline by an extra 0.57% per year following the hurricane. Finally, including all the counties in the hurricane region as controls also leads to similar results.

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 affected sample. In particular, 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.

6 Interpretation and Discussion

The construction estimates show that hurricanes have non-monotonic medium-run effects on that sector, with an initial increase in wages followed by a gradual return to pre-hurricane levels three to eight years after the hurricane. At the same time, there is a fall in single family housing starts. However, the effects on general economic variables, such as population, employment, and wages, are 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 \$640 per capita in non-disaster government transfers translates to a total of \$50 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 represent a large fraction of 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 \$96 (\$7.5 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, employment 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.

One possible explanation for the increase in unemployment payments and overall government transfers is changes in the demographic composition of an area. 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 slight increase in the fraction of population that is between 50 and 64, but it 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 non-monotonic. If the non-disaster transfers were driven by demographic changes, the change in the age profile should 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.

Whether the presence of unemployment insurance for those living in disaster areas is welfare-improving on a national 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.

7 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 increases 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 damages 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; a comprehensive picture of post-disaster economic dynamics is lacking.

I estimate the medium-run economic effects of hurricanes on US counties, focusing on population, employment, wages, and transfers to individuals. Population, the employment rate and wages are largely unaffected in the ten years following the hurricane, while construction employment and new housing starts decline 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 \$640 per capita, 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 \$23 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.

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.

My results also show gradual demographic changes in the affected county. The fraction of the population under 20 increases while the fraction of the population 65 and older falls. 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 earnings and transfer trajectories. Whether this is because of different decisions or constraints of individuals or because of differential hurricane impacts is an 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. Estimating the impact of federal disaster aid is another important area for future research.

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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 A6-A8, 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 A6 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 A7 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 A8 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 $E_c [Event]$). I assume that $\beta = 10$, $\gamma = 0.9$, and $\theta = 0.001$. ε_{ct} 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

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

$\{\beta_{ct}^{-6}, \beta_{ct}^6\}$ 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 A9 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 fixed effects combined with high autocorrelation 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

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

	(1)	(2)	(3)	(4)
	Mobile capital		Immobile capital	
	No moving costs	Moving costs	No moving costs - m	Moving costs - c
No transfers, inelastic labor supply - n			$dw_{nm}, dr_{nm} < 0,$ $dL_{nm} = dN_{nm} < 0,$ $dV(s) = 0$	$0 > dw_{nm} > dw_{nc},$ $0 > dr_{nc} > dr_{nm},$ $dL_{nc} = dN_{nc} = dN_{nm} < 0,$ $dV(s) \leq 0$
	No change			
Transfers, elastic labor supply - t			$dw_{tm} = dw_{nm} < 0,$ $dr_{tm} = dr_{nm} < 0,$ $dL_{tm} = dN_{tm} = dN_{nm} < 0,$ $dV(s) = 0, dT(s) = 0$	$dw_{tc}, dr_{tc} < 0, dL_{tc} <$ $dN_{tc} < dN_{nm} < 0,$ $dV(s) \leq 0, dT(s) > 0$

