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

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Abstract

Little is known about how aggregate economic shocks are mitigated by social safety nets. I use hurricanes as an exogenous shock to the economies of US counties and show that non-disaster government transfers, such as unemployment insurance and public medical spending, increase substantially in the decade after landfall. Indeed, I estimate that the net present value of the increase in non-disaster transfers is more than double that of direct disaster aid. Among the implications of these findings are that the fiscal costs of natural disasters are much larger than previously thought and that existing social safety net programs help to mitigate the effects of macroeconomic shocks.

JEL codes: Q54, H84, H53.

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1 Introduction

Non-idiosyncratic shocks, which are difficult to insure against in the private market, often prompt the government to act as an insurer of last resort. Indeed, many social safety nets can be viewed as insurance against regional or national, in addition to idiosyncratic, shocks. While a rich literature has examined the optimal level and duration of unemployment insurance, its focus is on how unemployment insurance affects individuals' behavior and welfare.[1] However, social safety nets may also mitigate aggregate shocks: for example, by providing a substantial number of workers with a better outside option, more generous unemployment insurance may counteract falling wages. To what extent social safety nets have this effect is an open and important question.

In the aftermath of a shock, the government frequently implements extra stimulus programs. For example, the government response to recessions often involves extra public spending or tax refunds. This raises the question of how much of the recovery can be attributed to event-specific government responses versus existing social safety nets. However, 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.

I estimate changes in counties' economic outcomes in the ten years following a capital shock, as measured by hurricane incidence. I employ an event study framework, comparing counties that experience one or more hurricanes to those that do not. I use this framework to estimate changes in local employment, wages, migration, and transfer payments. I then evaluate whether social safety nets can plausibly mitigate the effects of such shocks. The main advantages to using hurricanes as sources of capital shocks are that they are exogenous, their onset is known precisely, and they are among the most damaging weather events in the US.

I interpret my estimates using a simple spatial equilibrium framework, which illustrates how transfers may prevent relocation and generally act as a buffer against negative capital shocks. My results suggest that the negative economic consequences of these shocks are substantially mitigated

[1] See Baily (1978); Townsend (1994); Gruber (1997); Chetty (2006); Chetty and Looney (2006).

through non-disaster social safety net programs. While I find no consistent evidence that average earnings change significantly in the ten years following a hurricane, the employment rate is estimated to be significantly lower $5-10$ years after. 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 ten years following a hurricane, an affected area receives extra transfers averaging about \$750 per capita in present discounted value (a $2-3\% increase$).[2] Transfers from businesses to individuals, which include insurance payments as a component, increase temporarily as well but add only an estimated \$30 to total transfers, with the majority of the increase occurring in the year of the hurricane. Together, the disaster and non-disaster 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.[3] Thus, non-disaster policy, as well as disaster aid and wealth, may be important factors in explaining the resilience to natural disasters in the United States relative to other countries.

My estimates also imply that the fiscal impacts of hurricanes are about three times as large if non-disaster transfers are counted in addition to disaster-specific aid. These spending levels correspond to a non-trivial cost of public funds. The *average* deadweight loss of taxation is estimated to be $12-30\%$ of revenue (Ballard, Shoven, and Whalley, 1985; Feldstein, 1999), while the *marginal* deadweight loss is likely much higher. A conservative deadweight loss estimate of 15% translates to about \$13 million in public fund costs per hurricane per affected county. 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.

In addition to providing general insight into post-shock dynamics, my research has significant implications for the economics of natural disasters. Extreme weather is a large and growing source of negative economic shocks due to larger population densities, ecosystem alteration, and population movements to hazardous areas (Board on Natural Disasters, 1999). Damages are likely to

[2] All monetary amounts have been converted to 2008 dollars using the Consumer Price Index

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

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. Although they are not intended for disasters, 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. Moreover, they are complementary to private insurance and disaster-specific aid: while the latter two types of aid target individuals directly affected by the disaster, the former are able to reach those who are affected indirectly, potentially several years after the event. Ignoring the role of traditional transfer programs risks understating the fiscal costs of disasters and attributing too much of a developed economy's resilience to its wealth or disaster-specific policies.

I contribute to two main strands of literature. The first focuses on the response of local economies to shocks, typically focusing on employment, population, and wages (e.g., Blanchard and Katz, 1992; Card, 2001; Cortes, 2008; Autor, Dorn, and Hanson, 2012). Using hurricanes provides me with a clearly exogenous capital shock whose occurrence is easy to measure. Moreover, with the exception of Autor, Dorn, and Hanson (2012), the existing research ignores the response of government transfer payments to shocks. I show that the inflow of federal funds into a county following a capital shock is substantial, exceeding official disaster aid on average. Thus, social safety nets likely play an important role in mitigating economic shocks.

The second strand of literature focuses on the economic impacts of natural disasters, typically considering a single outcome or single event (Leiter et al., 2009; Brown et al., 2006; Hsiang, 2010) or looking at effects from one to four quarters (Strobl and Walsh, 2009; Brown et al., 2006) or three to four years after the event (Murphy and Strobl, 2010; Belasen and Polachek, 2008; Strobl, 2011). 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. 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. I contribute to this literature by looking at a much more comprehensive set of outcomes for a large set of disasters over a longer time period. Moreover, I show that ignoring non-disaster transfer flows would paint an incomplete picture of post-disaster dynamics.

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

In this section, I describe how aggregate economic shocks can be mitigated by the availability of transfer payments. The goal is to provide intuition about the links between a shock and changes in population, wages, employment, and transfers, which is useful for interpreting the results.[4] Hurricanes in the modern US can be thought of as negative capital shocks: with the exception of Hurricane Katrina, they have not caused substantial loss of life. Thus, I use a simple production function framework in a spatial equilibrium setting.

I assume many identical locations, and that a shock in one location does not affect other locations. 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. Capital and labor are complements. Suppose that one location experiences a negative capital shock. Generally, the degree to which population, labor supply, and wages change depends on capital and individual mobility costs, as well as the presence of unemployment insurance or other transfer programs. Although I do not test for the presence of capital or moving costs, I describe how these affect the dynamics for completeness.

If capital is perfectly mobile between locations (i.e., adjustment costs are zero), a capital shock

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

will have no effect on the equilibrium population or any other economic indicators because the affected location is "small" and capital will be immediately restored to its pre-shock levels. This is true regardless of individual moving costs or the existence of transfer programs.

If capital is not perfectly mobile, there will be observed changes in the local economy. If individuals face zero moving costs, the wage will be unchanged, but population will decline. Intuitively, when moving costs are zero, 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 move away from the area to work elsewhere unless the wage rate is equal to the pre-shock wage. Because moving is instantaneous, the wage will remain unchanged, but population will fall. 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 plays no role in post-shock dynamics: the margin of adjustment is moving. This is because individuals' utility levels are unchanged by the capital shock, as they can costlessly move to another location with identical wages. Thus, those who preferred to work rather than take transfers before the shock will continue to have the same preference.

When both capital and individuals are not perfectly mobile (but some of the individuals have negligible moving costs), and transfer payments do not exist, the population will also fall, but to a smaller extent than in the case of perfect individual mobility. Unlike that case, individuals will also decrease their labor supply without moving away, so the employment rate will decline. 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 individuals would have no incentive to lower their labor supply or move. But because the level of capital is reduced, it is impossible to return to an equilibrium with the same wage, population, and labor supply. 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, transfer payments are present, 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). The employment *rate* will also be lower. However, the change in *total* labor supply and in the wage rate relative to the no transfer case is ambiguous. Per capita labor supply is expected to fall more as some individuals take the outside option of transfers instead of working. The presence of transfer payments will thus counteract the decrease in wages that occurs due to reduced capital levels. Likewise, some individuals will chose to take transfers and remain in the area instead of moving away.[5] 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 falls, more people remain 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 level.

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 it has no eye). The outer parts of the hurricane are called "spiral bands." These are characterized by heavy rains but typically do not have hurricane-force winds.

For hurricane data, I use the Best Tracks (HURDAT) dataset from the National Oceanic and

[5]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.

Atmospheric Administration (NOAA).[6] 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. However, the eye of the hurricane is typically not very large, and, as I show later, counties through which the center passes suffer much more extensive damage. Thus, the absence of width data 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 analysis 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 tropical storm is a cyclone with wind speeds of $39-73$ miles per hour. Cyclones with lower wind speeds are called "tropical depressions." A storm is considered a hurricane if maximum 1-minute sustained wind speeds exceed 74 miles per hour. Category 1 and 2 hurricanes are "minor hurricanes," characterized by maximum wind speeds of $74-110$ mph. Category 3 and higher hurricanes have wind speeds greater than 111 mph and are called "major hurricanes."

Between 1980 and 1996, 5.6 North Atlantic hurricanes formed each year, on average, 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 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. If the year 2005 is excluded, that figure is \$2.2 billion per hurricane or \$3.7 billion per year.[7]

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

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

time period affected Alabama, Georgia, Florida, Louisiana, Mississippi, North Carolina, South Carolina, Texas, and Virginia (hereafter the "hurricane region"). Figure I shows the geographic distribution of hurricane hits that occurred between 1980 and 1996. Dark grey counties are those that experience hurricane-force winds of 74 miles per hour or more at some point between 1980 and 1996. 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 hurricane during this time, and virtually all the major hurricanes occur within the nine states listed above. I therefore limit my analysis to this region. Although it may be preferable to focus on the major hurricanes, they are relatively rare (only 8 made landfall between 1980 and 1996). For this reason, I focus on the 21 minor and major hurricanes that affected the hurricane region during that time.

[FIGURE I ABOUT HERE]

In order to gauge the potential economic impact of hurricanes, it is helpful to look at the damages they cause.[8] I use estimates of direct damages from HAZUS-MH, published by FEMA.[9] Table I shows the damage statistics for the 8 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.

[TABLE I ABOUT HERE]

[8]Here, I only consider hurricane damages. In Appendix B and Table A.1 in the Online Appendix, I consider hurricane damages relative to other extreme weather events. I show that hurricanes are, on average, the most damaging of the common meteorological events in the hurricane region.

[9]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. The software is available by request from http://www.fema.gov/plan/prevent/hazus/index.shtm.

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 are displaced as a result of a central hit by a major hurricane. 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 (a) are listed as affected in the FEMA simulations but do not have the center of the storm passing through them, according to my calculations, and (b) are direct neighbors of the affected counties ("affected direct neighbors"). The damage estimates are much smaller. 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. Including all affected neighboring counties in this summary (Panel C), whether or not they border the directly affected counties, makes the relative damages of centrally affected counties even larger. 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. This is because wind speeds dissipate non-linearly with distance from the storm center. Nevertheless, I exclude observations from counties that are within 25 miles of a county that experiences a hurricane if those counties do not themselves experience a hurricane according to my calculations.[10] Doing so minimizes the possibility that I mistakenly classify counties that are affected by a given hurricane as unaffected. It also reduces the likelihood that my estimates are contaminated by spatial effects. To maintain sample size, I exclude only those observations that are within the 21-year time window of interest.

