The Role of Transfer Payments in Mitigating Shocks: Evidence from the Impact of Hurricanes

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Abstract

Little is known empirically about how aggregate economic shocks are mitigated by social safety nets. I examine the effect of hurricanes on US counties. While I find no significant changes in population, earnings, and the employment rate 0-10 years after landfall, there is a substantial increase in non-disaster government transfers. An affected county receives additional non-disaster government transfers totaling $654 per capita, which suggests that the lack of changes in basic economic indicators may be in part due to existing social safety nets. The fiscal costs of natural disasters are also much larger than the cost of disaster aid alone.

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1 Introduction

A large literature has examined the optimal level and duration of unemployment insurance (e.g., Baily, 1978; Chetty, 2006). Many of these papers focus on how social safety nets affect individuals' behavior and welfare (e.g., Townsend, 1994; Gruber, 1997; Chetty and Looney, 2006). However, social safety nets may also mitigate aggregate rather than idiosyncratic shocks. To what extent they do so is an open and important question. If safety net benefits have an effect on the aggregate economy that is larger than the sum of their effect on the individual, then the optimal level of benefit generosity is different than if only the individual is affected. One reason why it is hard to determine whether social safety nets play a role in macroeconomic outcomes is lack of identification. It is difficult to find shocks that are exogenous to the variables of interest and whose onset is easily measured.

In this paper, I attempt to evaluate whether social safety nets can plausibly mitigate the effect of hurricanes. The main advantages to using hurricane incidence as a capital shock are that hurricanes are exogenous, their onset is known precisely, and they 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 post-hurricane economic dynamics, which reveals any non-monotonicities in how counties adjust to this negative shock. I interpret my estimates using a simple spatial equilibrium framework, which illustrates how transfers prevent relocation and generally act as a buffer against negative capital shocks.

Moreover, considering the effects of hurricanes is important in its own right. 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 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, Keen and Mani, 2003). Damages are likely to continue growing as climate change is expected to increase the number and intensity of extreme events (Meehl et al., 2007; Schneider et al., 2007). Freeman, Keen and Mani (2003) estimate that damages will reach \$367 billion a year by 2050, a 750 percent increase in real terms.

However, we know 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

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

disaster relief and mitigation programs. And, although this is rarely discussed in relation to disaster policy, transfer programs designed for general economic downturns 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 policies. In addition, the fiscal costs of disasters will appear smaller than they actually are.

Although I cannot directly estimate the causal impact of social safety nets, my results suggest that the 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 23% higher in the eleven years following the hurricane while total non-disaster transfer payments are 2% higher. Correspondingly, population, the employment rate, and wages do not change significantly, and the 95% confidence intervals for changes in these variables are consistent with the estimated transfer changes. In addition to the funds provided through official disaster declarations, which average \$356 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 about \$654 per capita in present discounted value. Transfers from businesses to individuals (insurance payments) increase temporarily as well, but add only an estimated \$37 to per capita transfers over the eleven years. Together, the transfers represent a large fraction of direct hurricane 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 also imply that the fiscal impacts of hurricanes are 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, Shoven and Whalley, 1985; Feldstein, 1999). In addition, because transfers are not paid for by the people receiving them, they may create moral hazard problems, leading individuals to live in riskier places and take fewer precautions than they would with actuarially fair insurance.

Finally, I find significant changes in the age structure of the county, and some evidence of changes in its racial composition. In particular, there is an increase in the fraction of population under 20 years of age and a slight decrease in the fraction of population 65 and older. The fraction of the population that is black falls slightly. The pattern of these changes is inconsistent with the transfer increases, so the change in transfers is not being driven by changes in the age structure.

I contribute to two main strands of literature. The first focuses on the optimal level and duration

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

of unemployment insurance (see e.g., Baily, 1978; Werning and Shimer, 2006; Chetty, 2006, 2008) and the potential for public social safety nets to improve individual welfare (e.g., Townsend, 1994; Gruber, 1997; Feldstein, 2005; Chetty and Looney, 2006). Similarly to Chetty and Looney (2006), who show that the provision of social insurance could be welfare improving even if consumption is smooth over a wide range of shocks, my results demonstrate that the absence of movement in basic economic indicators does not necessarily imply that the welfare loss of the shock is small.

A number of papers also consider how unemployment insurance generosity should vary over the business cycle. Kroft and Notowidigdo (2011), Landais, Michaillat and Saez (2011), and Jung and Kuester (2011) show that the optimal wage replacement rate of unemployment insurance is counter-cyclical. Landais, Michaillat and Saez (2011) show that this holds for the duration of benefits as well. By contrast, Mitman and Rabinovich (2011) find that unemployment benefits are pro-cyclical. Although I cannot directly estimate the optimal level of unemployment benefits following a local economic shock, my results and conceptual framework demonstrate that the adjustments following a local economic shock can be qualitatively different from those following a national shock.

The second strand of literature focuses on the economic impacts of natural disasters, typically considering a single outcome or single event (Leiter, Oberhofer and Raschky, 2009; Brown, Mason and Tiller, 2006) or looking at effects from one to four quarters (Strobl and Walsh, 2009) to three to four years after the event (Murphy and Strobl, 2010). In one of the few studies to consider long-run effects, Hornbeck (2011) 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 increased sharply and remained 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 (2011) 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 by connecting the outcomes together in a cohesive framework.

Several papers examine the importance of area characteristics, institutions and wealth in determining disaster-related losses and deaths (Kahn, 2005; Nordhaus, 2010; Toya and Skidmore, 2007). 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 set of papers by considering the role of transfer payments and by looking at the economic effects of disasters rather than the damages they cause.

In another related study, Yang (2008) estimates the effect of hurricanes on international financial flows and finds that four-fifths of the estimated damages in poorer countries are replaced 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. Like Yang, I estimate the impact of hurricanes on monetary transfers but focus on within-country flows related to social and private insurance and expand the analysis to include economic effects.

The rest of the paper is organized as follows. Section 2 presents the conceptual framework. Section 3 provides background information on hurricanes, US federal disaster aid, and the data used for analysis. Section 4 describes the empirical strategy. Sections 5 and 6 present and discuss the results, respectively. Section 7 concludes.

2 Conceptual Framework

Hurricanes in the modern US can be thought of as negative capital shocks: with the exception of Hurricane Katrina, they do not cause substantial loss of life. Thus, I use a simple production function framework to guide the discussion of the results. I describe how economic outcomes are affected by a capital shock under various assumptions about moving costs, capital adjustment costs and the availability of transfer payments.[3] I present the framework assuming that there are many identical locations, so that a change in one location does not affect 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.

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 (i.e., there are no adjustment costs), 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. Intuitively, when moving costs are 0, 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 moving away from the area to work elsewhere until the wage rate is equal to the pre-shock wage. The degree to which population falls depends on how the wage changes with the labor supply and how quickly capital can adjust. In this case, the presence of transfers (assuming their generosity is unchanged) plays no role in post-shock dynamics: the margin of adjustment is moving.

[3]A simple formal model can be found in the Online Appendix.

When both capital and individuals are not perfectly mobile (but some of the individuals have negligible moving costs), and there are no transfer payments, the population will also fall, but to a smaller extent than in the case of perfect individual mobility. Unlike that case, individuals may also decrease their labor supply without moving away, so there may be a decline in the employment rate. Although the decrease in labor supply counteracts the wage drop somewhat, the equilibrium wage will be lower. Intuitively, suppose that the equilibrium wage is unchanged. Then there would be no incentive for individuals to lower their labor supply or move. But because the level of capital is lower, a new equilibrium with the same wage, population, and labor supply is not possible. Thus, all three of these variables will adjust to some extent. The relative decline of population and labor supply depends on the relative magnitudes of moving costs and disutility of labor supply.

If, in addition to imperfectly mobile capital and individuals, there are transfer payments, the population decline following a capital shock will be weakly smaller than without transfers (because some of the individuals who would have moved now prefer to stay and take transfers), while the change in total labor supply and the wage rate relative to the no transfer case is ambiguous. Per capita labor supply should fall more as some individuals take the outside option of transfers instead of working. This will counteract the decrease in wages due to the lower capital. Likewise, some individuals will chose to take transfers and remain in the area instead of moving away.[4] This implies that the net effect on total labor supply and thus on wages (relative to the no transfer case) is ambiguous: although labor supply per capita is relatively lower, there are relatively more people remaining in the area. However, the new equilibrium wage cannot be higher than the pre-shock wage, as an inflow of movers from other areas would drive it down to its pre-shock levels.

3 Background and Data

Hurricanes in the United States. Hurricanes that affect the US form in the Atlantic Ocean. 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 a cyclone encounters cold water or land, it loses strength quickly and dissipates. 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

[4] Transfer payments can be either a decreasing function of the wage (i.e., compensate individuals living in an area for lower wages, as in Notowidigdo (2011)) or unemployment insurance payments that the individual can choose instead of working.

hurricane are called "spiral bands". These are characterized by heavy rains but typically do not have hurricane-force winds.

For hurricane data, I use the Best Tracks (HURDAT) dataset from the National Oceanic and Atmospheric Administration (NOAA).[5] It contains the location of the storm center and wind speed (in six hour intervals) for each North Atlantic cyclone since 1851. To determine which counties the storm passed through, I assume that the storm path is linear between the given points. Data on storm width are unfortunately not available, which 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. Although the hurricane data span a long time period, annual county-level economic data are only available for 1970-2006. Because my econometric approach uses 10 leads and lags and a balanced panel of hurricanes, the storms in my sample are those that occurred between 1980 and 1996.

North Atlantic hurricanes 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. Hurricanes that make it to land cause 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.[6]

US hurricanes are geographically concentrated. Most of the landfalling hurricanes over this time period affected 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

[5] Available from http://www.nhc.noaa.gov/pastall.shtml#hurdat. Accessed April 2009.
[6] Author calculations using data from Nordhaus (2006).

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.