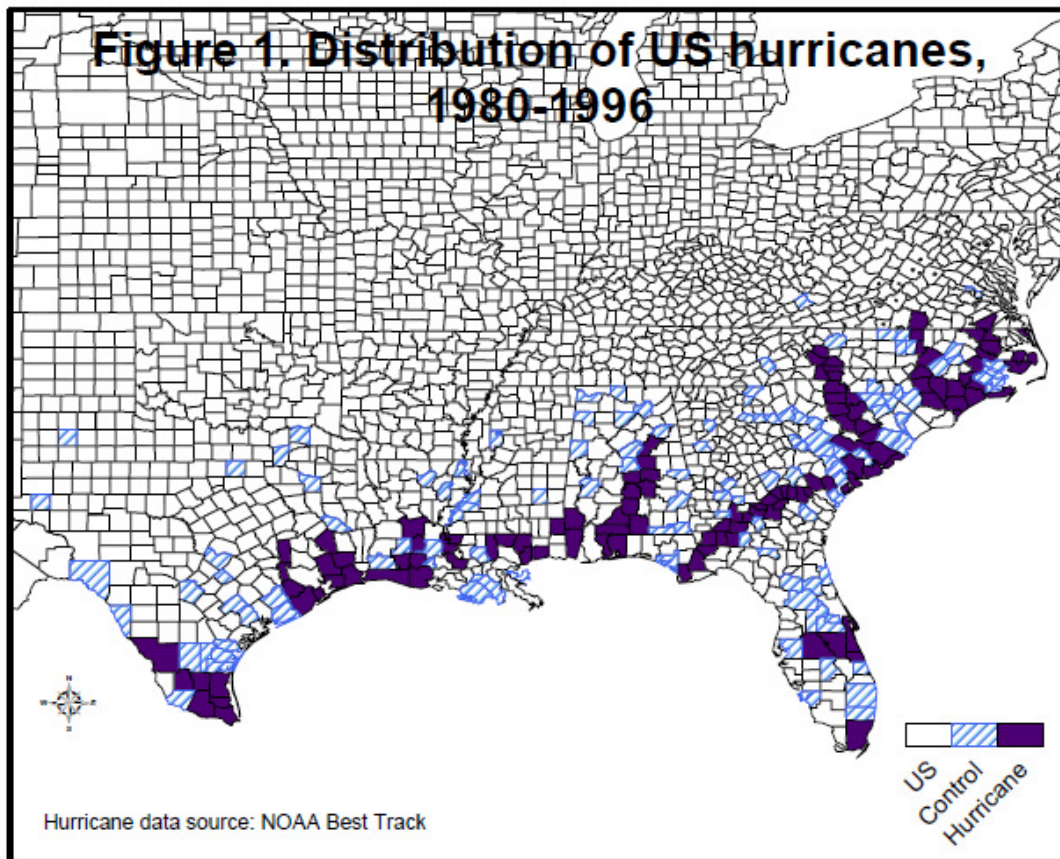


Table 2: Damages caused by major US hurricanes, 1980-1996

	(1)	(2)	(3)	(4)
	Mean	Standard deviation	Maximum	Obs.
<i>Panel A: centrally affected counties</i>				
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
<i>Panel B: peripherally affected counties</i>				
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 region¹

	(1)	(2)	(3)	(4)	(5)	(6)
	Log damages	Per capita damages	Flood insurance payments (log)	Log damages	Per capita damages	Flood insurance payments (log)
Major hurricane	4.236 (0.426)***	678.279 (309.795)*	3.090 (0.410)***			
Minor hurricane	2.417 (0.250)***	65.184 (46.066)	1.515 (0.247)***			
Category = 1				2.151 (0.297)***	72.735 (57.567)	1.131 (0.263)***
Category = 2				3.253 (0.411)***	39.028 (19.173)*	2.769 (0.492)***
Category = 3				4.049 (0.311)***	710.213 (399.246)	3.100 (0.471)***
Category = 4 or 5				4.642 (0.915)***	607.060 (316.198)*	3.019 (0.850)***
Tornado	2.061 (0.197)***	12.507 (6.847)	-0.008 (0.070)	2.061 (0.196)***	12.441 (7.174)	-0.011 (0.070)
Flood	0.862 (0.102)***	0.380 (5.690)	0.762 (0.065)***	0.864 (0.102)***	0.299 (5.757)	0.758 (0.065)***
Severe storm	0.958 (0.180)***	8.952 (3.915)*	-0.205 (0.078)***	0.956 (0.181)***	9.075 (4.213)*	-0.201 (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 SHELUDS. Flood insurance payments data is from the Consolidated Federal Funds Report (CFFR). Time period is 1980-1996 for damages, 1983-1996 for flood claims.

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

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

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

¹Assumes aid money is split evenly among all counties in sample

²Assumes 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 region¹ by 1980-1996 hurricane experience.

	(1)	(2)	(3)	(4)	(5)
	One hurricane	Difference from no hurricanes	p-value of difference	Difference from matching	p-value of difference
<i>Panel A: 1970 characteristics</i>					
Coastal indicator	0.49	0.08	0.205	0.02	0.826
Land area, sq. mi	666.33	27.76	0.578	-54.02	0.363
Population (log)	10.32	0.47	0.000	-0.34	0.022
Population density (person/sq. mile)	87.29	-99.47	0.006	-24.52	0.181
Employment rate (fraction)	0.57	0.02	0.184	0.01	0.524
Net earnings per capita (log)	9.37	0.00	0.952	-0.02	0.508
Per capita transfers from government (log)	7.30	-0.09	0.002	-0.03	0.372
Per capita transfers from businesses (log)	4.05	0.00	0.918	-0.01	0.471
Per capita family assistance (log)	-2.81	0.05	0.590	0.04	0.689
Per capita public medical benefits (log)	-1.42	-0.05	0.231	0.00	0.955
Per capita UI payments (log)	3.81	0.23	0.001	-0.02	0.784
Per capita new single family housing (log)	-5.07	0.04	0.391	0.05	0.362
<i>Panel B: 1970-1979 trend</i>					
Population (log)	0.0120	-0.0025	0.184	-0.0043	0.066
Population density (person/sq. mile)	0.3774	-0.9444	0.288	-1.5121	0.022
Employment rate (fraction)	-0.0002	0.0003	0.710	-0.0003	0.791
Net earnings per capita (log)	0.0190	0.0004	0.861	-0.0003	0.893
Per capita transfers from government (log)	0.0631	0.0043	0.042	0.0003	0.910
Per capita transfers from businesses (log)	0.0151	-0.0001	0.718	-0.0002	0.526
Per capita family assistance (log)	0.0386	0.0177	0.047	0.0161	0.116
Per capita public medical benefits (log)	0.0889	-0.0013	0.673	-0.0011	0.755
Per capita unemployment insurance payments (log)	0.0864	-0.0065	0.518	-0.0047	0.643
Per capita new single family housing (log)	0.0075	-0.0100	0.177	-0.0099	0.296
Number of counties ²	119	811		195	