Federal Disaster Aid. Federal disaster aid is given to a county if the state's governor files

[10]The distance between two counties is defined as the direct distance between their centroids.

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 long-term recovery spending exists 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.[11] The bulk of the non-hurricane disaster spending (\$10.1 billion) was due to the Northridge earthquake in 1994. Excluding the Northridge earthquake implies that hurricane-related spending 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 compute the approximate average of disaster transfers per county.

Table II shows the summary statistics for federal aid related to hurricanes between 1980 – 1996.[12] Because data on federal disaster aid is provided on the level of a declaration, which includes multiple counties in a state, an assumption about how the money is divided among counties is necessary. As I show in the previous section, counties through which the center of the storm passes experience much more damage than their neighbors. Therefore, one 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

[11] 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.

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

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 two times as much on average, \$128 – 133 million. Per capita spending in 1980-1996 averaged \$356 per hurricane and \$412 per major hurricane. An extreme assumption of a 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 major hurricanes affected Florida. Thus, even "typical" hurricanes are associated with non-trivial amounts of federal disaster spending.

[TABLE II ABOUT HERE]

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. Based on the previous analysis of damages to centrally affected counties, it seems most reasonable to assume that they receive all the aid and that it is allocated between them in proportion to their relative populations. This assumption corresponds to estimated disaster transfers of \$356 per capita. In the following sections, I use this number 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). Annual county-level population by race and age are from the Surveillance Epidemiology and End Results (SEER) population database. Both series span the years 1970-2006.

I define the employment rate as the ratio of total employment, as reported by REIS, to the number of people aged fifteen and older, as reported by SEER.[13] Total employment is defined as the total number of wage and salary jobs, rather than the total number of workers. Average earnings per job (which I later refer to as simply "average earnings") are reported by REIS and include wage and salary disbursements, supplements to wages and salaries, and proprietors' income. Earnings do *not* include transfer payments.

In addition to analyzing changes in total government transfers, I consider changes in their components. Total transfers from government to individuals include unemployment insurance. Unemployment insurance compensation consists primarily of standard state-administered unemployment insurance schemes, but also includes unemployment compensation for federal employees, railroad workers, and veterans. Government transfers also include income maintenance (which in turn includes Supplemental Security Income (SSI), family assistance, and food stamps), retirement and disability insurance benefits, public medical benefits other than Medicare, Medicare, 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.

Table III presents the summary statistics for the estimation sample. The average county in the sample has $81,000$ residents; the average amount of earnings per job is \$$32,500$. About 32% of the residents are 20 and under, 13% are 65 and older, and 27% are black. The average employment rate is 56%.[14] Per capita transfers from the government average \$$3,700$ per year, of which \$580 is public medical spending, \$690 is Medicare spending, \$490 is income maintenance, and \$94 is unemployment insurance. Finally, transfers from businesses average \$90 per capita per year.[15]

[TABLE III ABOUT HERE]

Sample of Analysis. In Table IV, I compare the 1970 characteristics and 1970-1979 trends of hurricane region counties that do and do not experience a hurricane between 1980 and 1996,

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

[14] In rare instances, the employment rate is calculated to be greater than 1. This could be for a number of reasons, including measurement error in population, workers who commute from other counties, and workers holding multiple jobs.

[15] Compared to the rest of the country, counties in the hurricane alley have significantly lower earnings, lower per capita transfers from the government, and smaller populations.

excluding non-hurricane (control) counties that are within 25 miles of hurricane (treated) counties. Columns 1 and 2 of Panel A show selected 1970 characteristics of treated counties and the difference from control counties, respectively.

70% of 127 counties that experience hurricanes between 1980 and 1996 are coastal, compared to about 25% of counties that have not had hurricanes over this period. They are also more populous than non-hurricane counties, have lower population densities, higher average earnings, and receive more per capita transfers from the federal government. Finally, the demographic composition of treated counties is different from the rest of the region: black residents and younger people make up a larger share of their population, while people aged 65 and over make up a smaller share. All these differences are highly significant, as shown in Column 3.

[TABLE IV ABOUT HERE]

Differences in levels are not problematic for estimation because county fixed effects can easily be included in every specification. However, differences in levels may indicate differences in trends. In Panel B, I test for differential changes in the time-varying characteristics between 1970 and 1979, before the occurrence of any hurricanes used in the estimation. Columns 1 and 2 show the mean annual changes in the hurricane counties and the difference from non-hurricane counties, respectively. Only two variables show different changes for these two groups of counties: per capita transfers from government and fraction of residents aged 20 and younger. Both differences are significant at the 1% level. Thus, although some concern about differential trends between these two groups exists, the differences are not as severe as those in levels.

One approach to address these differences is to control for them directly. Following previous literature, I do this by including linear trends that are allowed to vary by the county's 1970 characteristics listed in Table IV (Acemoglu, Autor, and Lyle, 2004; Hoynes and Schanzenbach, 2009). In addition, propensity score matching can be employed to select comparable counties as controls. However, to maintain sample size and power, I use all counties in the hurricane region that are at least 25 miles away from the affected counties as the preferred control group and employ matching estimators as a robustness check. I discuss the robustness of the results to varying the set of controls and to varying the control group in Section 5.2.

4 Empirical Strategy

Regression Framework. I employ an event study framework. The identifying assumption is that, conditional on the location and the year, the occurrence of a hurricane is uncorrelated with unobservables. This is reasonable because even forecasting the severity of the hurricane season as a whole is difficult, much less the paths those hurricanes will take.

I regress outcomes on a set of hurricane indicators ranging from 10 years before to 10 years after a hurricane, controlling for county and year fixed effects. I also include linear trends in each of the following 1970 characteristics: land area, whether the county is coastal, population (in logs), the fraction of the population that is black, population density, the employment rate, per capita net earnings (in logs), per capita transfers from the federal government (in logs), and per capita transfers from businesses (in logs).

The estimating equation is:

$$O_{ct} = \sum_{\tau=-10}^{10} \beta_\tau H_{c,t-\tau} + \theta X_{c,1970}t + \alpha_c + \alpha_t + \beta_{ct}^{-11} + \beta_{ct}^{11} + \varepsilon_{ct} \tag{1}$$

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

where O_{ct} is some economic outcome, such as the log of per capita transfers or the employment rate. The variable H_{ct} is a hurricane indicator, equal to 1 if the county is reported to have experienced a hurricane in year t, according to the NOAA Best Tracks data. The year of the hurricane's landfall corresponds to ($\tau = 0$). I normalize the effect in the year before the hurricane ($\tau = 1$) to zero. $X_{c,1970}$ is a set of 1970 county characteristics, and t is a linear time variable. Therefore, $X_{c,1970}t$ is the interaction between the two. The variables α_c and α_t are county and year fixed effects. β_{ct}^{-11} and β_{ct}^{11} are estimated coefficients for dummy variables that indicate a county experiencing a hurricane before and after the window of interest, respectively. The regression sample is constructed such that every main lead and lag is estimated using the same set of hurricanes. Standard errors are spatially clustered following Conley (1999). I allow for spatial correlation of up to 300 kilometers around the county's centroid and for autocorrelation of order 5. My conclusions are unchanged if I cluster standard errors by county.

When estimating the above equation, I combine hurricane indicators into two-year bins to increase the power of the estimation.[16] The combined lags are years 1 and 2, 3 and 4, 5 and 6, 7 and 8, 9 and 10 after the hurricane. The combined leads are the same pairs of years prior to the hurricane. Year 0, which is the year that the hurricane makes landfall in a county, is not combined with any other year because the assumption that the effects in year 0 and year 1 are similar may not hold. In this modified specification, the average effect of combined leads 1 and 2 is assumed to be 0, so the estimated coefficients should be interpreted as the change relative to the two years before the hurricane.

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

$$\sum_{t=0}^{10} \frac{1}{(1+r)^t} \left(e^{\mu+\beta_t} - e^{\mu} \right)$$

where μ is the mean of a particular outcome, such as the log of per capita transfers, in treated counties in the year before the hurricane. The quantities β_t are the coefficients from the regression that combines consecutive years (thus, for example, β_1 and β_2 will be equal to each other). The coefficients are exponentiated because many of the outcomes of interest are in logs.

To summarize the impact of a hurricane more concisely and increase the power of the estimates, I use another specification that combines post-hurricane years $0-4$ and $5-10$ and assumes no differences in pre-hurricane outcomes within the 21-year window of interest. These assumptions appear to fit the patterns observed in the data reasonably well. The exact specification is:

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

$$
\begin{aligned}
O_{ct} &= \gamma_1 max(H_{ct}, H_{c,t-1}, ..., H_{c,t-4}) + \gamma_2 max(H_{c,t-5}, H_{c,t-6}, ..., H_{c,t-10}) \\
&\quad + \theta X_{c,1970} t + \alpha_c + \alpha_t + \beta_{ct}^{-11} + \beta_{ct}^{11} + \varepsilon_{ct}
\end{aligned} \tag{2}
$$

Because of unobserved heterogeneity across hurricanes, my preferred sample consists only of hurricanes for which I can estimate the full set of leads and lags. In practice, this restriction means I am estimating the effects using hurricanes that occurred between 1980 and 1996. If a county experiences a hurricane during 1970-1979 or 1997-2006, I exclude all observations for that county 10 years before and after the hurricane. This allows me to exclude potentially confounding 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.

An alternative to using hurricane incidence would be to use hurricane damages as the independent variable. To my knowledge, 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). However, these data are estimates made by local emergency officials fairly close to the time of occurrence. At best, they appear to be very imprecise. Second, damages are not only a function of the hurricane's strength, but also 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 variables of interest 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, superior coordination, or better governance).

5 Results

5.1 Economic Effects of Hurricanes

In this section, I present the estimated effects of a hurricane. Specifically, I graph the coefficients from Equation 1 in Section 4.[17] Following each figure is a table with corresponding estimates from Equation 2.

Effect on population and demographics. Figure II shows the estimated effects on population and demographics. Although the point estimates measuring the change in population are negative, none is statistically significant. The fraction of those under 20 years of age steadily grows, while the fraction of residents who are 65 and older is unchanged. One possible explanation for this demographic change is a shift in the composition of job opportunities that makes the county a relatively more attractive place for families with children. The fraction of black residents is slightly lower $7-10$ years after the hurricane, and the lags are jointly significant. None of the leads are individually or jointly significant, indicating that the parallel trends assumption holds for these variables.

[FIGURE II ABOUT HERE]

Table V shows the complementary estimates that combine years 0-4 and years 5-10 and assume no pre-hurricane differences between the treatment and control groups. The comparison period is thus the average during the 10 years preceding the hurricane rather than the two years immediately before. These estimates show that population is 1% higher in years $0-4$ after the hurricane. The fraction of the population that is 20 and under is 0.3 percentage points higher in years $5-10$, while the fraction that is 65 years old and older is 0.1 percentage points lower in each of the ten years after the hurricane. The fraction of the population that is black is estimated to be unchanged.