In order to gauge the potential economic impact of hurricanes, it is helpful to look at the damages they cause.[7] I use estimates of direct damages from HAZUS-MH, published by FEMA.[8] Table 1 shows the damage statistics for the eight major hurricanes that affected the hurricane region between 1980 and 1996. 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 experienced \$340 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.

HAZUS-MH also provides estimates of non-structural losses, such as building content and inventory losses, and 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. 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 (a) listed as affected in the FEMA simulations but do not have the center of the storm passing through them and (b) are direct neighbors of the affected counties ("peripherally affected neighbors"). The damage estimates are much smaller.[9] For example, the average damage to buildings is only \$19 million or about 17 times smaller than the average damage in a centrally affected county, and the average loss ratio is 0.33%, which is about 4 times smaller. Per capita total losses are also about 5 times smaller, averaging \$256 per capita, and total losses are about 20 times smaller. Only 32 households are estimated to be displaced, on average, and only 8 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. Moreover, minor hurricanes, which have lower maximum wind speeds and represent the majority of hurricanes in my sample, are likely to have even smaller effects in neighboring counties, as wind speeds dissipate non-linearly with distance from the storm

[7] Here, I consider the absolute damages. Appendix B in the Online Appendix considers relative damages and shows that hurricanes are, on average, the most damaging of the common meteorological events in the US.

[8] HAZUS-MH is software meant to help state, local, and Federal government officials prepare for disasters and to help the private sector estimate risk exposure. The software combines scientific and engineering knowledge with detailed historic data to produce damage estimates that are likely to be more accurate than those made using simpler estimates or reports. In addition to simulating hypothetical damages, HAZUS contains highly detailed damage estimates of past major hurricanes. Available by request from http://www.fema.gov/plan/prevent/hazus/index.shtm

[9] Including all peripherally affected counties in this summary, whether or not they border the directly affected counties, makes the relative damages of centrally affected counties even larger.

center.

Federal Disaster Aid. 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. The Federal Emergency Management Agency (FEMA) also provides personnel, legal help, counseling, and special unemployment insurance for people unemployed due to the disaster. Although there is some long-term recovery spending in extreme cases, most of the transfers to individuals occur within six months of the declaration and most of the public infrastructure spending occurs within two-three years (FEMA, personal communication).

Between 1980 and 1996, the federal government spent $6.4 billion (2008 dollars) on hurricane-related disaster aid and $23 billion on other disasters.[10] 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 accounted for about a third of all disaster aid during this time period. Unfortunately, annual county-level data on disaster spending over time is not available, so I cannot incorporate disaster spending into my main empirical framework. However, the available data do allow me to approximately compute the average amount of disaster transfers per county.

Table 2 shows the summary statistics for federal aid related to hurricanes between 1980 – 1996.[11] 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. Per capita spending in 1980-1996 averaged $356 per hurricane and $412 per major hurricane (2008 dollars). An extreme assumption of a

[10]PERI Presidential Disaster Declarations database (Sylves and Racca, 2010). 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.

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

uniform split across counties (regardless of their population) implies a larger per-capita average of $\$1,137$ per hurricane and $\$2,018$ per major hurricane. 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 disaster spending.

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 $10.3 – 11 million per county, $24.6 – 30.1 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 $63 to $187 in the proportional split case and from $191 to $954 in the uniform split case. In the following sections, I use the preferred number of $356 per capita as a benchmark to compare spending by disaster relief agencies to hurricane-related spending by non-disaster transfer programs.

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 the Surveillance Epidemiology and End Results (SEER) population database. Data on 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.[12] 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.

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.

Sample of Analysis. Ideally, one would estimate the effect of hurricanes by looking at differences over time between identical counties in the hurricane region that do and do not experience a

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

hurricane between 1980 and 1996. However, finding a valid control group is not straightforward. In Table 3, I compare characteristics and trends of counties that do not experience any hurricanes between 1980 and 1996 to counties that experience one hurricane.[13]

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 50% of 119 counties that experience one hurricane are coastal, compared to 21% of 711 counties that have not had hurricanes over this period. Counties that experience hurricanes are more populous than non-hurricane counties and have lower population densities. These differences are highly significant (as shown in Column 3). Counties with hurricanes also have larger per capita transfers from the federal government.

Differences in levels are not problematic for estimation because county fixed effects are included in every specification. However, differences in levels may indicate differences in trends. In Panel B, I test for differential trends in the time-varying characteristics during the years 1970-1979 (before any hurricanes in the sample occur). Columns 1 and 2 show the trend in the hurricane counties and their difference from the trend in non-hurricane counties. Only one variable shows differential trends for these two groups of counties: per capita transfers from government, significant at the 1% level.

Another way to construct the control group is by requiring balance in hurricane risk. I construct a hurricane risk variable using historic (1851-1970) hurricane data. I estimate a county's 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.[14] 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. Propensity score matching eliminates all trend differences that are significant at the 5% level. Because the propensity-matched sample is more similar to the treatment group than all counties in this region, I use the former as my preferred control group. Figure 1 shows the treatment and control counties.

4 Empirical Strategy

Differences in Differences Regression Framework. First, I outline the basic differences-in-differences specifications that I use to estimate the effect of hurricanes. The identifying assumption is that, conditional on the location and the year, the occurrence of a hurricane is uncorrelated with

[13] I omit the few counties that experience more than one hurricane between 1980 and 1996. Results are similar if counties with more than one hurricane are included.

[14] Using two-nearest neighbor rather than nearest neighbor matching ensures that the number of counties in the control group is adequate. When nearest neighbor matching is used, some non-hurricane counties are assigned as nearest neighbors multiple times, resulting in a very small control group.

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.

Hurricanes may have an effect on the mean of an economic indicator, its trend, or both. The regression equation for testing for a mean shift while controlling for a differential time trend is:

$$\begin{aligned} O_{ct} = {} & \theta_1 \mathbf{1}[\text{Hurr in past 10 years}]_{ct} \\ & + \gamma_1 \mathbf{1}[\text{Hurr within 10 years}]_{ct} y + \gamma_2 \mathbf{1}[\text{Hurr outside 10 years}]_{ct} y \\ & + \beta^{11} \mathbf{1}[post11]_{ct} + \beta^{-11} \mathbf{1}[pre11]_{ct} + \alpha_c + \alpha_t + \mathbf{1}[coastal]\,\alpha_t + \varepsilon_{ct} \end{aligned} \tag{1}$$

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. I include indicator variables $\mathbf{1}[post11]_{ct}$ and $\mathbf{1}[pre11]_{ct}$ 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. 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). α_c and α_t are county and year fixed effects. $\mathbf{1}[coastal]\,\alpha_t$ 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 coastal population has grown disproportionately in the past 30 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 $\mathbf{1}[\text{Hurr within 10 years}]_{ct} y$. $\mathbf{1}[\text{Hurr within 10 years}]_{ct}$ is an indicator equal to 1 if county c experienced a hurricane in the ten years before or in the ten years after time y, where y is the number of years since the hurricane in event time. γ_2, the coefficient on $\mathbf{1}[\text{Hurr outside 10 years}]_{ct} y$, controls for the overall trend in hurricane counties outside of the twenty-one year window of interest.

The growth rate of economic indicators 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:

$$
\begin{aligned}
O_{ct} \quad = \quad & \theta_1 \mathbf{1}[\text{Hurr in past 10 years}]_{ct} + \theta_2 \mathbf{1}[\text{Hurr in past 10 years}]_{ct} y \qquad (2) \\
& + \gamma_1 \mathbf{1}[\text{Hurr within 10 years}]_{ct} y + \gamma_2 \mathbf{1}[\text{Hurr outside 10 years}]_{ct} y \\
& + \beta^{11} \mathbf{1}[post11]_{ct} + \beta^{-11} \mathbf{1}[pre11]_{ct} + \alpha_c + \alpha_t + 1\left[coastal\right] \alpha_t + \varepsilon_{ct}
\end{aligned}
$$

$\mathbf{1}[\text{Hurr in past 10 years}]_{ct} y$ is the interaction of the eleven-year post-hurricane indicator with the number of years since the hurricane. All other variables remain the same. The test for a mean shift without a trend break amounts to testing $\theta_1 = 0$ in equation (1), while the test for a mean shift with a trend break amounts to testing $\theta_1 = 0$ and $\theta_2 = 0$ in equation (2).

These specifications summarize the impact of a hurricane concisely and are the most powerful when the assumption of monotonic effects holds. In addition, if the assumption of parallel trends does not hold, this specification is still informative, as it controls for differential time trends.

I also estimate the net present value of transfers by computing:

$$\sum_{t=0}^{10} r^t \left(e^{\mu + \theta_1 + t\theta_2} - e^{\mu} \right)$$

where $t = 0$ is the year of the hurricane hit and μ is the mean of the logged per capita variable. θ_1 and θ_2 are coefficients corresponding to the mean shift and trend break estimates, as shown in equation (2). If the trend break estimate is insignificant, I compute the net present value using only the mean shift estimate from equation (1). I use the discount rate of $\frac{1}{1+r} = \frac{1}{1.03}$.

I do not use damage estimates as the independent variable for several reasons. First, the only database that contains county-level damage estimates for all hurricanes between 1970 and 2006 is the Spatial Hazard Events and Losses Database (Hazards and Vulnerability Research Institute, 2009). 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 the Online Appendix. 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 themselves. For example, a county with larger 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 a given outcome variable.

Event Study Regression Framework. To identify any non-monotonic effects of hurricanes, I also employ an event study framework. Specifically, I regress outcomes on a set of hurricane indicators ranging from 10 years before to 10 years after a hurricane, controlling for county, year, and coastal-by-year fixed effects. The basic event study framework for estimating the year-by-year effect of a hurricane up to ten years after its occurrence is:

$$O_{ct} = \sum_{\tau=-10}^{10} \beta_\tau H_{c,t-\tau} + \beta_{ct}^{-11} + \beta_{ct}^{11} + \alpha_c + \alpha_t + 1\,[coastal]\,\alpha_t + \varepsilon_{ct} \tag{3}$$

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

O_{ct} is some economic outcome and 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. As in the previous section, I control for county, year, and coastal-county-by-year fixed effects with α_c, α_t, and $1\,[coastal]\,\alpha_t$.