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

²Number may be smaller for some variables because of missing values.

Source: 1970 REIS, 1970 CBP and 1970 Census. Standard errors in parentheses. Bold font indicates significance at the 5% level or less. Monetary values are in 2008 dollars.

Figure 2. The effect of a hurricane on the construction sector

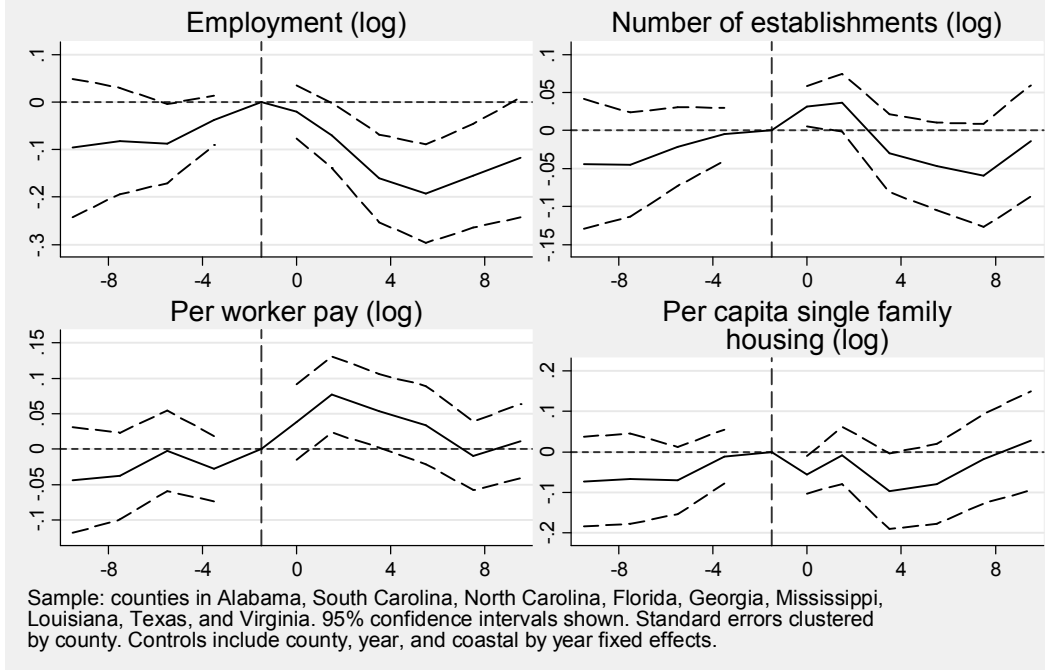


Table 6: Mean shift and trend break tests for Figure 2

	Construction employment (log)		Construction establishments (log)		Construction per worker wage (log)		Per capita single family housing construction (log)	
Post hurricane	-0.0698 (0.0375)*	-0.0899 (0.0432)**	0.0188 (0.0232)	0.0055 (0.0230)	0.0804 (0.0263)***	0.0697 (0.0276)**	-0.0744 (0.0392)*	-0.0763 (0.0397)*
Post hurricane time trend		-0.0204 (0.0119)*		-0.0133 (0.0065)**		-0.0108 (0.0052)**		-0.0019 (0.0100)
Overall time trend	0.0002 (0.0044)	0.0118 (0.0093)	-0.0012 (0.0033)	0.0064 (0.0054)	-0.0023 (0.0023)	0.0038 (0.0044)	0.0078 (0.0048)	0.0088 (0.0074)
Mean of dep. var.	6.90		4.33		10.16		-5.40	
Observations	4,744	4,744	6,166	6,166	4,744	4,744	6,630	6,630
R-squared	0.95	0.95	0.97	0.97	0.87	0.87	0.63	0.63
Estimated 5-year change		-0.1916 (0.0917)**		-0.0611 (0.0417)		0.0158 (0.0441)		-0.0856 (0.0697)
Estimated 11-year change		-0.2934 (0.1483)**		-0.1276 (0.0710)*		-0.0381 (0.0672)		-0.0949 (0.1152)