[TABLE V ABOUT HERE]

[17]The point estimates corresponding to the figures can be found in the Online Appendix (Tables A.2-A.4).

Effect on earnings, employment and transfers. Figure III shows the estimated effect of a hurricane on the employment rate, earnings, and transfers. Average earnings are unaffected in the year of the hurricane, but fall by 1.5 – 3.0% in the subsequent years. Correspondingly, the employment rate is estimated to be unaffected in the years immediately after the hurricane but dips slightly by 0.6 – 0.7% in years 5 – 8 following the hurricane. Overall per capita transfers from the government to individuals increase by 1.9 – 3.3% in years 1 – 10 after the hurricane. Per capita transfers to individuals from businesses increase by 15.8% in the year of a hurricane and then return to their pre-hurricane levels. This makes sense, as insurance payouts occur soon after a natural disaster. For all of these outcomes, the post-hurricane estimates are jointly different from zero at the 10% level or lower, while none of the pre-hurricane coefficients are jointly significant.

[FIGURE III ABOUT HERE]

Table VI shows the estimates combining years 0-4 and 5-10. Average earnings per job are 1.4% lower in years 5 – 10, while the employment rate is estimated to be 0.6 – 0.9 percentage points lower. Per capita transfers from the government are 2% higher in years 0 – 4, on average, and 3% higher in years 5 – 10. Per capita transfers from businesses are 3.7% higher in years 0 – 4 after the hurricane, but subsequently return to pre-hurricane levels.

[TABLE VI ABOUT HERE]

Effect on specific government transfers. Figure IV shows the estimated changes in key components of government transfers: unemployment insurance (UI), income maintenance, public medical spending net of Medicare, and Medicare. Per capita unemployment insurance payments increase by 14.5% in the year of the hurricane and are subsequently 12.2 – 19.6% above pre-hurricane levels. They appear to be on their way to pre-hurricane levels at the end of the estimation period. Per capita income maintenance, which includes Supplemental Security Income (SSI), family assistance, and food stamps, is 4.0 – 6.2% higher in years 3 – 10. Per capita public medical spending (excluding Medicare) is 7.0 – 10.5% higher in years 1 – 6 following the hurricane. However, per capita Medicare spending is not significantly affected by the hurricane. The last two results suggest that the rise in medical spending is not due to worsening health outcomes; in that case, we would expect Medicare spending to increase as well.

[FIGURE IV ABOUT HERE]

Table VII shows the combined estimates. Per capital unemployment insurance payments are 16.5% and 15.6% higher in years $0-4$ and $5-10$, respectively. Per capita income maintenance is $3.5-6.5\%$ higher in the ten years after the hurricane. Per capita public medical spending is estimated to be $3.5-7.6\%$ higher, while per capita Medicare spending is 1.4% *lower* in the five years immediately following the hurricane.

One compositional explanation for the increase in transfers is the observed change in the demographics of the hurricane-affected areas. However, the change in the age and race compositions is inconsistent with the changes in non-disaster transfers. Total government transfers include social security and disability payments. There is no a priori reason to think that a larger number of young people and a decline in the number of elderly would increase the total transfers. Young people are more likely to be unemployed than the elderly, but most of the people in the "under 20 years old" category are unlikely to be receiving unemployment insurance payments. Moreover, event study 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 patterns of change in the age profile and race would correspond to those for 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.

[TABLE VII ABOUT HERE]

Decomposing the change in transfers. Table VIII shows the estimated total flow of various transfers $0-10$ years after the hurricane. For reference, I also show the estimated change in average earnings over this time period. Column 1 shows the estimates corresponding to Equation 1, while Column 2 shows the estimated changes using coefficients from Equation 2. Both sets of estimates yield very similar results. Assuming a 3% discount rate, the present discounted value (PDV) of all government transfers is about \$750 per capita, and the PDV of transfers from businesses is \$30 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 \$750 per capita should be viewed as a lower bound. By comparison, the PDV of average earnings in the ten years after the hurricane is estimated to be $\$3,500 - \$6,000$ lower.

[TABLE VIII ABOUT HERE]

The subcomponents of total government transfers to individuals are: retirement and disability insurance benefits (which includes workers' compensation), public medical benefits (excluding Medicare), Medicare, income maintenance, 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 public medical, unemployment, and income maintenance benefits explain the overwhelming majority of the net increase in total non-disaster transfers. Specifically, public medical benefits increase significantly by $\$200 - \$240$ per capita in PDV, while the estimated change in Medicare spending is not significant.[18] Because Medicare spending does not increase significantly, 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 $\$130 - \$145$ per capita in PDV. Income maintenance increases by $\$155 - \$190$ per person. There is no significant change in SSI spending or retirement and disability insurance benefits in Column 1, while Column 2 estimates a decrease of \$25 and an increase of \$110, respectively. Per capita educational assistance is estimated to be $\$16 - \$21$ lower in the years following the hurricane.

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

5.2 Robustness Tests

Varying the controls. Recall that the main specification includes county and year fixed effects, as well as linear trends in counties' 1970 characteristics. I vary the included controls by omitting the linear trends in characteristics, including state-specific linear trends, and including state-by-year fixed effects. In general, the point estimates are very robust and the significance levels are very similar across the different sets of controls, while most of the pre-trends are insignificant. Figure V shows the robustness of the event study government transfer estimates to different controls. The biggest difference in estimates comes from including state-by-year fixed effects, which in general make estimates smaller in absolute value and less significant. Including state-specific linear trends and/or omitting the linear trends in characteristics makes little difference. The same is generally true for other outcomes as well.

The combined estimates (Equation 2) are similarly robust to varying the controls.[19] As with the event study estimates, the coefficients are very similar across the different controls, with the exception of specifications that include both state-year fixed effects and linear trends in counties' 1970 characteristics, in which case the estimates are generally lower in magnitude and sometimes insignificant.

[FIGURE V ABOUT HERE]

Varying the control group. Figure VI shows the robustness of government transfer estimates to four simple variations in the control group. Specifically, I (1) omit unaffected neighbors within 50 miles of affected counties (as opposed to 25-mile neighbors in the main sample), (2) omit unaffected direct neighbors only, regardless of distance, (3) use all counties in the hurricane region, and, finally, (4) assume that direct neighbors of affected counties are also affected. The resulting point estimates and significance levels are very similar in most cases, both for the event study and combined estimates. The exception is the specification that assumes that direct neighbors are also affected. In this case, the point estimates for many of the outcomes are lower in magnitude and less

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

significant. This validates the notion discussed in Section 3: direct neighbors are not significantly affected by hurricanes most of the time.

[FIGURE VI ABOUT HERE]

It is also worthwhile to check how the estimated total flow of transfers varies depending on the control group. The results are shown in Table IX for two of the control groups: all counties in the hurricane region and the group where 50-mile neighbors are omitted. Columns 1 and 2 show the estimates corresponding to the event study specification for these two groups, while Columns 3 and 4 show the combined specification estimates. Overall, the estimates using all non-hurricane counties as the control are very close to the main estimates, while those omitting 50-mile neighbors are slightly larger. The estimates where direct neighbors are omitted from the control group are similar to the main sample, while the estimates assuming direct neighbors are affected as well are generally smaller.

[TABLE IX ABOUT HERE]

Propensity score matching. One concern may be that the control groups discussed above are not comparable to the treated group. As discussed in Section 3, significant differences between hurricane and non-hurricane counties exist, even within the hurricane region. These differences likely arise because certain physical characteristics of a county, such as being near the coast, are correlated with the probability of being hit by a hurricane. These physical characteristics, in turn, may lead to differences in economic and demographic characteristics (e.g., because coastal areas tend to be populated by wealthier individuals).

Although I address this concern by including characteristic-specific trends in the regression analysis, an alternative approach is to choose a control group that has a similar hurricane risk profile to the treated counties. I construct a hurricane risk variable using Best Tracks hurricane data between 1851 and 1970. Specifically, I estimate a county's propensity to be hit by hurricanes by spatially smoothing observed hurricane hits over this time period. I then use two nearest neighbor propensity score matching with replacement to select a control group from the non-hurricane counties.

In addition to requiring balance in hurricane risk, one can also require balance in 1970 covariates. Specifically, I select control counties that are similar in land area, propensity to be coastal, population (in logs), population density, fraction of population that is black, the employment rate, per capita earnings (in logs), per capita transfers from the federal government (in logs), and per capita transfers from businesses (in logs). In both cases, I require that each control county be located at least 25 miles away from the counties experiencing a particular hurricane.

The differences between the treated and the new control counties are examined in Appendix Table A.5. Propensity score matching eliminates many of the significant differences in levels and all but one trend differences, which is only significant at a 10% level. Moreover, the more complex matching procedure results in smaller absolute differences between the treatment and control counties.

[FIGURE VII ABOUT HERE]

Figure VII shows the event study results for total per capita transfers from the government for these two control groups. They are in general very similar to the original estimates.

6 Discussion

In the aftermath of a hurricane, the average US county can expect to see a slight fall in both mean earnings and the employment rate in the ten years following a hurricane. However, my results show that the most pronounced effect is in the form of persistently higher government transfers. Although the relative increase in transfers is small, on the order of $2-3\%$, the net present value of \$750 is more than twice as large as the average amount of disaster-specific aid received by these counties. Non-disaster transfers replace somewhere between 10 and 20% of the lost earnings.

Whether the presence of social safety nets for those living in disaster-prone areas is welfare-improving on a national level is not straightforward to determine. 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, insurance may allow credit constrained individuals to avoid moving costs during the recovery period and mitigate falls in wages. On the other hand, disaster and non-disaster transfers may be creating a moral hazard problem. Disaster risk is not currently accounted for in unemployment insurance premiums, for example. This omission subsidizes business activity in disaster-prone areas, which decreases social welfare. In addition, many other distortions in insurance and aid policy could discourage insurance and encourage people to live in disaster-prone areas. This makes even a theoretical welfare analysis of social safety nets difficult in this context.

However, it is possible to evaluate the magnitude of the cost of public funds. For a county with the average population of $80,000$, the estimated increase of \$750 per capita in non-disaster government transfers translates to a total of \$60 million in extra transfers. These estimates imply that the fiscal impact of natural disasters is three times as large if non-disaster transfers are also considered. The deadweight loss of taxation is estimated to be $12-30\%$ of revenue (Ballard et al., 1985; Feldstein, 1999). Assuming a 15% deadweight loss and using the estimated amount of disaster spending of \$356 per capita implies a real cost of \$53 per capita per hurricane or \$4.2 million for a county with a population of $80,000$. For non-disaster transfers of \$750 per capita, the corresponding deadweight loss estimates are \$110 per capita per hurricane or \$9 million per county per hurricane. 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. Of course, these costs must be weighed against potential benefits provided by the social safety net, a topic outside the scope of this paper.

The designs of disaster and non-disaster government programs suggest that they may be complementary. Social insurance programs can 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.[20] 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 provides benefits only to those who can show that they lost their jobs directly as a result of the disaster.[21] Individuals who lose their jobs as a result of an economic downturn months to years later would be unable to claim these benefits. If hurricanes have lasting effects, as seems to be the case in the US, 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.