When estimating the above equation, I combine hurricane indicators into two-year bins to increase the power of the estimation.[15] 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. 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. 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.

5 Empirical Results

5.1 Economic Effects of Hurricanes

In this section, I present the estimated effects of a hurricane. First, I present the results of the trend break and mean shift tests described in equations (1) and (2). Following each table, I graph

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

the coefficients from equation (3) in Section 4.[16] The trend break/mean shift estimates and the disaggregated results 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.

Effect on the construction sector. Table 4 shows the mean shift and trend break test results for the construction sector, measured in terms of employment, wages, the number of firm locations and single family home construction. The number of construction firm locations (establishments) declines by 1.6% each year with no change in the mean. Construction employment is on average 7.6% lower in the ten years following the hurricane, and declines by 2.0% per year. The overall decline in employment suggests a drop in construction demand. This is confirmed by estimates of per capita single family housing starts, which are 8% lower on average. Wages increase by an average of 6.8%, but then fall by 0.9% each year, suggesting there may be a temporary change in the composition of construction labor demand (e.g., more demand for specialized workers) or lower labor supply.

Figure 2 shows the disaggregated estimates corresponding to Table 4. The y-axis shows the estimated coefficient and the 95% confidence interval.[17] 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).

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 $8-23\%$ below pre-hurricane levels. Similarly, the number of establishments falls by $6-11\%$ $3-10$ years after the hurricane. It is not clear whether the decline is temporary: $9-10$ years later, the construction sector employment is still significantly lower than the year before the hurricane, but appears to be slowly increasing. Construction wages increase by $5-9\%$ in years $1-4$ and per capita single family housing starts are $8.8-10.5\%$ lower $3-6$ years after the hurricane, with no significant changes in other years. The hurricane lag variables are jointly significant at the 5% level or less for all the outcomes.

One possible interpretation of the decline in the local construction sector is spatial: the construction industry may have simply moved to nearby counties without any net effect on the sector. The implications of spatial changes, while non-trivial for the local economy, are different than if there's a widespread capital shock. However, the fall in per capita housing starts provides evidence of a significant decrease in construction demand. Thus, the downturn in the local construction

[16] The point estimates from the figures can be found in the Online Appendix (Tables A1-A4).

[17] Standard errors are spatially clustered, allowing for spatial correlation in errors over a radius of 300 kilometers and serial correlation in errors over 5 years. I thank Solomon Hsiang for sharing his code with me.

sector is not solely driven by spatial shifts in construction activity.

Effect on population and demographics. Table 5 shows the trend break and mean shift tests for population and demographics. There is a slight decline in the trend of the fraction of residents who are black (-0.0005). The fraction of population under 20 grows by 0.0006 in each year after the hurricane (a 0.2% annual increase relative to the mean), while the fraction 65 and older shrinks by 0.003 each year. These changes are significant at the 5% and 10% levels, respectively. One possible explanation for this demographic change is a shift in the composition of job opportunities that makes the county a relatively less attractive place to retire and a relatively more attractive place for younger families.

Figure 3 shows the corresponding disaggregated effects. 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 somewhat lower in the years after the hurricane and an F-test indicates that the lags are jointly significant. The fraction of residents who are 65 and older falls steadily following the hurricane (although the lags are not jointly significant), while the fraction of those under 20 years of age steadily grows.

Effect on earnings, employment and transfers. In Table 6, I show the estimated effect of a hurricane on the employment rate, earnings, and transfers. There is no change in the employment rate or per capita net earnings. Using 95% confidence bounds, I can rule out a decrease in mean earnings greater than 1.8% and a decrease in the mean employment rate greater than 0.5% The mean shift test for transfers indicates a 2.1% average increase in per capita government to individual transfers, equivalent to about \$69 per person per year. Per capita business to individual transfers in the eleven years following the hurricane are estimated to be 4.8% higher than the pre-hurricane transfers, or about \$3.9 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 \$654 per capita, and the PDV of transfers from businesses is \$37 per capita. Thus, post-hurricane transfers from general social programs are larger than transfers from disaster-specific programs and much larger than insurance payments. Because the non-disaster transfers are still significantly larger 10 years after the hurricane, the estimate of \$654 per capita should be viewed as a lower bound.

Figure 4 shows the corresponding disaggregated effects, which confirm that the employment rate and per capita earnings remain unchanged. Overall per capita transfers from the government to individuals increase by $2.6-3.7\%$ $1-10$ years after the hurricane. Per capita transfers to individuals from businesses increase by 11.7% in the year of a hurricane and then return to their pre-hurricane levels.

Decomposing the change in transfers. The subcomponents of total government transfers to individuals are: retirement and disability insurance benefits (which includes workers' compensation), medical benefits (which includes Medicare and Medicaid), income maintenance (which includes Supplemental Security Income, family assistance, and foot stamps), unemployment benefits, veterans' benefits, and federal education assistance. A separate analysis of each of these components (following the same procedure as for total transfers) reveals that increases in medical and unemployment benefits explain the overwhelming majority of the net increase in total non-disaster transfers. Specifically, public medical benefits increase significantly by \$435 per capita in PDV, of which \$106 is Medicare spending. The estimated change in Medicare spending is not significant. [18] Because there is no significant increase in Medicare spending, the increase in public medical spending is likely due to changes in the number of people eligible for public medical benefits rather than increased medical spending on existing recipients.

Unemployment benefits increase by about \$280 per capita in PDV. There is no significant change in aggregate income maintenance (although some subcomponents, such as family assistance, do increase slightly) and no significant change in retirement and disability insurance benefits, per capita federal education assistance, or per capita veteran benefits. Thus, the majority of the increase in transfers is accounted for by unemployment insurance and public medical benefits.

Accounting for lack of change in basic economic indicators. It may at first seem puzzling that per capita unemployment insurance and Medicaid payments increase with no corresponding change in either employment or income. However, a simple back of the envelope calculation shows that the estimated changes in transfers are consistent with the 95% confidence intervals for the estimated changes in the other variables. Unemployment payments of \$280 per capita over 11 years are equivalent to about \$22 per person per year. If the average annual benefit per unemployed worker is $\$10,000$ (in 2008 dollars), the estimated change in transfers implies an additional 0.0022 unemployed per capita, whereas the 95% confidence interval for the mean change in the employment rate is -0.005 to 0.013. Other explanations for the lack of change in the employment rate exist as well. Suppose the hurricane increases the rate of labor force participation, which in turn leads to an increase in the layoff rate of those who are employed. Then unemployment payments may increase without a corresponding change in the employment rate. Second, the composition of the unemployed may change. For example, if the hurricane causes a relative increase in the demand for low-skilled labor unemployment payments will be on average larger without a corresponding change in the unemployment rate.

It is more difficult to translate the estimated change in public medical spending into an implied estimate for the change in income. Medicaid eligibility is based on an income threshold, so a full calculation would require knowledge of how the distribution of income is affected. However, relative to the 95% confidence interval for the mean change in annual earnings per capita, the

[18] In my sample, Medicare spending represents 59% of total public spending, on average. Thus, the proportional change in non-Medicare public spending is much larger than the change in Medicare.

estimated mean change in public medical spending is reasonable. Specifically, the lower bound of the change in earnings is $-\$268$ per person per year, while the estimated mean change in medical spending is \$46 per person per year.

5.2 Extensions and Robustness Tests

Varying the control group. The results presented above are largely robust across different samples, with the qualitative conclusions remaining unchanged and similar estimated magnitudes.[19] Restricting the sample to only counties affected once by a hurricane between 1980 and 1996 results in similar estimates. All the previous results remain significant with the exception of transfers from businesses, which become marginally insignificant, and the change in the black share of the population, which becomes insignificant. Increasing the number of nearest neighbors used for matching to 5 (which makes the number of counties in the control and treatment groups approximately equal) likewise does not affect the conclusions. I construct another control group by applying propensity score matching to 1970 covariates as well as historic hurricane data; this sample also yields very similar results. Finally, keeping all the counties in the hurricane region results in positive but insignificant estimated increases in per capita non-disaster transfers. However, the increases in the unemployment insurance payments and public medical spending remain highly significant and similar in magnitude to the preferred estimates.

Differential migration and change in demographics. One potential threat to validity is that those likely to receive government transfers may be moving into the counties affected by hurricanes from nearby counties. This would mean that there is no aggregate impact on transfers, only a compositional change. To address this, 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 eliminated. The estimated change in per capita non-disaster transfers is similar to the original estimate and highly significant.[20]

Another potential explanation for the increase in transfers is the observed change in the demographic composition of a hurricane-affected area. However, the 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"

[19] The full set of results is available upon request.

[20] One other way to test for differential migration is to look at changes in transfers on the state level. Unfortunately, the affected population represents 12% of the state population on average. Thus, the power to detect an aggregate affect is low.

category are unlikely to be receiving unemployment insurance payments. Moreover, disaggregated estimates indicate that the compositional change is gradual and monotonic, while the increase in overall transfers is not. 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.

Hurricane intensity and transfers. It may be of interest to consider how the intensity of a hurricane affects the amount of transfers flowing into a county. Because hurricane intensity is expected to change with global warming (see Emanuel (2005); Knutson and Tuleya (2004); Oouchi et al. (2006)), a significant relationship between transfers and wind speeds may have non-trivial implications for the fiscal impacts of climate change. However, unlike the relationship between damages and wind speeds (see Nordhaus (2010)), the estimated effect of wind speeds on non-disaster transfers is small. The estimation results can be found in the Online Appendix.

State-by-year fixed effects. 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 Discussion

According to the World Labour Report 2000, seventy-five percent of the world's unemployed are not receiving any benefit payments (International Labour Office, 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.