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 3. The effect of a hurricane on population and demographics

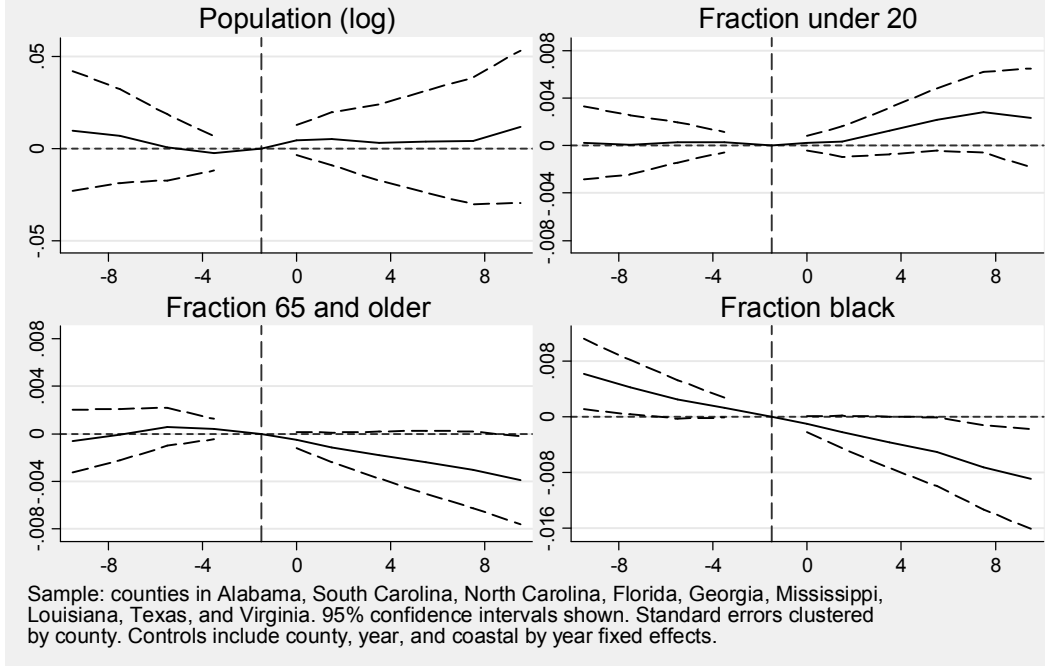


Table 7: Mean shift and trend break tests for Figure 3

	Fraction black residents		Fraction 65 and older		Fraction 20 and younger		Population (log)	
Post hurricane	0.0007	0.0006	-0.0005	-0.0010	-0.0001	0.0002	0.0040	0.0068
	(0.0007)	(0.0007)	(0.0005)	(0.0006)*	(0.0005)	(0.0004)	(0.0048)	(0.0046)
Post hurricane time trend		-0.0001		-0.0005		0.0003		0.0028
		(0.0003)		(0.0002)**		(0.0002)*		(0.0016)*
Overall time trend	-0.0008	-0.0008	-0.0002	0.0001	0.0001	0.0000	-0.0001	-0.0017
	(0.0003)**	(0.0003)**	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0019)	(0.0020)
Mean of dep. var.	0.28		0.12		0.31		10.56	
Observations	6,860	6,860	6,899	6,899	6,899	6,899	6,899	6,899
R-squared	0.98	0.98	0.92	0.92	0.95	0.95	0.99	0.99
Estimated 5-year change		0.0000		-0.0034		0.0019		0.0209
		(0.0016)		(0.0013)***		(0.0011)*		(0.0096)**
Estimated 11-year change		-0.0006		-0.0058		0.0036		0.0349
		(0.0027)		(0.0023)**		(0.0020)*		(0.0167)**

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 employment, earnings, and transfers