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 measurable economic shocks are hard to come by. Hurricanes in the US are ideal sources of capital shocks. In addition to being exogenous and unanticipated, they are very damaging and frequent enough to be amenable to a statistical examination.

I estimate the economic effects of capital shocks on US counties, focusing on population, employment, wages, and transfers to individuals $0-10$ years after the event. My findings suggest that traditional social safety nets play an important role in recovery from capital shocks: in the ten years following a hurricane, non-disaster related transfers, mainly income maintenance, public medical spending, and unemployment insurance, increase substantially and persistently. At the same time, both the employment rate and average earnings decline significantly but temporarily. Although my research design does not allow me to test the effect of social safety net programs on

[20]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).

[21]This spending is included in the calculations of disaster-related transfers.

post-disaster economics directly, it is easy to show theoretically that transfer programs can act as buffers against adverse economic impacts following a regional capital shock.

I estimate that transfers from traditional safety net programs over the ten years following the hurricane total $750 per capita on average, which is much larger than the disaster-related transfers of $356 per capita. This implies that the fiscal cost of hurricanes is about three times as large as previously thought. Insurance payments increase temporarily in the year of the hurricane but add only an estimated $30 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 complementary to public and private disaster insurance.

In addition to being informative about regional shocks generally, my study has important implications for disaster policy. Both 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. 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. A comprehensive picture of post-disaster economic dynamics, which I provide in this paper, is necessary for creating informed policy.

Moreover, 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). Traditionally, unemployment insurance has been viewed as a program that protects individuals from *idiosyncratic* shocks. However, my analysis suggests that social safety nets also have important implications for regional economic outcomes in the aftermath of an adverse shock, such as a natural disaster.

My findings suggest several policy implications. First, policymakers may want to consider the potential role of transfer programs in mitigating aggregate shocks. 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 areas that deserve further study.

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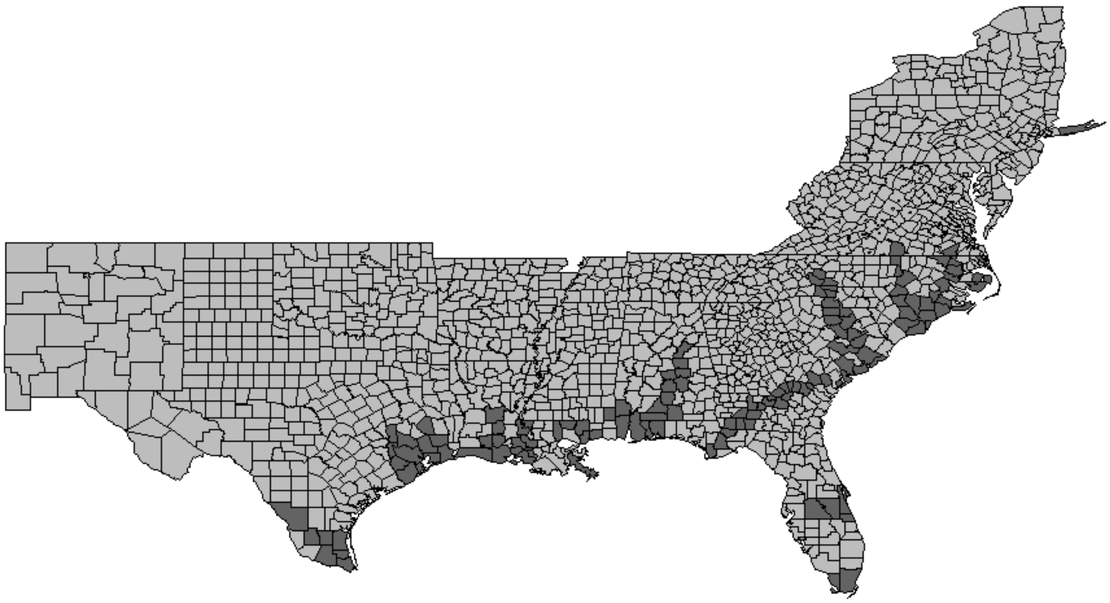
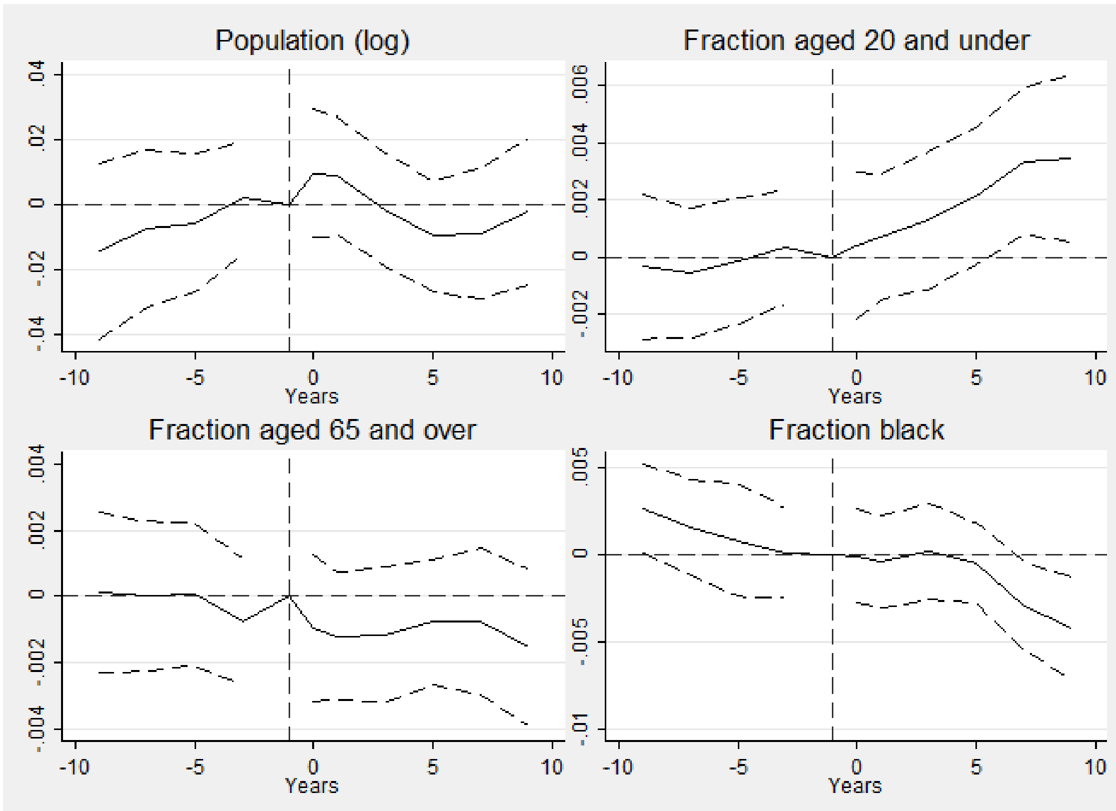
Figures

Figure I: Counties affected by hurricanes



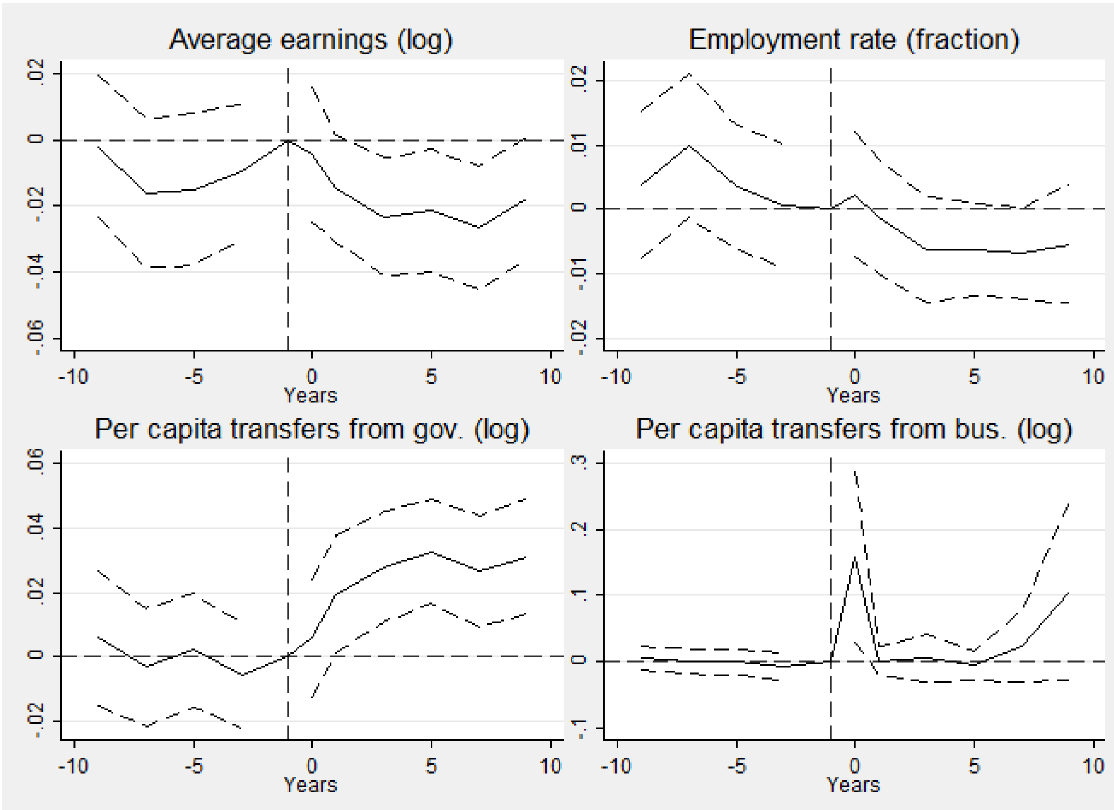
Darker shade indicates counties affected by at least one hurricane between 1980 and 1996.