The designs of 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.[21] 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 calculations of disaster-related transfers), it provides benefits only to those who can show that they

[21] Disaster aid to individuals typically makes up less than half of total disaster aid; the rest is allocated to activities such as debris cleanup and restoration of public buildings and roads (FEMA, personal communication).

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. The presence of standard social safety net programs, on the other hand, can serve as insurance against delayed effects of natural disasters.

For a county with the average population of $78,000$, the estimated increase of \$654 per capita in non-disaster government transfers translates to a total of \$51 million. These estimates imply that the fiscal impact of natural disasters is more than twice as large if non-disaster transfers are also considered. The deadweight loss of taxation is estimated to be $12-30\%$ of revenue (Ballard, Shoven and Whalley, 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 \$98 (\$7.7 million) per capita per hurricane for non-disaster transfers. Taking the upper estimate of 30% doubles these estimates. The *marginal* deadweight loss of taxation, which is the relevant figure if one is considering mitigating the effects of hurricanes, is likely to be much larger. Feldstein (1999) estimates it to be $\$1-\$2$ per dollar of revenue.

Whether the presence of unemployment insurance for those living in disaster-prone 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 the recovery period and increase wages. On the other hand, disaster risk is not currently accounted for in unemployment insurance premiums, for example. 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

The extent to which social safety nets can help weather aggregate economic shocks is an important question. It is also difficult to answer because exogenous and easily identifiable economic shocks are hard to come by. In this paper, I examine the role of transfer programs in a county's economic dynamics following a hurricane. Hurricanes are exogenous and unanticipated capital shocks. Moreover, they are very damaging and frequent enough to be amenable to a statistical examination.

I estimate the medium-run economic effects of hurricanes on US counties, focusing on population, employment, wages, and transfers to individuals. My findings suggest that traditional social safety nets play an important role in post-disaster economics and capital shocks more generally. While hurricanes have long-run negative effects on construction employment and single family housing starts, their effects on population, employment, and wages are insignificant. At the same time, non-disaster related transfers, mainly public medical spending and unemployment insurance, increase substantially and persistently. Although my research design does not allow me to directly test the effect of social safety net programs on post-disaster economics, it is easy to show theoretically that transfer programs can act as buffers against adverse economic impacts following local capital destruction. Thus, ignoring traditional transfer programs may attribute too much of a developed economy's economic resilience to its wealth or disaster response policies and not enough to general social policies.

Real transfers from traditional safety net programs over the ten years following the hurricane are estimated to total \$654 per capita, much larger than the disaster-related transfers of \$356 per capita. This implies that the fiscal cost of hurricanes is more than twice as large as previously thought. Insurance payments increase temporarily in the year of the hurricane but add only an estimated \$37 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.

Studying hurricanes is also important for informing disaster policy. Both the population and wealth in disaster-prone areas are growing. If these 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. Increases in future 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 damages and deaths caused by extreme weather events, both theoretically and empirically. Informed policy thus has the potential to mitigate weather-related damages and subsequent economic impacts. However, a comprehensive picture of post-disaster economic dynamics is necessary for creating informed policy.

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 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 research design. Given that much of the world's population does not have access to social or disaster insurance and is at an increasing risk of natural disasters, the causal effect of social insurance on disaster impacts and whether it creates moral hazard are two other areas that deserve further study.

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Figures

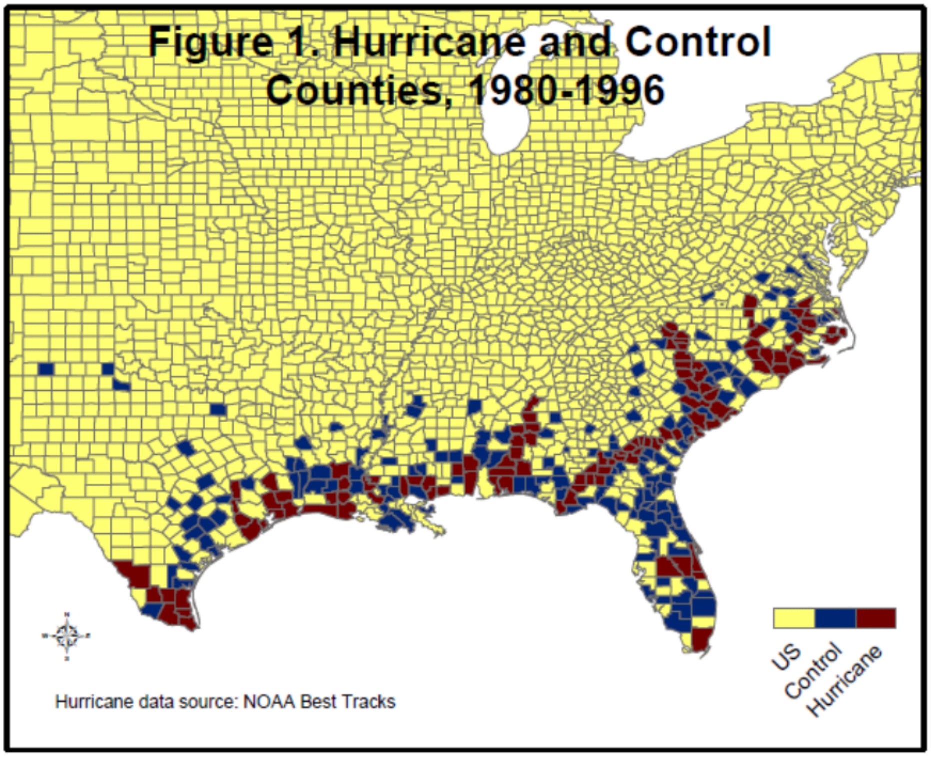
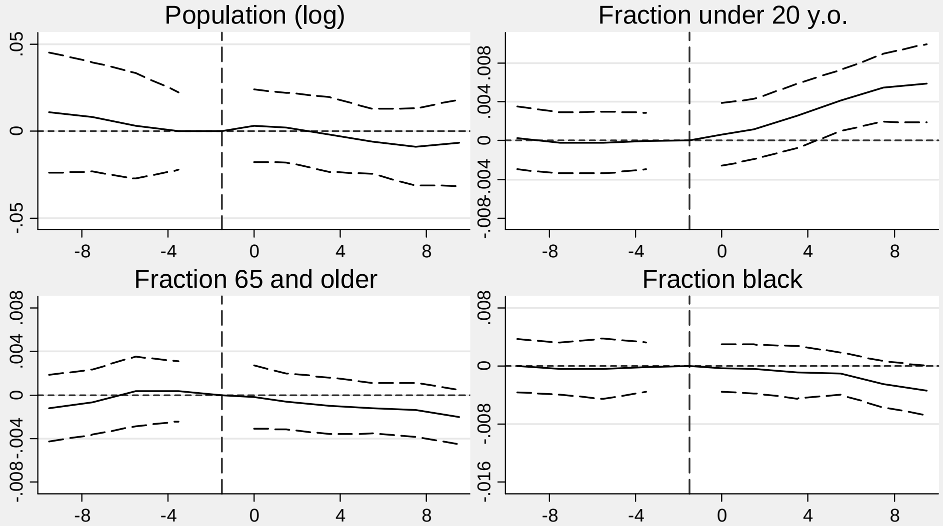


Figure 2. The effect of a hurricane on the construction sector

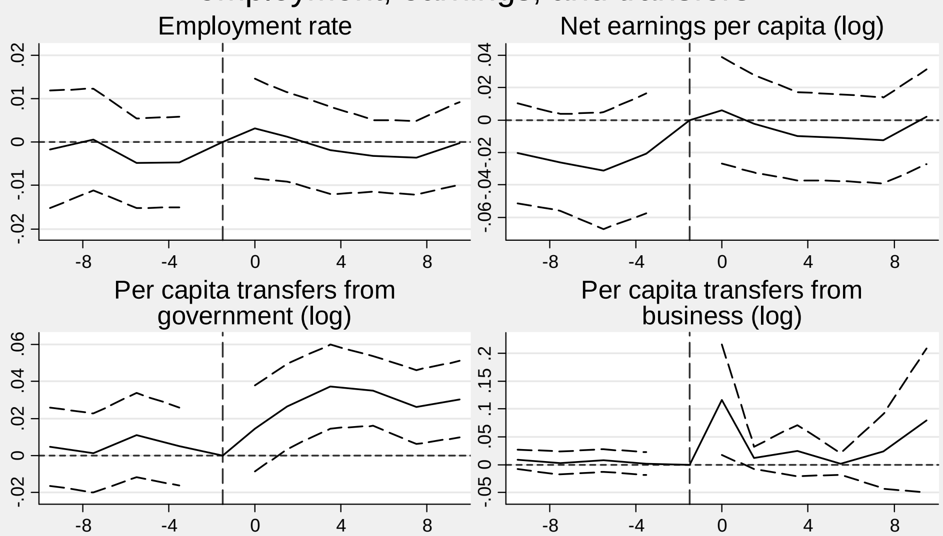
Sample: counties in Alabama, South Carolina, North Carolina, Florida, Georgia, Mississippi, Louisiana, Texas, and Virginia. 95% confidence intervals shown. Standard errors clustered spatially. Controls include county, year, and coastal by year fixed effects.