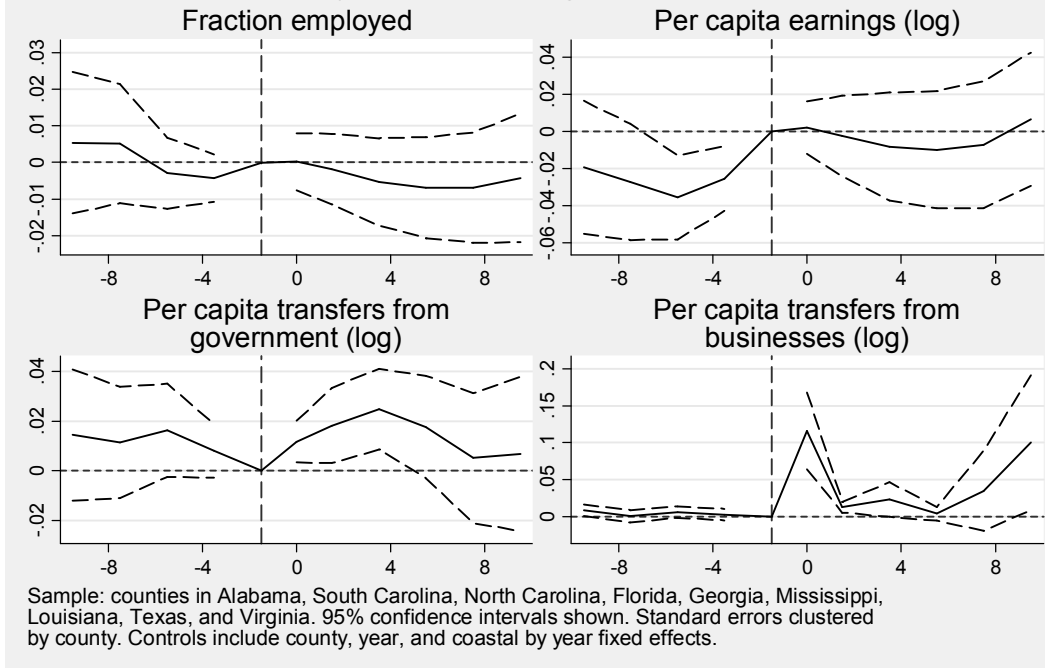


Table 8: Mean shift and trend break tests for Figure 4

	Employment rate (fraction)		Per capita transfer from government (logs)		Per capita transfer from businesses (logs)		Per capita net earnings (log)	
Post hurricane	0.0019	0.0025	0.0205	0.0200	0.0302	0.0328	0.0061	0.0044
	(0.0057)	(0.0063)	(0.0071)***	(0.0068)***	(0.0152)**	(0.0120)***	(0.0136)	(0.0151)
Post hurricane time trend		0.0006		-0.0005		0.0027		-0.0017
		(0.0013)		(0.0023)		(0.0037)		(0.0031)
Overall time trend	-0.0007	-0.0010	-0.0016	-0.0013	0.0007	-0.0008	0.0011	0.0021
	(0.0009)	(0.0013)	(0.0012)	(0.0017)	(0.0022)	(0.0005)	(0.0012)	(0.0024)
Mean of dep. var.	0.58	0.58	8.09	8.09	4.37	4.37	9.61	9.61
Estimated mean change (levels)	3.40E-03	4.46E-03	67.40	65.84	2.43	2.65	91.55	65.68
Observations	6,860	6,860	6,860	6,860	6,706	6,706	6,860	6,860
R-squared	0.87	0.87	0.96	0.96	0.87	0.87	0.90	0.90
Estimated 5-year change		0.0054		0.0177		0.0463		-0.0043
		(0.0113)		(0.0137)		(0.0110)***		(0.0275)
Estimated 11-year change		0.0084		0.0153		0.0598		-0.0129
		(0.0174)		(0.0244)		(0.0280)**		(0.0427)

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 various government transfers