Figure II: The effect of a hurricane on demographics



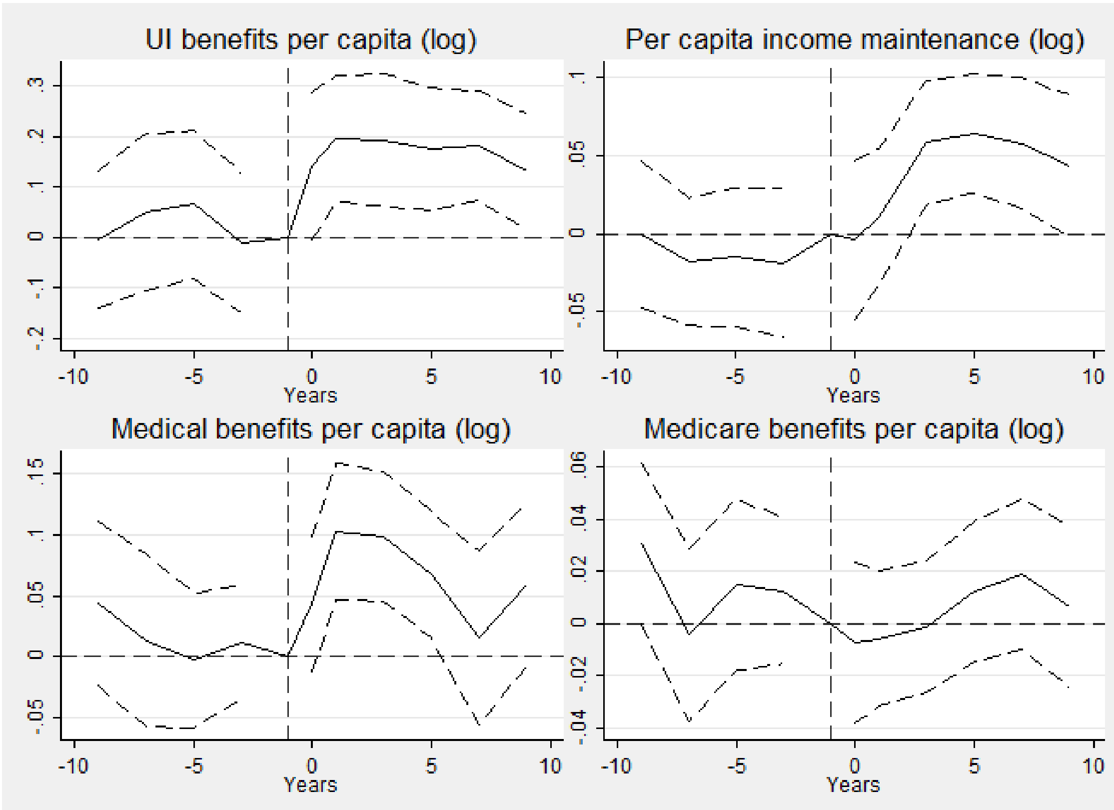
Outcome variable shown above corresponding plot. Point estimates from Equation 1 and 95% confidence intervals shown. Standard errors clustered spatially, allowing for spatial correlation up to 300 km and intertemporal correlation for up to five years. Controls include year fixed effects, county fixed effects, trends linear in 1970 county characteristics, and dummies for hurricane occurrence outside of the time window of interest. Sample excludes observations from unaffected counties within 25 miles of affected counties for ten years before and ten years after the hurricane.

Figure III: The effect of a hurricane on earnings and transfers



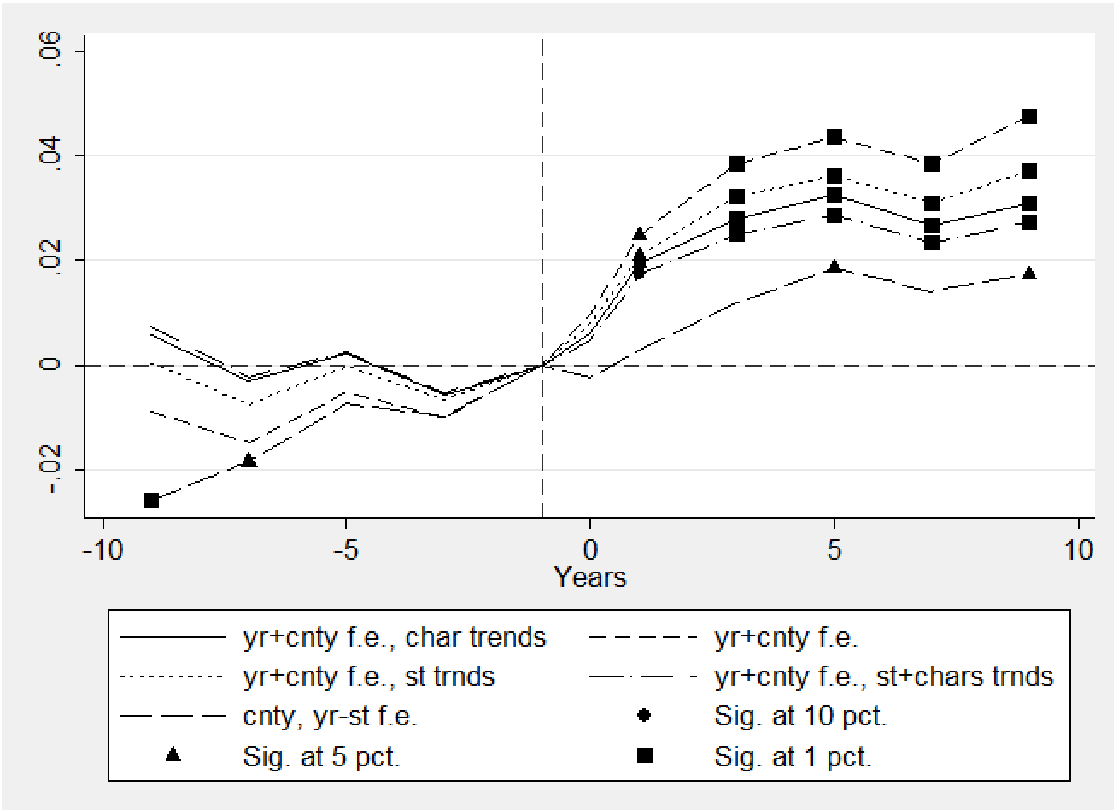
Outcome variable shown above corresponding plot. Point estimates from Equation 1 and 95% confidence intervals shown. Standard errors clustered spatially, allowing for spatial correlation up to 300 km and intertemporal correlation for up to five years. Controls include year fixed effects, county fixed effects, trends linear in 1970 county characteristics, and dummies for hurricane occurrence outside of the time window of interest. Sample excludes observations from unaffected counties within 25 miles of affected counties for ten years before and ten years after the hurricane.

Figure IV: The effect of a hurricane on specific transfers



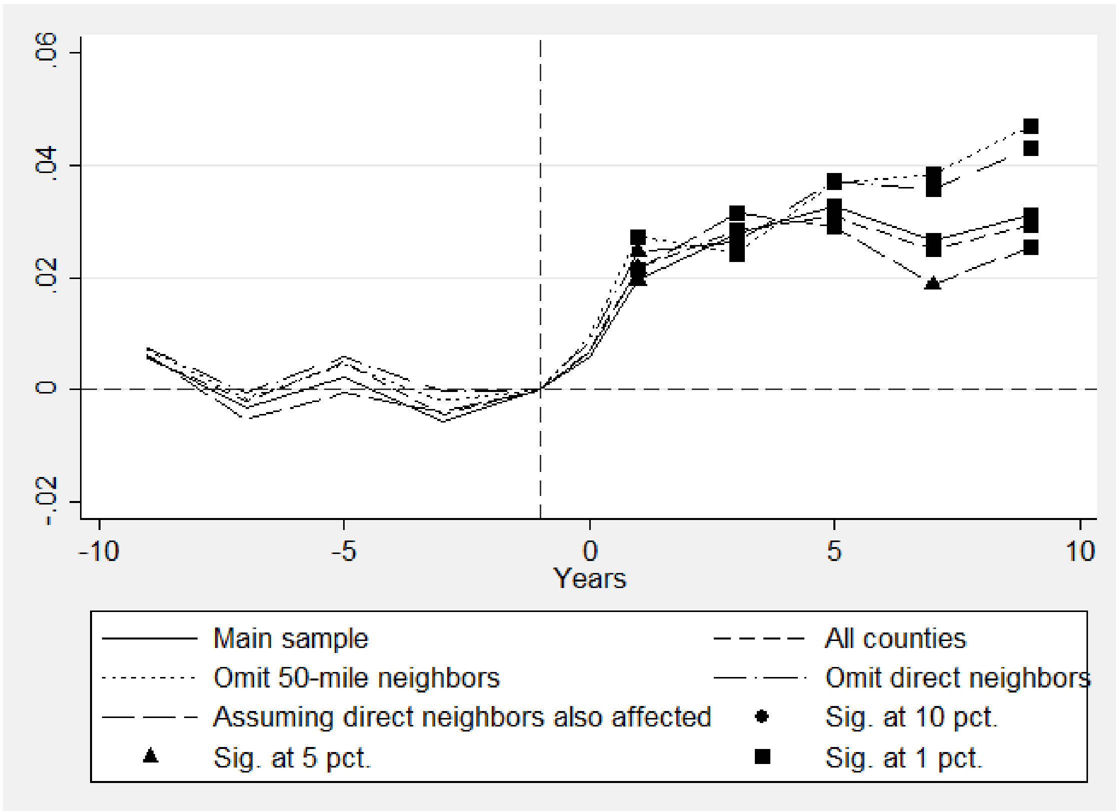
Outcome variable shown above corresponding plot. Point estimates from Equation 1 and 95% confidence intervals shown. Standard errors clustered spatially, allowing for spatial correlation up to 300 km and intertemporal correlation for up to five years. Controls include year fixed effects, county fixed effects, trends linear in 1970 county characteristics, and dummies for hurricane occurrence outside of the time window of interest. Sample excludes observations from unaffected counties within 25 miles of affected counties for ten years before and ten years after the hurricane.

Figure V: Robustness of transfer estimates to different controls



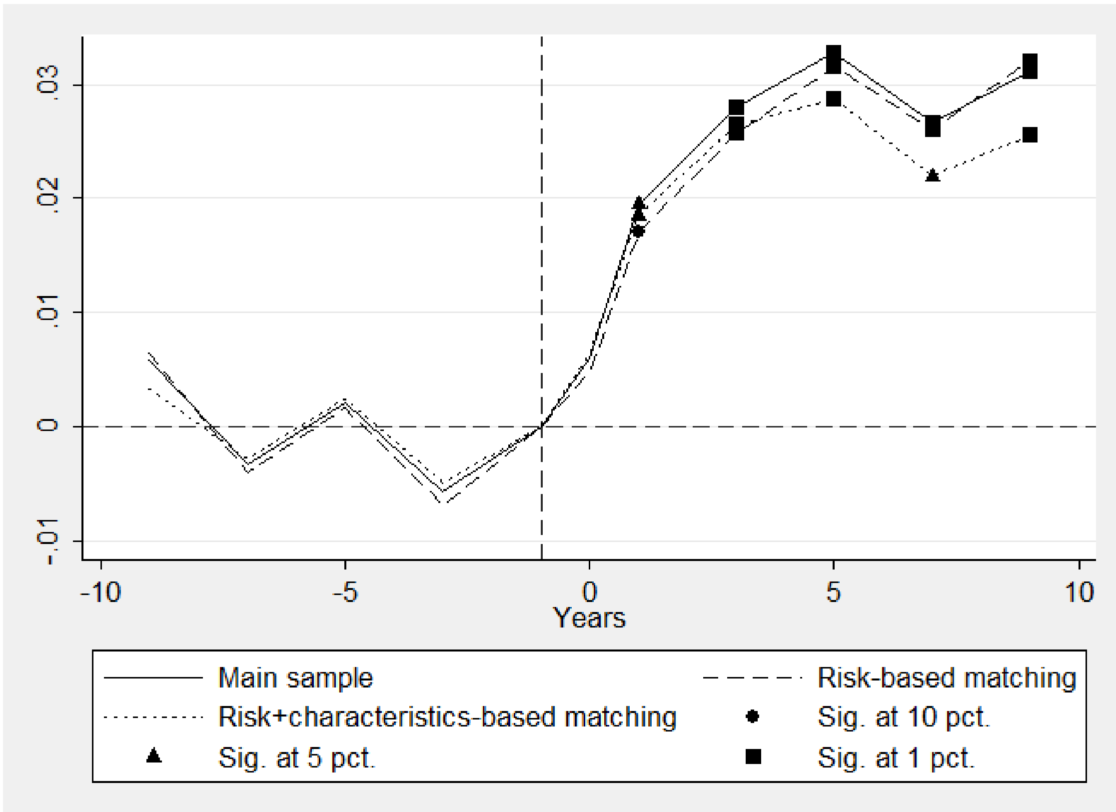
Outcome variable is log of total government transfers per capita. The lines represent the point estimates from Equation 1, while the symbols represent significance levels. "yr+cnty f.e." stands for year and county fixed effects; "char trends" represents linear trends in 1970 characteristics; "yr-st f.e." stands for year-by-state fixed effects; "st trends" stands for linear state-specific trends. Standard errors clustered spatially, allowing for spatial correlation up to 300 km and intertemporal correlation for up to five years. Sample excludes observations from unaffected counties within 25 miles of affected counties for ten years before and ten years after the hurricane.