Figure 3. The effect of a hurricane on population and demographics



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

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



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

Tables

Table 1: Damages caused by major US hurricanes, 1980-1996

	(1) Mean	(2) Standard deviation	(3) Maximum	(4) Obs.
Panel A: centrally affected counties				
Total building value ($1000's)	8,943,979	27,200,000	224,000,000	99
Building damage ($1000's)	338,868	2,101,017	20,300,000	97
Total losses ($1000's)	570,558	3,662,500	35,400,000	97
Loss ratio (percent)	1.46	3.85	23.62	97
Displaced households	1,546	10,702	104,559	99
People requiring shelter	449	3,078	29,945	99
Panel B: peripherally affected neighbors				
Total building value ($1000's)	4,305,318	7,899,075	55,300,000	125
Building damage ($1000's)	19,247	64,702	388,928	123
Total losses ($1000's)	26,607	93,775	632,972	123
Loss ratio (percent)	0.33	0.81	5.20	123
Displaced households	32	143	1,193	124
People requiring shelter	8	38	331	124
Panel C: all peripherally affected counties				
Total building value ($1000's)	4,818,569	10,200,000	126,000,000	365
Building damage ($1000's)	9,002	41,973	388,928	353
Total losses ($1000's)	11,925	59,344	632,972	353
Loss ratio (percent)	0.15	0.50	5.20	353
Displaced households	13	89	1,193	366
People requiring shelter	3	24	331	366

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

Table 2: Descriptive statistics for hurricane aid, 1980 - 1996

	(1) Uniform split (millions)[1]	(2) Proportional split (millions)[2]	(3) Per capita - uniform split[1]	(4) Per capita - proportional split[2]
	Panel A: centrally affected counties only			
Centrally affected, all hurricanes (N = 89)	58	58.7	1,137	356
	(187)	(260)	(3,193)	(307)
Centrally affected, major hurricanes (N = 27)	128	133	2,018	412
	(332)	(467)	(5,623)	(343)
	Panel B: all counties listed in declaration			
All observations (N = 568)	11	10.3	191	63
	(53.9)	(72.7)	(702)	(98)
Centrally affected, all hurricanes (N = 89)	24.6	30.1	460	131
	(94.1)	(152)	(1,594)	(140)
Centrally affected, major hurricanes (N = 27)	59.2	73.4	954	187
	(167)	(273)	(2,824)	(184)

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

Table 3: Comparison of hurricane region[1] by 1980-1996 hurricane experience.

	(1) One hurricane	(2) Difference from no hurricanes	(3) p-value of difference	(4) Difference from matching	(5) p-value of difference
	Panel A: 1970 characteristics				
Coastal indicator	0.51	0.30	**0.000**	-0.05	0.524
Land area, sq. mi	675	51	0.361	49	0.408
Population (log)	10.37	0.56	**0.000**	0.46	**0.003**
Population density (person/sq. mile)	88.36	-113.33	**0.005**	36.31	**0.012**
Employment rate (fraction)	0.58	0.03	0.104	0.04	0.077
Net earnings per capita (log)	9.37	-0.01	0.707	0.02	0.615
Per capita transfers from government (log)	7.28	-0.11	**0.000**	-0.08	**0.036**
Per capita transfers from businesses (log)	4.05	-0.01	0.387	0.00	0.791
Per capita new single family housing (log)	-5.08	0.03	0.500	-0.04	0.475
	Panel B: 1970-1979 trend				
Population (log)	0.014	0.0013	0.477	0.0031	0.232
Employment rate (fraction)	0.000	0.0001	0.900	-0.0017	0.143
Net earnings per capita (log)	0.019	0.0011	0.609	-0.0026	0.369
Per capita transfers from government (log)	0.059	-0.0056	**0.008**	-0.0048	0.071
Per capita transfers from businesses (log)	0.015	0.0001	0.750	0.0003	0.559
Per capita new single family housing (log)	0.017	0.0076	0.283	0.0031	0.716
Number of counties[2]	119	711		52	

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

Table 4: 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	-0.0567	-0.0760	0.0237	0.0074	0.0773	0.0682	-0.0807	-0.0802
	(0.0458)	(0.0447)*	(0.0255)	(0.0250)	(0.0232)***	(0.0247)***	(0.0408)**	(0.0406)**
Post hurricane time trend		-0.0195		-0.0163		-0.0091		0.0005
		(0.0055)***		(0.0037)***		(0.0040)**		(0.0066)
Overall time trend	-0.0034	0.0077	-0.0059	0.0034	-0.0034	0.0018	0.0092	0.0089
	(0.0035)	(0.0054)	(0.0022)***	(0.0034)	(0.0020)	(0.0035)	(0.0035)***	(0.0044)**
Mean of dep. var.	6.90		4.33		10.16		-5.40	
Observations	4,978	4,978	7,524	7,524	4,940	4,940	8,436	8,436
R-squared	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99

Standard errors (spatially clustered) 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 5: Mean shift and trend break tests for Figure 3

	Fraction black residents		Fraction 65 and older		Fraction 20 and younger		Population (log)	
Post hurricane	0.0004	0.0000	-0.0007	-0.0010	0.0000	0.0006	0.0057	0.0073
	(0.0017)	(0.0017)	(0.0013)	(0.0013)	(0.0015)	(0.0015)	(0.0109)	(0.0115)
Post hurricane time trend		-0.0005		-0.0003		0.0006		0.0015
		(0.0002)**		(0.0002)*		(0.0002)**		(0.0020)
Overall time trend	-0.0003	0.0000	0.0000	0.0002	0.0003	0.0000	-0.0011	-0.0019
	(0.0001)**	(0.0002)	(0.0001)	(0.0002)	(0.0001)**	(0.0002)	(0.0011)	(0.0018)
Mean of dep. var.	0.28		0.12		0.31		10.56	
Observations	8,892	8,892	8,931	8,931	8,931	8,931	8,931	8,931
R-squared	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00

Standard errors (spatially clustered) 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 6: Mean shift and trend break tests for Figure 4

	Employment rate (fraction)		Per capita transfer from businesses (logs)		Per capita transfer from government (logs)		Per capita net earnings (log)	
Post hurricane	0.0037	0.0032	0.0475	0.0456	0.0209	0.0213	0.0062	0.0035
	(0.0046)	(0.0046)	(0.0285)*	(0.0237)*	(0.0099)**	(0.0102)**	(0.0125)	(0.0126)
Post hurricane time trend		-0.0005		-0.0019		0.0004		-0.0027
		(0.0007)		(0.0055)		(0.0013)		(0.0019)
Overall time trend	-0.0002	0.0000	-0.0027	-0.0016	0.0002	0.0000	0.0010	0.0026
	(0.0004)	(0.0007)	(0.0033)	(0.0009)*	(0.0008)	(0.0011)	(0.0010)	(0.0016)
Mean of dep. var.	0.58		4.37		8.09		9.61	
Observations	8,814	8,814	8,385	8,385	8,814	8,814	8,814	8,814
R-squared	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00

Standard errors (spatially clustered) 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.

Appendix: For Online Publication

Appendix A. Simple Model of the Role of Transfers in Capital Shocks

Setup and Initial Equilibrium

Assume that there are many identical locations, so that changes in one location do not have substantive effects on others. Representative firms in each location produce a homogenous good with a standard production function $F(K, L)$, where K is capital and L is labor. Every location is initially at equilibrium. The population consists of a continuum of identical individuals and has an initial mass of 1. Labor supply is binary. The individual disutility of supplying labor is ε_i, which is distributed iid with the cdf $G(\varepsilon)$. If individuals do not work, they are assumed to receive transfer payments equal to $\theta\bar{w}$, where $\bar{w}$ is some baseline wage. This transfer program resembles unemployment insurance, in that individuals cannot work and receive transfer payments at the same time.

Specifically, each individual i chooses consumption c and binary labor supply $l \in \{0,1\}$ to solve the following utility maximization problem:

$$\begin{aligned} & \max_{c,l} c^{1-\gamma} - \varepsilon_i l \\ \text{s.t. } c \quad \leq & \quad wl + \theta\bar{w}(1-l) \end{aligned}$$

where w is the prevailing wage rate in the location. Thus, individual i will choose to work if $w^{1-\gamma} - (\theta\bar{w})^{1-\gamma} \geq \varepsilon_i$. The aggregate labor supply function will be:

$$L = G\left(w^{1-\gamma} - (\theta\bar{w})^{1-\gamma}\right) \tag{4}$$

Production in each location is assumed to be Cobb-Douglas:

$$F(K,L) = K_0^{\alpha} L^{1-\alpha}$$

where K is capital and L is labor. K_0 denotes the initial level of capital.

The equilibrium wage in each location is the marginal product of labor:

$$w_0^* = (1-\alpha) K_0^{\alpha} L^{-\alpha}$$

This equation can be re-written as

$$L = K_0 \left(\frac{w_0^*}{1-\alpha} \right)^{-\frac{1}{\alpha}} \tag{5}$$

Subtracting equation (4) from (5), we get the equilibrium relationship:

$$K_0 \left(\frac{w_0^*}{1-\alpha} \right)^{-\frac{1}{\alpha}} - G\left((w_0^*)^{1-\gamma} - (\theta \bar{w})^{1-\gamma} \right) = 0$$

This equation can be solved numerically for w_0^*, from which L_0^* can be computed.

Adjustment Following a Capital Shock

Now suppose that one location experiences a negative capital shock and capital is not perfectly mobile. Specifically, assume that capital in one of the locations falls to $K_1 < K_0$, immediate adjustment is not possible, and transfers equal θw_0^*.[22] Because there is a large number of locations, other locations are unaffected, either directly or indirectly. In particular, this implies that individuals moving away from the affected location do not have an effect on the equilibrium in other locations.

Individuals will move away from the affected location if:

$$\max\left\{ (w_0^* - m_i)^{1-\gamma} - \varepsilon_i, (\theta w_0^* - m_i)^{1-\gamma} \right\} > \max\left\{ (w_1)^{1-\gamma} - \varepsilon_i, (\theta w_0^*)^{1-\gamma} \right\}$$

where w_1 is the new wage in the affected location and m_i is the moving cost of the individual. I assume that (a) m_i is iid with the distribution $F(m)$, (b) $m_i > 0$ for all i (although some m_i's may be arbitrarily small), and (c) individuals' moving costs are independent of their labor supply disutility.