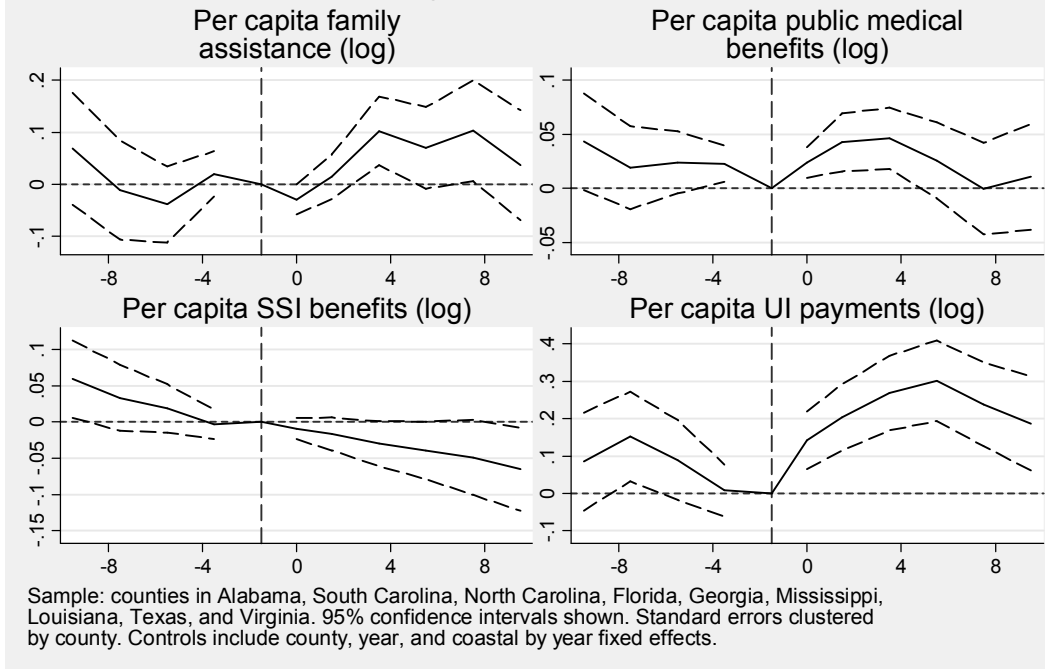


Table 9: Mean shift and trend break tests for Figure 5

	Per capita family assistance (logs)		Per capita public medical benefits (log)		Per capita SSI benefits (log)		Per capita unemployment insurance (log)	
Post hurricane	0.0350	0.0459	0.0470	0.0461	0.0109	0.0115	0.2178	0.2346
	(0.0271)	(0.0269)*	(0.0137)***	(0.0127)***	(0.0109)	(0.0111)	(0.0538)***	(0.0559)***
Post hurricane time trend		0.0109		-0.0009		0.0006		0.0168
		(0.0097)		(0.0035)		(0.0038)		(0.0107)
Overall time trend	0.0013	-0.0049	-0.0042	-0.0037	-0.0066	-0.0070	-0.0051	-0.0147
	(0.0041)	(0.0070)	(0.0022)*	(0.0029)	(0.0024)***	(0.0035)**	(0.0048)	(0.0085)*
Mean of dep. var.	-2.87	-2.87	-0.02	-0.02	-1.93	-1.93	4.37	4.37
Estimated mean change (levels)	2.01E-03	2.66E-03	4.70E-02	4.61E-02	1.60E-03	1.69E-03	19.17	20.83
Observations	6,709	6,709	6,860	6,860	6,860	6,860	6,821	6,821
R-squared	0.82	0.82	0.97	0.97	0.86	0.86	0.65	0.65
Estimated 5-year change		0.1002		0.0418		0.0145		0.3185
		(0.0593)*		(0.0200)**		(0.0245)		(0.0877)***
Estimated 11-year change		0.1545		0.0374		0.0175		0.4025
		(0.1052)		(0.0355)		(0.0428)		(0.1342)***

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 10: 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	-0.0059 (0.0277)	0.0495 (0.0289)*	0.0109 (0.0110)	0.0628 (0.0239)***	0.2499 (0.0808)***
Mean change in top quartile	0.0186 (0.0414)	-0.0493 (0.0255)*	-0.0012 (0.0132)	-0.0814 (0.0298)***	-0.0223 (0.0822)
Trend change in bottom quartile	0.0028 (0.0020)	-0.0112 (0.0057)*	-0.0003 (0.0018)	-0.0002 (0.0040)	0.0286 (0.0162)*
Trend change in top quartile	0.0003 (0.0023)	0.0102 (0.0052)*	0.0014 (0.0018)	-0.0001 (0.0037)	-0.0263 (0.0161)
Estimated 11-year change in bottom quartile	0.0273 (0.0357)	-0.0209 (0.0573)	0.0138 (0.0210)	0.0582 (0.0317)*	0.5040 (0.1711)***
Estimated 11-year change in top quartile	0.0199 (0.0467)	0.0030 (0.0368)	0.0057 (0.0170)	-0.0816 (0.0284)***	-0.1593 (0.1089)
Difference in means/11-year changes (bottom - top)	-0.0245	0.0987	0.0121	0.1442	0.2722
p-value of difference	0.714	0.901	0.595	0.006	0.066
Observations	6,899	6,860	6,860	6,860	6,821
R-squared	0.99	0.90	0.88	0.97	0.66

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: The effect of a hurricane on the construction sector