Figure VI: Robustness of transfer estimates to different samples



Outcome variable is log of total government transfers per capita. The lines represent the point estimates from Equation 1, while the symbols represent significance levels. "Main sample" includes all counties in the hurricane alley and excludes observations from unaffected counties within 25 miles of affected counties for ten years before and ten years after the hurricane. "All counties" uses all observations in the hurricane alley. "Omit 50-mile neighbors" excludes observations from unaffected counties within 50 miles of affected counties for ten years before and ten years after the hurricane. "Omit direct neighbors" excludes corresponding observations from unaffected neighbors that directly border the affected county. "Assuming direct neighbors also affected" classifies unaffected adjacent neighbors of affected counties as affected. Standard errors clustered spatially, allowing for spatial correlation up to 300 km and intertemporal correlation for up to five years. Controls include year fixed effects, county fixed effects, trends linear in 1970 county characteristics, and dummies for hurricane occurrence outside of the time window of interest.

Figure VII: Robustness of transfer estimates to propensity score matching



Outcome variable is log of total government transfers per capita. The lines represent the point estimates from Equation 1, while the symbols represent significance levels. "Main sample" includes all counties in the hurricane alley and excludes observations from unaffected counties within 25 miles of affected counties for ten years before and ten years after the hurricane. "Risk-based matching" selects a subsample of control counties based on their similarity to the affected counties in historic hurricane risk. "Risk+characteristics-based matching" selects a subsample of control counties based on their similarity to the affected counties in historic hurricane risk and 1970 characteristics. Standard errors clustered spatially, allowing for spatial correlation up to 300 km and intertemporal correlation for up to five years. Controls include year fixed effects, county fixed effects, trends linear in 1970 county characteristics, and dummies for hurricane occurrence outside of the time window of interest.

Tables

Table I: 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	27,240,788	224,182,064	99
Building damage (1000's)	338,868	2,101,017	20,276,334	97
Total losses (1000's)	570,558	3,662,500	35,426,992	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: affected direct neighbors				
Total building value (1000's)	4,282,765	7,871,487	55,334,012	126
Building damage (1000's)	19,095	64,461	388,928	124
Total losses (1000's)	26,395	93,422	632,972	124
Loss ratio (percent)	0.33	0.81	5.20	124
Displaced households	32	142	1,193	125
People requiring shelter	8	38	331	125
Panel C: all affected neighbors				
Total building value (1000's)	4,818,569	10,213,268	125,710,576	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. Centrally affected counties are those classified as affected by my procedure. Affected direct neighbors are counties that are directly adjacent to centrally affected counties and are classified as affected by HAZUS-MH but not by my procedure. All affected neighbors are counties that are classified as affected by HAZUS-MH but not by my procedure, regardless of whether they are directly adjacent to centrally affected counties or not.

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

	(1) Uniform split	(2) Proportional split	(3) Per capita - uniform split	(4) Per capita - proportional split
Panel A: centrally affected counties				
Centrally affected, all hurricanes (N = 89)	58,697,364	58,697,364	1,137	356
	(187,126,272)	(260,072,592)	(3,193)	(307)
Centrally affected, major hurricanes (N = 27)	128,242,296	132,949,720	2,018	412
	(332,330,400)	(466,673,184)	(5,623)	(343)
Panel B: all counties listed in declaration				
All counties in declaration (N = 568)	10,986,738	10,338,369	191	63
	(53,913,696)	(72,675,792)	(702)	(98)
Centrally affected, all hurricanes (N = 89)	24,596,418	30,079,786	460	131
	(94,058,904)	(151,777,648)	(1,594)	(140)
Centrally affected, major hurricanes (N = 27)	59,196,700	73,419,952	954	187
	(167,230,864)	(272,658,400)	(2,824)	(184)

Source: NOAA Best Tracks data, PERI disaster declarations. Standard errors in parentheses. All amounts are in 2008 dollars. Uniform split assumes aid money is split evenly among all counties in given sample. Proportional split assumes aid money is split in proportion to the population of counties in given sample. The per capita summaries (Columns 3 and 4) further divide these amounts by the county's population.

Table III: Summary statistics

	(1) Mean	(2) Std. Dev.	(3) Min	(4) Max	(5) Obs
Population	86,178	211,692	5,216	3,912,196	12,717
Fraction 20 and under	0.32	0.05	0.17	0.52	12,717
Fraction 65 and over	0.13	0.04	0.02	0.36	12,717
Fraction black	0.27	0.17	0	0.87	12,717
Fraction employed	0.56	0.14	0.18	1.39	12,717
Average earnings per job	32,834	7,119	11,369	77,334	12,717
Per capita transfers from gov.	3,655	1,552	462	11,189	12,717
Per capita transfers from bus.	89	60	25	3,546	12,717
Unemployment insurance per capita	94	67	3	737	12,508
Income maintenance per capita	491	281	15	2,102	12,717
Medicare spending per capita	689	474	27	3,328	12,717
Public medical spending per capita	575	494	2	3,266	11,068

Source: REIS. Monetary values are in 2008 dollars. Sample includes all counties in the hurricane alley and excludes observations from unaffected counties within 25 miles of affected counties for ten years before and ten years after the hurricane. In addition, counties in the sample must have a continuous record for the outcome variable.

Table IV: Comparison of hurricane region counties by 1980-1996 hurricane experience

	(1) One+ hurricanes	(2) Difference from no hurricanes	(3) p-value
Panel A: 1970 characteristics			
Coastal indicator	0.70	0.447	0.000
Land area (square miles)	755	116	0.004
Population (log)	10.44	0.598	0.000
Population density (persons/sq. mile)	91	-35	0.060
Employment rate (fraction)	0.56	0.010	0.420
Average earnings (log)	10.31	0.056	0.003
Per capita transfers from gov. (log)	7.29	-0.105	0.000
Per capita transfers from bus. (log)	4.05	-0.009	0.170
Fraction black	0.28	0.054	0.000
Fraction 65 and over	0.09	-0.022	0.000
Fraction 20 and under	0.41	0.022	0.000
Panel B: 1970-1979 changes in characteristics			
Chg. population (log)	0.16	0.012	0.405
Chg. employment rate (fraction)	0.01	0.003	0.626
Chg. average earnings (log)	0.11	-0.016	0.185
Chg. per capita transfers from gov. (log)	0.50	0.038	0.007
Chg. per capita transfers from bus. (log)	0.31	0.003	0.220
Chg. fraction black	-0.02	-0.001	0.734
Chg. fraction 65 and over	0.02	0.001	0.660
Chg. fraction 20 and under	-0.06	-0.009	0.000
Number of counties	127	846	

Source: 1970 and 1979 REIS. Monetary values are in 2008 dollars. Number of observations varies slightly because of missing values. Samples drawn from counties in Alabama, Georgia, Florida, Louisiana, Mississippi, North Carolina, South Carolina, Texas, and Virginia. Sample excludes observations from unaffected counties within 25 miles of affected counties for ten years before and ten years after the hurricane.

Table V: The effect of hurricanes on demographics

	(1) Population (log)	(2) Fraction 20 and under	(3) Fraction 65 and older	(4) Fraction black
0-4 years after hurricane	0.010**	0.001	-0.001**	-0.001
	(0.004)	(0.001)	(0.000)	(0.002)
5-10 years after hurricane	-0.003	0.003***	-0.001**	-0.003
	(0.003)	(0.001)	(0.000)	(0.003)
Mean of dep. var.	10.814	0.317	0.118	0.255
Observations	12,717	12,717	12,717	12,717
R-squared	1.000	0.999	0.994	0.339

Estimated using Equation 2. Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Standard errors (in parentheses) clustered spatially for all outcomes except the fraction of the population that is black, which is clustered by county due to failure to compute spatial standard errors. Spatially clustered standard errors allow for spatial correlation up to 300 km and intertemporal correlation for up to five years. Controls include year fixed effects, county fixed effects, trends linear in 1970 county characteristics, and dummies for hurricane occurrence outside of the time window of interest. Sample excludes observations from unaffected counties within 25 miles of affected counties for ten years before and ten years after the hurricane.

Table VI: The effect of hurricanes on earnings and transfers

	(1) Average earnings (log)	(2) Employment rate (fraction)	(3) Per capita transfers from government (log)	(4) Per capita transfers from business (log)
0-4 years after hurricane	-0.008	-0.006**	0.020***	0.037**
	(0.005)	(0.002)	(0.004)	(0.016)
5-10 years after hurricane	-0.014***	-0.009***	0.030***	0.040
	(0.005)	(0.001)	(0.003)	(0.025)
Mean of dep. var.	10.426	0.588	8.035	4.435
Observations	12,717	12,717	12,717	12,717
R-squared	1.000	0.994	1.000	0.999

Estimated using Equation 2. Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Standard errors (in parentheses) clustered spatially, allowing for spatial correlation up to 300 km and intertemporal correlation for up to five years. Controls include year fixed effects, county fixed effects, trends linear in 1970 county characteristics, and dummies for hurricane occurrence outside of the time window of interest. Sample excludes observations from unaffected counties within 25 miles of affected counties for ten years before and ten years after the hurricane.