Because $m_i > 0$ for all i, moving and taking transfers is strictly dominated by staying and taking transfers. In addition, the disutility of labor supply is unknown at the time the moving decision is made. Thus, the equation above can be simplified to

$$(w_0^* - m_i)^{1-\gamma} - E[\varepsilon] > \max\left\{ (w_1)^{1-\gamma} - E[\varepsilon], (\theta w_0^*)^{1-\gamma} \right\}$$

There exists the marginal mover, indexed by m^*, who in equilibrium will satisfy $\left(w_0^* - m^*\right)^{1-\gamma} - E[\varepsilon] = (w_1^*)^{1-\gamma} - E[\varepsilon]$. This implies $w_0^* - m^* = w_1^*$. The mass of the remaining population will be equal to $1 - F(m^*)$. Within the remaining population, ε will still be iid $G(\varepsilon)$. Thus, there will also be $\tilde{\varepsilon}$ such that $(w_1^*)^{1-\gamma} - \tilde{\varepsilon} = \left(\theta w_0^*\right)^{1-\gamma}$.

[22] The qualitative conclusions will hold with imperfect adjustment, as long as capital adjustment costs are larger than individual moving costs.

Total labor supply in the new equilibrium will be

$$L_1^* = G(\tilde{\varepsilon})(1 - F(m^*)) = (1 - F(m^*))\,G\left((w_1^*)^{1-\gamma} - (\theta w_0^*)^{1-\gamma}\right) \tag{6}$$

From the wage equals marginal product of labor condition, we have

$$L_1^* = K_1 \left(\frac{w_1^*}{1-\alpha}\right)^{-\frac{1}{\alpha}} \tag{7}$$

Subtracting equation (4) from (3), we have the new equilibrium condition for the wage:

$$(1 - F(w^* - w_1^*))\,G\left((w_1^*)^{1-\gamma} - (\theta w_0^*)^{1-\gamma}\right) - K_1 \left(\frac{w_1^*}{1-\alpha}\right)^{-\frac{1}{\alpha}} = 0$$

We can solve this equation for the new wage w_1^*, then use w_1^* to solve for m^*. In the next section, I use the model above to demonstrate the potential effect of transfer generosity on the post-shock equilibrium. Specifically, I use simulations to explore how varying θ affects the changes in wage $(w_0^* - w_1^*)$, labor supply $\left(L_1^* - L_0^*\right)$, and the change in the population $(-F(m^*))$.

Simulation

I assume $\gamma = -1,\ \alpha = 0.7,\ K_0 = 5.00$ and $K_1 = 4.75$. Moving costs are distributed according to the Weibull cumulative distribution function, with scale parameter 1 and shape parameter 1.5. Disutility of labor is standard normal. Unemployment transfers are assumed to replace some fraction of the pre-shock wage. I assume this fraction remains unchanged after the shock, so the results are not driven by greater transfer generosity in the affected county.

To summarize the results, I plot the changes in wages, population, and total employment as a function of the transfer generosity. Figure A1 shows the fraction of the population leaving following the negative shock as a function of the transfer generosity. With no transfers, population in the affected area falls by about 0.38%. When transfers replace about 50% of the pre-shock wage, the population drop is 0.34%, 10% less than the population fall with no transfer payments. As transfer generosity approaches full replacement, the population drop approaches 0.18%.

Figure A2 shows the change in labor supply after the shock, expressed as a percentage of the pre-shock labor supply. With no transfers, labor supply is almost unchanged. Once wage replacement reaches 50%, labor supply falls by about 10%. At the extreme, labor supply is 50% lower with full replacement. It does not fall below this because disutility of labor is assumed to be standard normal, so half of the population prefers working, all else equal. The same pattern would hold if absolute differences in labor supply were plotted.

Finally, Figure A3 shows the change in wages after the shock, expressed as a percentage of the pre-shock wage. Not surprisingly (given the changes in labor supply), the wage drop decreases with transfer generosity. With no transfer payments, wages are about 2.3% lower than before. At full replacement, the wage drop is only 1%. The same pattern would hold if absolute differences in wages were plotted. The exact shapes and magnitudes of these curves depend on assumptions about the distribution of moving costs and the utility function, but the qualitative pattern holds for a variety of parameters.

Of course, this simulation is very stylized and not meant to make correct quantitative predictions. However, it demonstrates an important qualitative point - that the presence of non-disaster transfers can have a non-trivial effect on post-shock adjustment. In particular, economies with larger transfer generosity experience a smaller drop in population and wages following a capital shock. Although employment falls more with increasing transfer generosity in this model, the net theoretical effect on employment (and thus on wages) is unclear: 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.

Appendix B. Relative Damages Caused by Hurricanes

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

$$\begin{aligned} D_{ct} &= a_c + a_t + \beta_1 Major\_hurricane_{ct} + \beta_2 Minor\_hurricane_{ct} \\ &\quad + \gamma_1 Flood_{ct} + \gamma_2 Tornado_{ct} + \gamma_3 Severe\_storm_{ct} + \varepsilon_{ct} \end{aligned} \tag{8}$$

$$\begin{aligned} D_{ct} &= a_c + a_t + \sum_{k=1}^{5} \beta_k 1\left[Category_{ct} = k\right] + \gamma_1 Flood_{ct} \\ &\quad + \gamma_2 Tornado_{ct} + \gamma_3 Severe\_storm_{ct} + \varepsilon_{ct} \end{aligned} \tag{9}$$

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

D_{ct} is log of property damages, property damages per capita or the log of flood insurance payments in that county. [23] All damage measures are in 2008 dollars. $Major\_hurricane_{ct}$ is an

[23] Data on damages and extreme weather events other than hurricanes are from the Hazards & Vulnerability Research

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.[24] The results are shown in Table A1. Column 1 compares the log of damages for different disasters. A major hurricane increases the reported property damages by 4.2 log points or over 400%. In levels, this implies that a major hurricane increases the total damages in a county by about $\$760,000$ (2008 dollars). The next most damaging event is a minor hurricane, which increases property damages by 2.4 log points or about $\$110,000$. In contrast, tornadoes, floods, and severe storms increase property damages by 2.1 $(\$76,000)$, 0.9 $(\$15,000)$, and 1.0 $(\$18,000)$ log points (dollars), respectively. A similar pattern holds when the dependent variable is property damages per capita, although some of the point estimates become statistically insignificant. This is possibly because hurricane-prone counties are more populous. Column 4 shows the effect of hurricanes broken down by category. As expected, Category 1 hurricanes are the least damaging, causing an extra 2.2 log points of damage $(\$84,000)$, while Category 4 and 5 storms are the most damaging, increasing property damages by 4.6 log points $(\$1,100,000)$. The least damaging hurricane is about as damaging as a tornado, and more damaging than a flood or severe storm.

An important caveat is that the damage measures are estimates made by local officials soon after the occurrence of the event. Using hurricane-level damage data from Nordhaus (2006), I estimate the direct damages from hurricanes to be about \$3.7 billion per year between 1970 and 2004, in 2008 dollars. Given that there are on average 1.5 landfalling hurricanes per year, the estimates in this section appear to understate the per-county damage of hurricanes (and possibly of other disasters as well). 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

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).

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

increase them by 1.5 log points or about $190,000$. Tornadoes have no significant impact on flood claims and the estimated effect of a severe storm is significantly negative.[25] 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 also causes 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.

Appendix C. Hurricane intensity and transfers

I also consider the effect of climate change on hurricane-related government spending and find that the relationship between transfers and intensity is fairly flat. I estimate that a 8.7% increase in average hurricane intensity (as measured by wind speeds) would increase annual non-disaster program spending by only about $1 million.

There is currently a lot of scientific uncertainty about the effect of global warming on the frequency and intensity of tropical cyclones (including hurricanes). Most studies on frequency find a reduction or no change in the number of tropical cyclones Gualdi, Scoccimarro and Navarra (2008); Knutson et al. (2008); Bengtsson et al. (2007); Oouchi et al. (2006). Much of the work on intensity points to an increase in the average hurricane intensity Emanuel (2005); Knutson and Tuleya (2004); Oouchi et al. (2006), although there is at least one study pointing to a decrease Bengtsson et al. (2007). Despite the uncertainty about the direction of the effect, most studies do find changes in either frequency or intensity. In this section, I discuss some implications of changes in hurricane intensity and frequency for fiscal spending on disasters.

To compute the effect of hurricane intensity on the amount of non-disaster transfer spending, I first estimate the relationship between wind speed (a measure of intensity) and federal non-disaster transfers, using variants of the trend break and mean shift equations:

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

$$
\begin{aligned}
O_{ct} &= \theta_1 \mathbf{1}[\mathrm{H}]_{ct} + \theta_2 \mathbf{1}[\mathrm{H}]_{ct} Log\left(WS_{ct}\right) + \beta^{11} post11_{ct} + \beta^{-11} pre11_{ct} \\
&\quad + \alpha_c + \alpha_t + 1\left[coastal\right]\alpha_t + \varepsilon_{ct}
\end{aligned} \tag{10}
$$

$$
\begin{aligned}
O_{ct} &= \theta_1 \mathbf{1}[\mathrm{H}]_{ct} + \theta_2 \mathbf{1}[\mathrm{H}]_{ct} Log\left(WS_{ct}\right) \\
&\quad + \gamma_1 \mathbf{1}[\mathrm{H}]_{ct} y + \gamma_2 * \mathbf{1}[\mathrm{H}]_{ct} Log\left(WS_{ct}\right) y + \beta^{11} post11_{ct} + \beta^{-11} pre11_{ct} \\
&\quad + \alpha_c + \alpha_t + 1\left[coastal\right]\alpha_t + \varepsilon_{ct}
\end{aligned} \tag{11}
$$

where O_{ct} is some economic outcome, $\mathbf{1}[\mathrm{H}]_{ct}$ is an indicator variable equal to 1 if the county has experienced a hurricane in the past 10 years, and WS_{ct} is the maximum recorded wind speed of that hurricane in the county. The rest of controls are as in the trend break and mean shift equations. Using these estimates, I then calculate counterfactual transfers by varying the observed intensity and frequency of hurricanes.