	Construction employment (log)	Construction establishments (log)	Construction per worker wage (log)	Per capita single family housing construction (log)
T = - 9 or - 10	-0.096 (0.073)	-0.044 (0.043)	-0.044 (0.037)	-0.073 (0.056)
T = - 7 or - 8	-0.082 (0.056)	-0.045 (0.034)	-0.038 (0.030)	-0.066 (0.056)
T = - 5 or - 6	-0.088 (0.041)**	-0.021 (0.026)	-0.002 (0.028)	-0.071 (0.042)*
T = - 3 or - 4	-0.038 (0.026)	-0.005 (0.017)	-0.028 (0.023)	-0.012 (0.033)
T = 0	-0.021 (0.028)	0.032 (0.013)**	0.038 (0.026)	-0.057 (0.023)**
T = 1 or 2	-0.071 (0.034)**	0.037 (0.019)*	0.077 (0.027)***	-0.009 (0.035)
T = 3 or 4	-0.160 (0.046)***	-0.030 (0.025)	0.054 (0.026)**	-0.097 (0.047)**
T = 5 or 6	-0.193 (0.052)***	-0.047 (0.029)	0.034 (0.027)	-0.079 (0.049)
T = 7 or 8	-0.155 (0.055)***	-0.059 (0.034)*	-0.009 (0.024)	-0.017 (0.055)
T = 9 or 10	-0.117 (0.063)*	-0.014 (0.037)	0.011 (0.026)	0.028 (0.061)
Mean of dep. var.	6.903	4.330	10.155	-5.396
Observations	4,744	6,166	4,744	6,630
R-squared	0.95	0.97	0.87	0.63
p-value of all leads F-test	0.279	0.655	0.345	0.305
p-value of all lags F-test	0.000	0.000	0.005	0.000
p-value of T=0 to T=4 lags F-test	0.001	0.000	0.020	0.003

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

Table A2: The effect of a hurricane on population and demographics

	Fraction black residents	Fraction 65 and older	Fraction 19 and younger	Population (log)
T = - 9 or - 10	0.006 (0.002)**	-0.001 (0.001)	0.000 (0.001)	0.010 (0.016)
T = - 7 or - 8	0.004 (0.001)**	0.000 (0.001)	0.000 (0.001)	0.007 (0.012)
T = - 5 or - 6	0.003 (0.001)*	0.001 (0.000)	0.000 (0.000)	0.001 (0.009)
T = - 3 or - 4	0.001 (0.000)*	0.000 (0.000)	0.000 (0.000)	-0.003 (0.004)
T = 0	-0.001 (0.000)*	-0.001 (0.000)	0.000 (0.000)	0.005 (0.004)
T = 1 or 2	-0.002 (0.001)*	-0.001 (0.000)*	0.000 (0.000)	0.005 (0.007)
T = 3 or 4	-0.004 (0.001)*	-0.002 (0.001)*	0.001 (0.000)	0.003 (0.010)
T = 5 or 6	-0.005 (0.002)**	-0.002 (0.001)*	0.002 (0.001)	0.004 (0.014)
T = 7 or 8	-0.007 (0.003)**	-0.003 (0.001)*	0.003 (0.001)	0.004 (0.017)
T = 9 or 10	-0.009 (0.003)**	-0.004 (0.001)**	0.002 (0.002)	0.012 (0.020)
Mean of dep. var.	0.285	0.123	0.312	10.558
Observations	6,860	6,899	6,899	6,899
R-squared	0.98	0.92	0.95	0.99
p-value of all leads F-test	0.066	0.095	0.271	0.245
p-value of all lags F-test	0.091	0.378	0.011	0.124
p-value of T=0 to T=4 lags F-test	0.125	0.199	0.040	0.150

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 employment, wages, and transfers