Table VII: The effect of hurricanes on transfers

	(1) Per capita UI (log)	(2) Per capita income maintenance (log)	(3) Per capita medical (log)	(4) Per capita Medicare (log)
0-4 years after hurricane	0.165***	0.035***	0.076***	-0.014**
	(0.031)	(0.013)	(0.015)	(0.007)
5-10 years after hurricane	0.146***	0.065***	0.035**	0.003
	(0.030)	(0.011)	(0.016)	(0.006)
Mean of dep. var.	4.397	5.958	5.882	6.256
Observations	12,508	12,717	11,068	12,717
R-squared	0.993	0.999	0.998	1.000

Estimated using Equation 2. Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Standard errors (in parentheses) clustered spatially, allowing for spatial correlation up to 300 km and intertemporal correlation for up to five years. Controls include year fixed effects, county fixed effects, trends linear in 1970 county characteristics, and dummies for hurricane occurrence outside of the time window of interest. Sample excludes observations from unaffected counties within 25 miles of affected counties for ten years before and ten years after the hurricane.

Table VIII: Total change in various transfers (Net Present Value)

	(1) Event study (Equation 1)	(2) Combined (Equation 2)
Average earnings	-6044***	-3501**
Total transfers from businesses	32**	32**
Total transfers from government=	748***	752***
Unemployment payments+	146***	130***
Public medical benefits+	241***	195***
Medicare benefits+	20	-28
Retirement and disability insurance benefits+	7	112***
Federal educational assistance+	-16**	-21***
Income maintenance=	155**	189***
SSI benefits+	-20	-23**
Food stamps+	90*	42**
Family assistance	39**	49***

Table shows net present value of additional inflows of various transfers 0-10 years after the hurricane. Assumed interest rate is 3 percent. Estimated with a nonlinear combination of coefficients from Equations 1 and 2. Significance levels: *10 percent, ** 5 percent, *** 1 percent.

Table IX: Robustness of transfer estimates

	(1)	(2)	(3)	(4)
	Event study (Equation 1)		Combined (Equation 2)	
	All counties	Omitting 50-mile neighbors	All counties	Omitting 50-mile neighbors
Average earnings	-6430***	-6886***	-3578***	-2271
Total transfers from businesses	29**	22**	31**	20**
Total transfers from government=	736***	957***	714***	910***
Unemployment payments+	131***	173***	103***	140***
Public medical benefits+	250***	293***	192***	255***
Medicare benefits+	25	99*	-16	77**
Retirement and disability insurance benefits+	32	116	138***	220***
Federal educational assistance+	-14**	-13	-22***	-17***
Income maintenance=	129**	236***	153***	214***
SSI benefits+	-22	-21	-30***	-33***
Food stamps+	71	93**	27	63***
Family assistance	35*	50**	40***	62***

Table shows net present value of additional inflows of various transfers 0-10 years after the hurricane. Assumed interest rate is 3 percent. Estimated with a nonlinear combination of coefficients from Equations 1 and 2. Significance levels: *10 percent, ** 5 percent, *** 1 percent.

Appendix: For Online Publication

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

Setup and Initial Equilibrium

Assume that many identical locations exist, 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:

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

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:

$$L = G\left(w^{1-\gamma} - (\theta\bar{w})^{1-\gamma}\right) \tag{3}$$

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

$$L = K_0 \left(\frac{w_0^*}{1-\alpha} \right)^{-\frac{1}{\alpha}} \tag{4}$$

Subtracting equation (3) from (4), 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 the number of locations is large, 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.

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

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 $(w_1^*)^{1-\gamma} - \tilde{\varepsilon} = \left(\theta w_0^*\right)^{1-\gamma}$.

Total labor supply in the new equilibrium will be

$$L_1^* = G(\tilde{\varepsilon})(1 - F(m^*)) = (1 - F(m^*))\, G\left((w_1^*)^{1-\gamma} - (\theta w_0^*)^{1-\gamma}\right) \tag{5}$$

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

$$L_1^* = K_1 \left(\frac{w_1^*}{1-\alpha}\right)^{-\frac{1}{\alpha}} \tag{6}$$

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 $\left(-F\left(m^*\right)\right)$.

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 A.2 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 A.1 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 A.3 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, more people remain 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:

$$
\begin{aligned}
D_{ct} &= a_c + a_t + \beta_1 Major\_hurricane_{ct} + \beta_2 Minor\_hurricane_{ct} \\
&\quad + \gamma_1 Flood_{ct} + \gamma_2 Tornado_{ct} + \gamma_3 Severe\_storm_{ct} + \varepsilon_{ct}
\end{aligned} \tag{7}
$$

$$
\begin{aligned}
D_{ct} &= a_c + a_t + \sum_{k=1}^{5} \beta_k 1\left[Category_{ct} = k\right] + \gamma_1 Flood_{ct} \\
&\quad + \gamma_2 Tornado_{ct} + \gamma_3 Severe\_storm_{ct} + \varepsilon_{ct}
\end{aligned} \tag{8}
$$

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

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 indicator for Category 3, 4, and 5 storms, while $Minor\_hurricane_{ct}$ is an indicator for Category 1 and 2 storms. $\mathbf{1}\left[Category_{ct} = k\right]$ is an indicator variable equal to 1 if the hurricane is classified as a Category k hurricane. Because very few hurricanes fall into Categories 4 and 5, 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

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

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 1.5 hurricanes make landfall each year, on average, 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

[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.

[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.

Appendix Figures

Figure A.1: Change in labor supply following capital shock

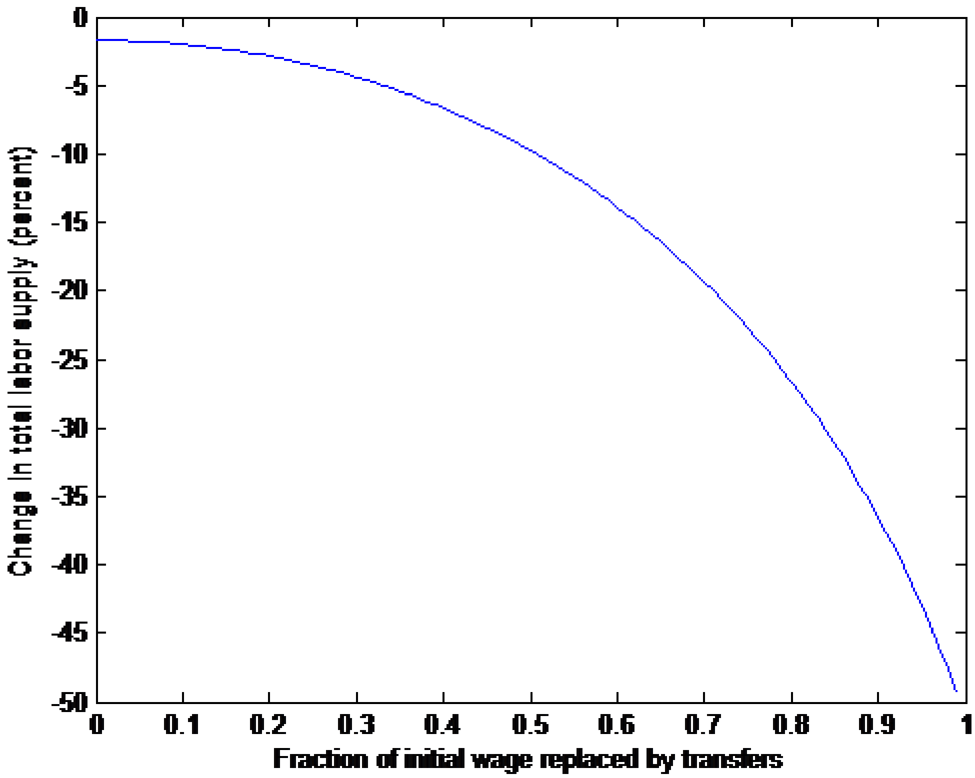


Figure A.2: Change in population following capital shock

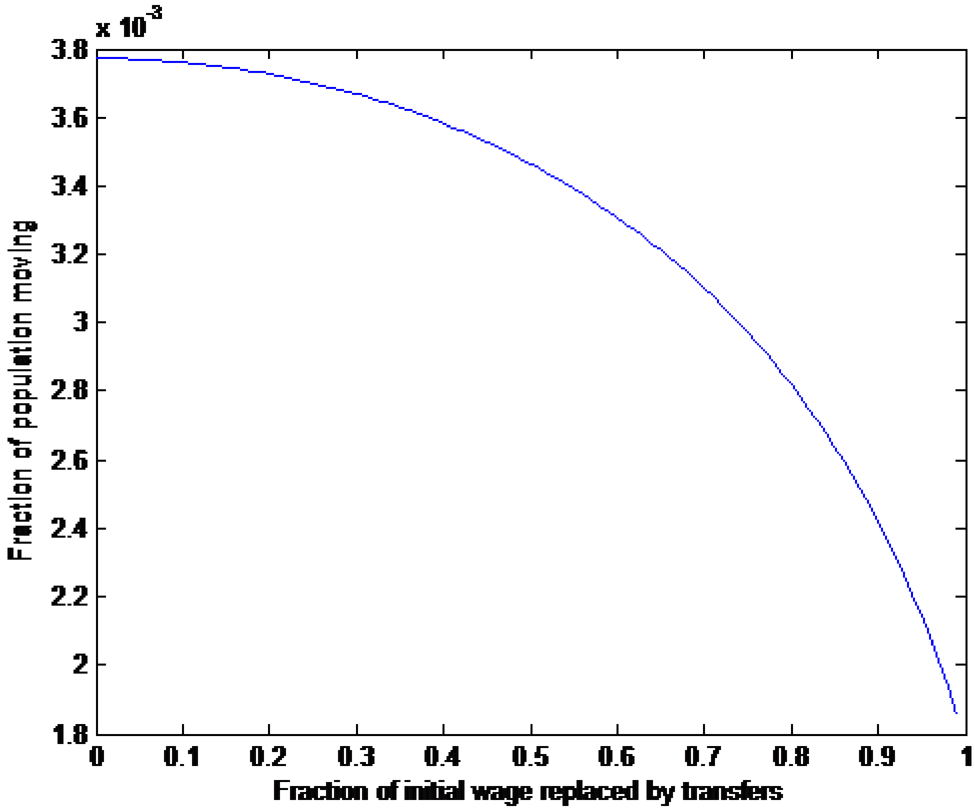
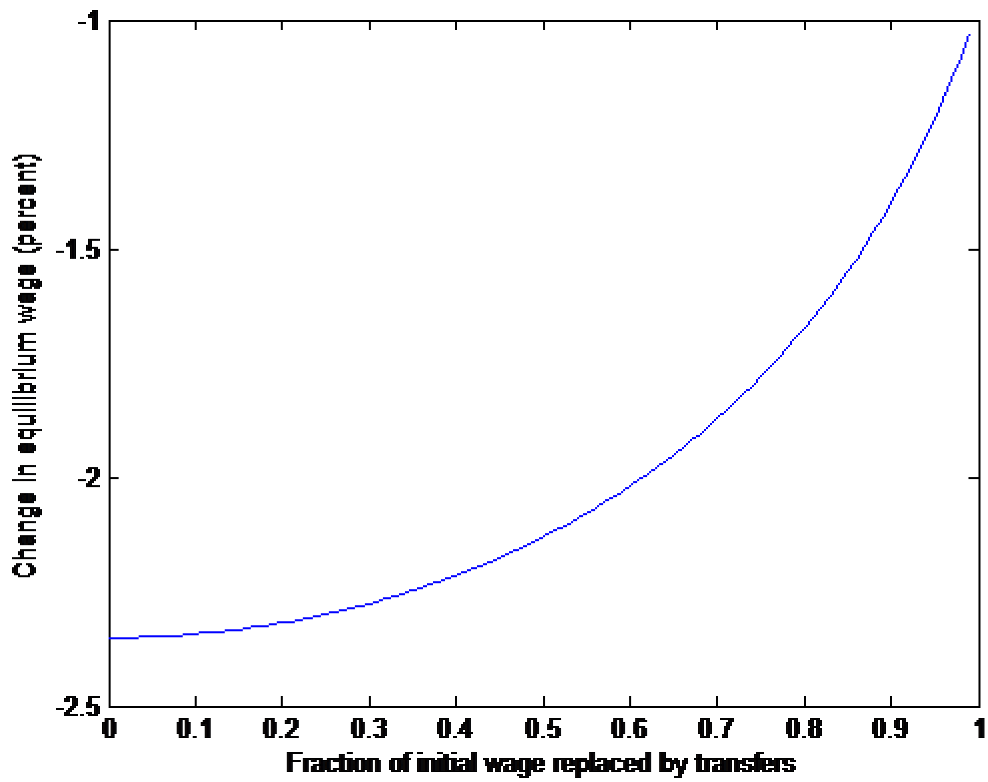