I estimate the net present value of per capita (disaster and non-disaster related) transfers following a hurricane with intensity W by computing:

$$
\sum_{t=0}^{10} r^t \left(e^{\mu+\theta_1+t\gamma_1+\theta_2 log(W)+\gamma_2 log(W)t} - e^{\mu}\right)
$$

where $t = 0$ is the year of the hurricane hit and μ is the mean of the logged per capita transfer payments. $\{\theta_1, \theta_2, \gamma_1, \gamma_2\}$are coefficients corresponding to the mean shift in hurricane, mean shift in wind, trend break in hurricane and trend break in wind, as shown in equation (11). I use the discount rate of $r = \frac{1}{1.03}$.

In Table A5, I show the effect of hurricane intensity on non-disaster transfers. The mean of transfer payments in the ten years after the hurricane is not significantly affected by wind speeds, but the time trend is. Specifically, transfers rise 1.2% faster for every additional mile per hour. Figure A4 plots the estimated net present value of per capita government transfers as a function of the wind speed using the coefficients from Table A5. It is estimated that a hurricane with 75 mph winds (Category 1) will lead to an increase in transfers of \$732 per capita in present discounted value. A hurricane with 111 mph winds (a weak Category 3 hurricane) will lead to transfer increases of \$738 per capita, while a weak Category 4 hurricane (131 mph winds) will raise them by \$743 per capita. Thus, the estimated relationship between non-disaster transfers and wind speeds is fairly flat. One possible reason for this is that disaster transfers rise steeply with wind speeds. Similar analysis for hurricane-related disaster transfers is not possible, however. This is because the information about disaster aid is available only on the level of a declaration, which typically includes numerous counties. Thus, identification of the relationship between disaster aid and wind speed is only possible at the hurricane level. Unfortunately, there are too few hurricanes in the sample to create reliable estimates.

To calculate the expected effect of climate change on non-disaster spending, I use the preferred estimate of Nordhaus (2010) - that mean hurricane wind speeds will increase by 8.7%. The annual increase in non-disaster transfers (assuming that the number of people affected per hurricane and the mean number of hurricanes per year remain the same) is $1 million. Thus, increases in hurricane intensity would not have a large impact on non-disaster related transfers.

Appendix Figures

Figure A1. Change in labor supply following capital shock

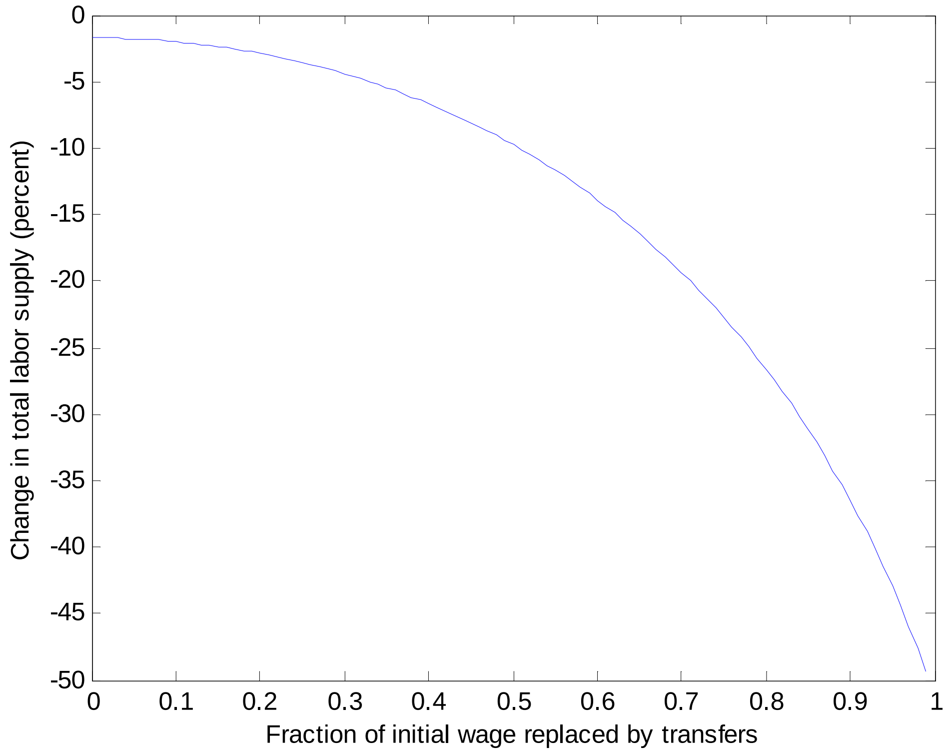


Figure A2. Change in population following capital shock

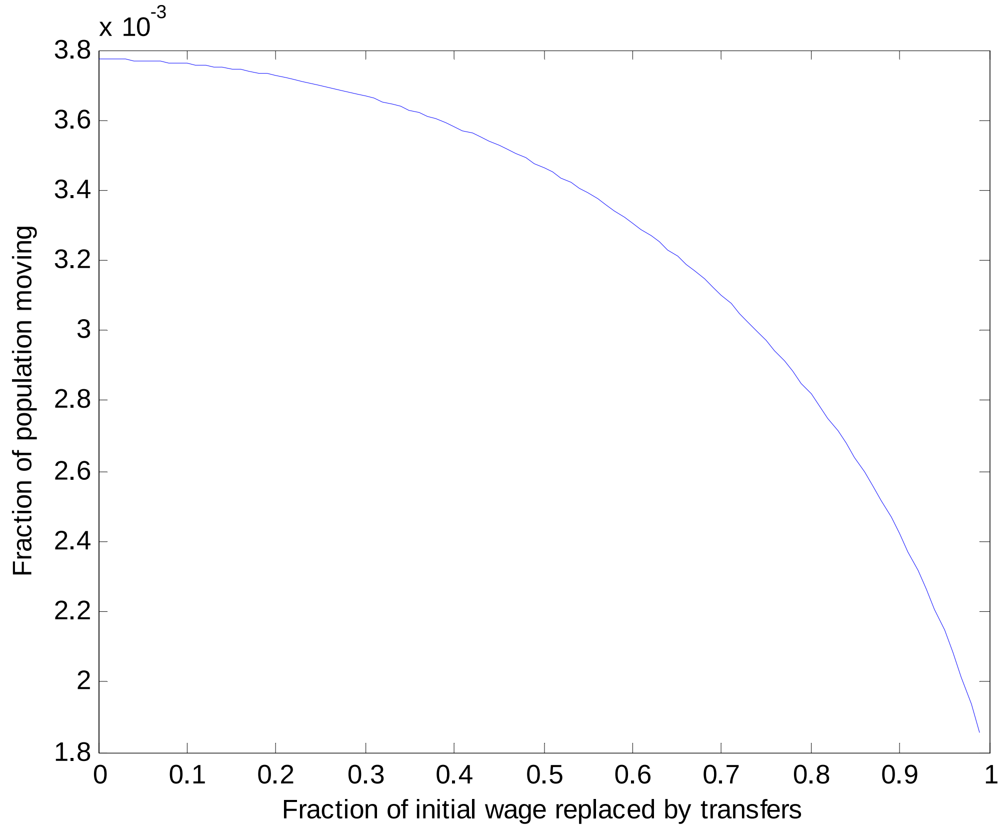


Figure A3. Change in wages following capital shock

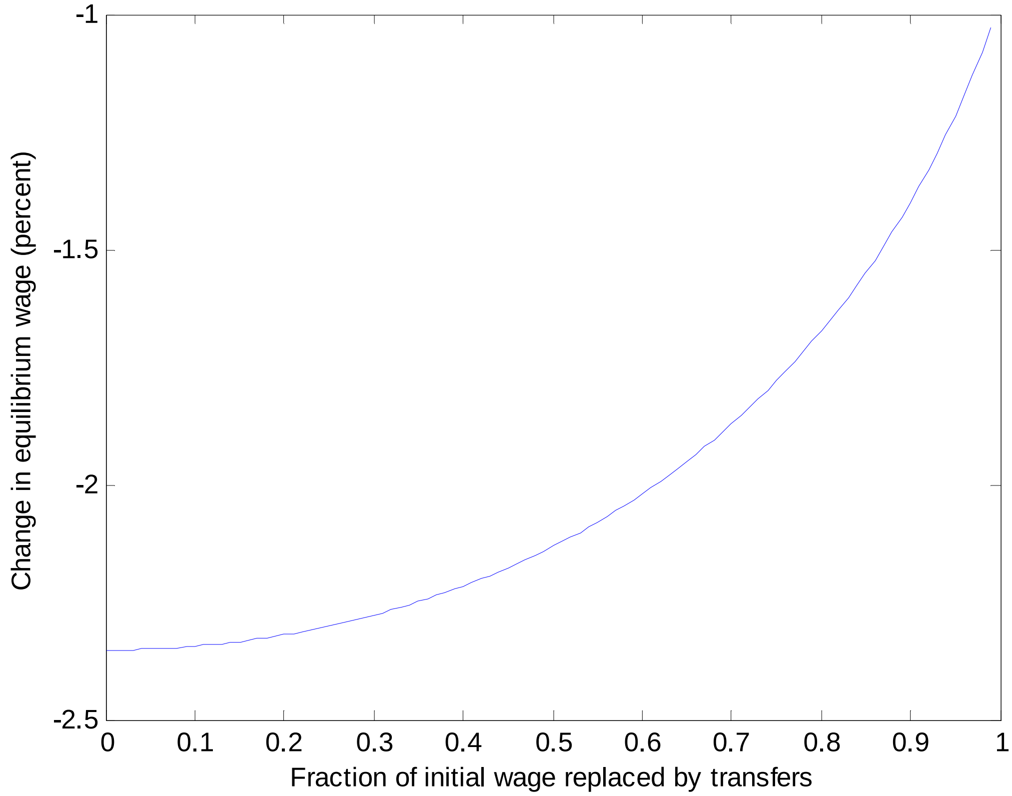
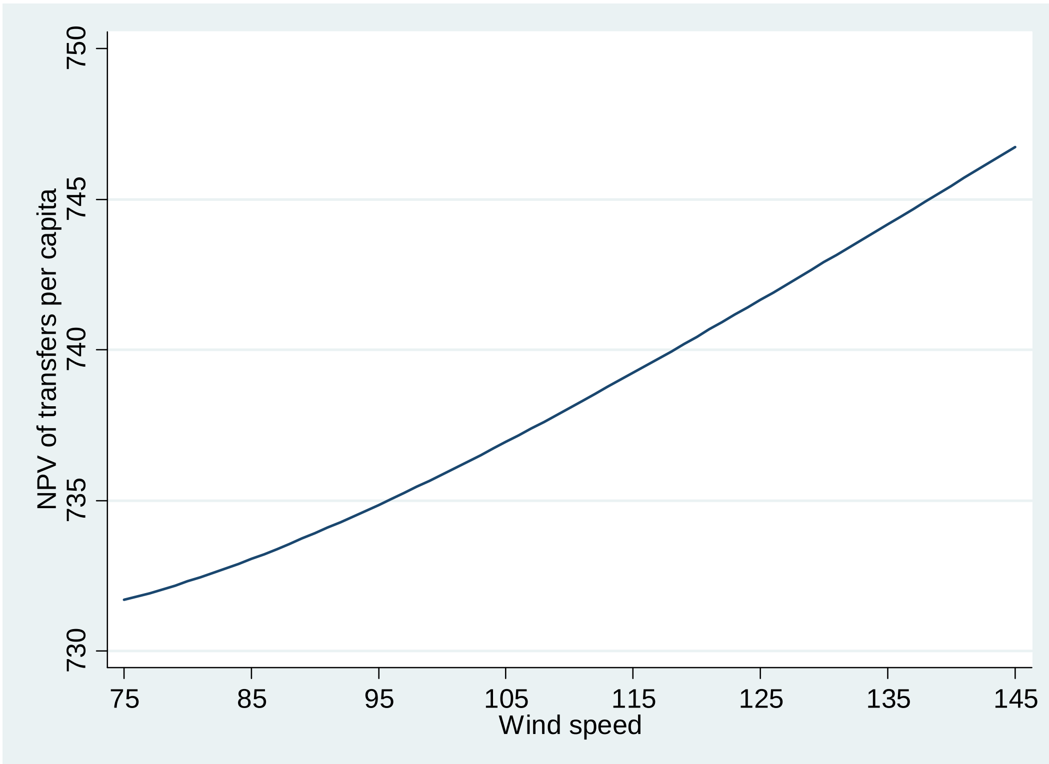