	Employment rate (fraction)	Per capita transfer from government (logs)	Per capita transfer from businesses (logs)	Per capita net earnings (log)
T = - 9 or - 10	0.005 (0.009)	0.014 (0.013)	0.009 (0.003)**	-0.019 (0.018)
T = - 7 or - 8	0.005 (0.008)	0.011 (0.011)	0.001 (0.004)	-0.027 (0.015)*
T = - 5 or - 6	-0.003 (0.004)	0.016 (0.009)*	0.006 (0.003)	-0.036 (0.011)***
T = - 3 or - 4	-0.004 (0.003)	0.008 (0.005)	0.003 (0.003)	-0.025 (0.008)***
T = 0	0.000 (0.003)	0.012 (0.004)***	0.116 (0.026)***	0.002 (0.007)
T = 1 or 2	-0.002 (0.004)	0.018 (0.007)**	0.013 (0.003)***	-0.003 (0.011)
T = 3 or 4	-0.005 (0.006)	0.025 (0.008)***	0.023 (0.011)*	-0.008 (0.014)
T = 5 or 6	-0.007 (0.006)	0.018 (0.010)*	0.004 (0.004)	-0.010 (0.015)
T = 7 or 8	-0.007 (0.007)	0.005 (0.013)	0.035 (0.027)	-0.007 (0.017)
T = 9 or 10	-0.004 (0.008)	0.007 (0.015)	0.100 (0.046)**	0.007 (0.018)
Mean of dep. var.	0.585	8.088	4.373	9.605
Observations	6,860	6,860	6,706	6,860
R-squared	0.87	0.96	0.87	0.90
p-value of all leads F-test	0.456	0.340	0.055	0.020
p-value of all lags F-test	0.757	0.003	0.000	0.107
p-value of T=0 to T=4 lags F-test	0.491	0.011	0.001	0.719

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 various government transfers

	Per capita family assistance (logs)	Per capita public medical benefits (log)	Per capita SSI benefits (log)	Per capita unemployment insurance (log)
T = - 9 or - 10	0.068 (0.054)	0.043 (0.022)*	0.059 (0.026)**	0.085 (0.066)
T = - 7 or - 8	-0.011 (0.048)	0.019 (0.019)	0.033 (0.023)	0.152 (0.061)**
T = - 5 or - 6	-0.039 (0.037)	0.024 (0.014)	0.019 (0.016)	0.089 (0.054)
T = - 3 or - 4	0.020 (0.022)	0.023 (0.008)***	-0.003 (0.010)	0.008 (0.035)
T = 0	-0.029 (0.014)**	0.024 (0.007)***	-0.009 (0.007)	0.142 (0.039)***
T = 1 or 2	0.015 (0.021)	0.043 (0.013)***	-0.017 (0.011)	0.204 (0.044)***
T = 3 or 4	0.103 (0.033)***	0.046 (0.014)***	-0.030 (0.015)*	0.268 (0.050)***
T = 5 or 6	0.070 (0.039)*	0.026 (0.017)	-0.039 (0.020)*	0.301 (0.054)***
T = 7 or 8	0.103 (0.049)**	0.000 (0.021)	-0.049 (0.026)*	0.239 (0.056)***
T = 9 or 10	0.037 (0.053)	0.011 (0.024)	-0.065 (0.029)**	0.187 (0.063)***
Mean of dep. var.	-2.873	-0.023	-1.926	4.367
Observations	6,709	6,860	6,860	6,821
R-squared	0.82	0.97	0.86	0.65
p-value of all leads F-test	0.000	0.002	0.002	0.004
p-value of all lags F-test	0.000	0.000	0.278	0.000
p-value of T=0 to T=4 lags F-test	0.000	0.005	0.113	0.000

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

Table A5: 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	-0.0224 (0.0207)	0.0534 (0.0236)**	0.0133 (0.0114)	0.0571 (0.0186)***	0.1898 (0.0851)**
Mean change in top quartile	0.0144 (0.0344)	-0.0365 (0.0241)	0.0046 (0.0160)	-0.0798 (0.0237)***	-0.0040 (0.1023)
Trend change in bottom quartile	0.0047 (0.0018)***	-0.0066 (0.0054)	-0.0002 (0.0016)	-0.0034 (0.0031)	0.0386 (0.0148)**
Trend change in top quartile	-0.0002 (0.0020)	0.0056 (0.0044)	0.0010 (0.0015)	0.0061 (0.0026)**	-0.0075 (0.0135)
Estimated 11-year change in bottom quartile	0.0235 (0.0285)	0.0033 (0.0527)	0.0162 (0.0189)	0.0381 (0.0287)	0.5301 (0.1659)***
Estimated 11-year change in top quartile	0.0137 (0.0384)	-0.0078 (0.0311)	0.0097 (0.0177)	-0.0484 (0.0217)**	-0.0416 (0.1102)
Difference in means/11-year changes (bottom - top)	-0.0368	0.0898	0.0087	0.1369	0.1939
p-value of difference	0.482	0.044	0.734	0.001	0.253
Observations	6,899	6,860	6,860	6,860	6,821
R-squared	0.99	0.90	0.88	0.97	0.66

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 A6: 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	36,809	36,809	12,168
R-squared	0.91	0.62	0.85	0.98	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 A7: 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	30,872	31,751	29,743
R-squared	0.97	0.95	0.94	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 A8: autocorrelation in local economic indicators

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

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

Table A9: 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

¹When 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".