Figure A4. Relationship between wind speed and transfers



Appendix Tables

Table A1: Determinants of property damages in hurricane region[1]

	Log damages	Per capita damages	Flood insurance payments (log)	Log damages	Per capita damages	Flood insurance payments (log)
Major hurricane	4.236	678.279	3.090			
	(0.426)***	(309.795)*	(0.410)***			
Minor hurricane	2.417	65.184	1.515			
	(0.250)***	(46.066)	(0.247)***			
Category = 1				2.151	72.735	1.131
				(0.297)***	(57.567)	(0.263)***
Category = 2				3.253	39.028	2.769
				(0.411)***	(19.173)*	(0.492)***
Category = 3				4.049	710.213	3.100
				(0.311)***	(399.246)	(0.471)***
Category = 4 or 5				4.642	607.060	3.019
				(0.915)***	(316.198)*	(0.850)***
Tornado	2.061	12.507	-0.008	2.061	12.441	-0.011
	(0.197)***	(6.847)	(0.070)	(0.196)***	(7.174)	(0.070)
Flood	0.862	0.380	0.762	0.864	0.299	0.758
	(0.102)***	(5.690)	(0.065)***	(0.102)***	(5.757)	(0.065)***
Severe storm	0.958	8.952	-0.205	0.956	9.075	-0.201
	(0.180)***	(3.915)*	(0.078)***	(0.181)***	(4.213)*	(0.079)**
Depvar mean (median)	9.31 (9.66)	11.00 (0.09)	10.87 (10.8)	9.31 (9.66)	11.00 (0.09)	10.87 (10.8)
Observations	18,592	24,331	7,033	18,592	24,331	7,033
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 2008 dollars. Includes county and year fixed effects. Property damage data is from SHELDUS. Flood insurance payments data is from the Consolidated Federal Funds Report (CFFR). Time period is 1979-2008 for damages, 1983-2008 for flood claims.

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

Table A2: 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	-0.050	-0.018	-0.018	-0.073
	(0.054)	(0.033)	(0.033)	(0.041)*
T = - 7 or - 8	-0.044	-0.021	-0.022	-0.065
	(0.045)	(0.024)	(0.027)	(0.051)
T = - 5 or - 6	-0.057	-0.006	0.013	-0.075
	(0.050)	(0.026)	(0.022)	(0.047)
T = - 3 or - 4	-0.019	0.011	0.001	-0.009
	(0.054)	(0.025)	(0.027)	(0.044)
T = 0	-0.015	0.024	0.031	-0.058
	(0.058)	(0.029)	(0.029)	(0.053)
T = 1 or 2	-0.083	0.021	0.089	-0.013
	(0.049)*	(0.025)	(0.026)***	(0.048)
T = 3 or 4	-0.182	-0.058	0.053	-0.105
	(0.042)***	(0.024)**	(0.027)*	(0.040)***
T = 5 or 6	-0.231	-0.091	0.029	-0.088
	(0.040)***	(0.020)***	(0.028)	(0.049)*
T = 7 or 8	-0.199	-0.114	-0.005	-0.017
	(0.040)***	(0.022)***	(0.027)	(0.050)
T = 9 or 10	-0.178	-0.088	0.009	0.033
	(0.041)***	(0.023)***	(0.028)	(0.058)
Mean of dep. var.	6.903	4.330	10.155	-5.396
Observations	4,332	6,573	4,294	7,378
R-squared	1.00	1.00	1.00	0.99
p-value of all leads F-test	0.754	0.766	0.716	0.121
p-value of all lags F-test	**0.000**	**0.000**	**0.001**	**0.026**
p-value of T=0 to T=4 lags F-test	**0.000**	**0.002**	**0.004**	**0.010**

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

Table A3: 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	0.000	-0.001	0.000	0.011
	(0.001)	(0.001)	(0.001)	(0.017)
T = - 7 or - 8	0.000	-0.001	0.000	0.008
	(0.001)	(0.001)	(0.001)	(0.016)
T = - 5 or - 6	0.000	0.000	0.000	0.003
	(0.002)	(0.001)	(0.001)	(0.015)
T = - 3 or - 4	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.011)
T = 0	0.000	0.000	0.001	0.003
	(0.001)	(0.001)	(0.001)	(0.010)
T = 1 or 2	0.000	-0.001	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.010)
T = 3 or 4	-0.001	-0.001	0.003	-0.002
	(0.001)	(0.001)	(0.001)	(0.010)
T = 5 or 6	-0.001	-0.001	0.004	-0.006
	(0.001)	(0.001)	(0.001)***	(0.009)
T = 7 or 8	-0.003	-0.001	0.005	-0.009
	(0.001)	(0.001)	(0.001)***	(0.011)
T = 9 or 10	-0.003	-0.002	0.006	-0.007
	(0.001)*	(0.001)	(0.002)***	(0.012)
Mean of dep. var.	0.285	0.123	0.312	10.558
Observations	7,775	7,814	7,814	7,814
R-squared	1.00	0.99	1.00	1.00
p-value of all leads F-test	1.000	0.890	0.999	0.953
p-value of all lags F-test	**0.000**	0.527	**0.001**	0.727
p-value of T=0 to T=4 lags F-test	0.899	0.760	0.323	0.931

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

Table A4: The effect of a hurricane on employment, wages, and transfers

	Employment rate (fraction)	Per capita transfer from businesses (logs)	Per capita transfer from government (logs)	Per capita net earnings (log)
T = - 9 or - 10	-0.002	0.009	0.005	-0.020
	(0.006)	(0.009)	(0.010)	(0.015)
T = - 7 or - 8	0.001	0.003	0.001	-0.026
	(0.005)	(0.010)	(0.010)	(0.015)*
T = - 5 or - 6	-0.005	0.008	0.011	-0.031
	(0.005)	(0.010)	(0.011)	(0.018)*
T = - 3 or - 4	-0.005	0.002	0.005	-0.021
	(0.005)	(0.010)	(0.010)	(0.018)
T = 0	0.003	0.117	0.015	0.006
	(0.005)	(0.050)**	(0.011)	(0.016)
T = 1 or 2	0.001	0.013	0.026	-0.002
	(0.005)	(0.010)	(0.011)**	(0.015)
T = 3 or 4	-0.002	0.025	0.037	-0.010
	(0.005)	(0.023)	(0.011)***	(0.013)
T = 5 or 6	-0.003	0.002	0.035	-0.011
	(0.004)	(0.009)	(0.009)***	(0.013)
T = 7 or 8	-0.004	0.024	0.026	-0.012
	(0.004)	(0.034)	(0.010)**	(0.013)
T = 9 or 10	0.000	0.080	0.030	0.002
	(0.004)	(0.066)	(0.010)***	(0.014)
Mean of dep. var.	0.585	4.373	8.088	9.605
Observations	7,727	7,316	7,727	7,727
R-squared	0.99	1.00	1.00	1.00
p-value of all leads F-test	0.826	0.746	0.902	0.397
p-value of all lags F-test	0.780	0.105	**0.002**	0.677
p-value of T=0 to T=4 lags F-test	0.823	0.342	**0.005**	0.719

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

Table A5: Wind speed and per capita non-disaster transfers

Post hurricane	-0.0062	0.2699
	(0.0797)	(0.1788)
Post hurricane x log wind speed	0.0030	-0.0555
	(0.0180)	(0.0401)
Post hurricane time trend		-0.0528
		(0.0278)*
Post hurricane x log wind speed time trend		0.0119
		(0.0062)*
Overall time trend	0.0016	-3.3E-06
	(0.0007)**	(0.0011)
Mean of dep. var.	8.09	8.09
Observations	8,814	8,814
R-squared	1.00	1.00

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