Figure A.3: Change in wages following capital shock



Appendix Tables

Table A.1: Determinants of property damages in hurricane region

	(1) Log damages	(2) Per capita damages	(3) Flood insurance payments (log)	(4) Log damages	(5) Per capita damages	(6) Flood insurance payments (log)
Minor hurricane	2.95***	68.32**	1.95***			
	(0.20)	(34.24)	(0.29)			
Major hurricane	5.16***	700.66***	3.74***			
	(0.49)	(265.46)	(0.59)			
Category = 1				2.75***	72.78*	1.74***
				(0.21)	(43.94)	(0.32)
Category = 2				3.58***	53.29**	2.60***
				(0.43)	(22.41)	(0.62)
Category = 3				5.02***	732.27**	3.94***
				(0.41)	(348.25)	(0.64)
Category = 4 or 5				5.47***	629.09*	3.11**
				(1.03)	(355.10)	(1.38)
Tornado	2.65***	13.87***	0.50***	2.65***	13.80***	0.50***
	(0.06)	(3.97)	(0.10)	(0.06)	(3.90)	(0.10)
Flood	1.34***	1.82	0.82***	1.34***	1.75	0.82***
	(0.05)	(3.68)	(0.08)	(0.05)	(3.74)	(0.08)
Severe storm	1.40***	9.79***	0.02	1.40***	9.86***	0.02
	(0.06)	(2.87)	(0.09)	(0.06)	(2.99)	(0.09)
Dep. var. mean	9.31	12.56	10.87	9.31	12.56	10.87
Observations	18,592	21,311	7,029	18,592	21,311	7,029
R-squared	0.24	0.04	0.08	0.24	0.04	0.08

Standard errors (clustered by county) in parentheses. Significance levels: *10 percent, ** 5 percent, *** 1 percent. Damages and flood claims are in 2008 dollars. Includes county and year fixed effects. Property damage data, tornado, flood, and severe storm incidence are 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. Hurricane region is defined as the states of Alabama, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Texas, and Virginia.

Table A.2: The effect of hurricanes on demographics

	(1) Population (log)	(2) Fraction 20 and under	(3) Fraction 65 and older	(4) Fraction black
T=-10 or -9	-0.014	-0.000	0.000	0.003**
	(0.014)	(0.001)	(0.001)	(0.001)
T=-8 or -7	-0.007	-0.001	0.000	0.002
	(0.012)	(0.001)	(0.001)	(0.001)
T=-6 or -5	-0.006	-0.000	0.000	0.001
	(0.011)	(0.001)	(0.001)	(0.002)
T=-4 or -3	0.002	0.000	-0.001	0.000
	(0.009)	(0.001)	(0.001)	(0.001)
T=-2 or -1	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
T=0	0.010	0.000	-0.001	-0.000
	(0.010)	(0.001)	(0.001)	(0.001)
T=1 or 2	0.009	0.001	-0.001	-0.000
	(0.009)	(0.001)	(0.001)	(0.001)
T=3 or 4	-0.002	0.001	-0.001	0.000
	(0.009)	(0.001)	(0.001)	(0.001)
T=5 or 6	-0.010	0.002*	-0.001	-0.000
	(0.009)	(0.001)	(0.001)	(0.001)
T=7 or 8	-0.009	0.003**	-0.001	-0.003**
	(0.010)	(0.001)	(0.001)	(0.001)
T=9 or 10	-0.002	0.003**	-0.002	-0.004***
	(0.011)	(0.001)	(0.001)	(0.001)
Mean of dep. var.	10.814	0.317	0.118	0.255
Observations	12,717	12,717	12,717	12,717
R-squared	1.000	0.999	0.994	0.997
p-value of F-test, leads 3-6	0.745	0.884	0.659	0.865
p-value of F-test, leads 3-10	0.740	0.957	0.918	0.303
p-value of F-test, lags 0-4	0.558	0.767	0.590	0.967
p-value of F-test, lags 0-10	0.320	0.026	0.847	0.004

Estimated using Equation 1. Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Standard errors (in parentheses) allow for spatial correlation for up to 300 km and intertemporal correlation for up to five years. Effect in years -2 and -1 assumed to be zero. Controls include year fixed effects, county fixed effects, trends linear in 1970 county characteristics, and dummies for hurricane occurrence outside of the time window of interest. Sample excludes observations from unaffected counties within 25 miles of affected counties for ten years before and ten years after the hurricane.

Table A.3: The effect of hurricanes on earnings, the employment rate, and transfers

	(1) Average earnings (log)	(2) Employment rate (fraction)	(3) Per capita transfers from government (log)	(4) Per capita transfers from business (log)
T=-10 or -9	-0.002	0.004	0.006	0.004
	(0.011)	(0.006)	(0.011)	(0.009)
T=-8 or -7	-0.016	0.010*	-0.003	-0.000
	(0.011)	(0.006)	(0.009)	(0.010)
T=-6 or -5	-0.015	0.003	0.002	-0.001
	(0.012)	(0.005)	(0.009)	(0.010)
T=-4 or -3	-0.010	0.001	-0.006	-0.008
	(0.010)	(0.005)	(0.008)	(0.010)
T=-2 or -1	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
T=0	-0.005	0.002	0.006	0.158**
	(0.010)	(0.005)	(0.009)	(0.066)
T=1 or 2	-0.015*	-0.001	0.019**	0.001
	(0.008)	(0.005)	(0.009)	(0.011)
T=3 or 4	-0.023***	-0.006	0.028***	0.004
	(0.009)	(0.004)	(0.009)	(0.019)
T=5 or 6	-0.021**	-0.006*	0.033***	-0.006
	(0.009)	(0.004)	(0.008)	(0.011)
T=7 or 8	-0.027***	-0.007*	0.027***	0.023
	(0.010)	(0.004)	(0.009)	(0.028)
T=9 or 10	-0.018*	-0.005	0.031***	0.106
	(0.010)	(0.005)	(0.009)	(0.068)
Mean of dep. var.	10.426	0.588	8.035	4.435
Observations	12,717	12,717	12,717	12,717
R-squared	1.000	0.994	1.000	0.999
p-value of F-test, leads 3-6	0.370	0.778	0.644	0.637
p-value of F-test, leads 3-10	0.485	0.428	0.763	0.626
p-value of F-test, lags 0-4	0.047	0.281	0.011	0.099
p-value of F-test, lags 0-10	0.023	0.033	0.000	0.074

Estimated using Equation 1. Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Standard errors (in parentheses) allow for spatial correlation for up to 300 km and intertemporal correlation for up to five years. Effect in years -2 and -1 assumed to be zero. Controls include year fixed effects, county fixed effects, trends linear in 1970 county characteristics, and dummies for hurricane occurrence outside of the time window of interest. Sample excludes observations from unaffected counties within 25 miles of affected counties for ten years before and ten years after the hurricane.

Table A.4: The effect of hurricanes on specific transfers

	(1) Per capita unemployment insurance (log)	(2) Per capita income maintenance (log)	(3) Per capita public medical (log)	(4) Per capita Medicare (log)
T=-10 or -9	-0.005	0.000	0.043	0.030*
	(0.069)	(0.024)	(0.034)	(0.016)
T=-8 or -7	0.049	-0.018	0.013	-0.004
	(0.079)	(0.021)	(0.036)	(0.017)
T=-6 or -5	0.065	-0.015	-0.003	0.015
	(0.075)	(0.023)	(0.028)	(0.017)
T=-4 or -3	-0.011	-0.018	0.012	0.012
	(0.071)	(0.025)	(0.024)	(0.014)
T=-2 or -1	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
T=0	0.141*	-0.004	0.043	-0.008
	(0.074)	(0.026)	(0.028)	(0.016)
T=1 or 2	0.194***	0.011	0.102***	-0.006
	(0.064)	(0.023)	(0.029)	(0.013)
T=3 or 4	0.192***	0.058***	0.099***	-0.001
	(0.067)	(0.020)	(0.027)	(0.013)
T=5 or 6	0.174***	0.064***	0.067**	0.012
	(0.062)	(0.019)	(0.026)	(0.014)
T=7 or 8	0.181***	0.058***	0.016	0.019
	(0.056)	(0.021)	(0.036)	(0.015)
T=9 or 10	0.131**	0.043*	0.059*	0.006
	(0.059)	(0.023)	(0.034)	(0.016)
Mean of dep. var.	4.397	5.958	5.882	6.256
Observations	12,508	12,717	11,068	12,717
R-squared	0.993	0.999	0.998	1.000
p-value of F-test, leads 3-6	0.586	0.695	0.813	0.571
p-value of F-test, leads 3-10	0.830	0.842	0.752	0.316
p-value of F-test, lags 0-4	0.006	0.006	0.000	0.945
p-value of F-test, lags 0-10	0.023	0.001	0.003	0.500

Estimated using Equation 1. Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Standard errors (in parentheses) allow for spatial correlation for up to 300 km and intertemporal correlation for up to five years. Effect in years -2 and -1 assumed to be zero. Controls include year fixed effects, county fixed effects, trends linear in 1970 county characteristics, and dummies for hurricane occurrence outside of the time window of interest. Sample excludes observations from unaffected counties within 25 miles of affected counties for ten years before and ten years after the hurricane.

Table A.5: Comparison of propensity score matches to treatment counties

	(1) One+ hurricanes	(2) Difference from simple matching	(3) p-value	(4) Difference from complex matching	(5) p-value
Panel A: 1970 characteristics					
Coastal indicator	0.70	0.032	0.567	0.201	0.000
Land area (square miles)	755	166	0.000	119	0.010
Population (log)	10.44	0.338	0.016	0.048	0.722
Population density (persons/sq. mile)	91	-73	0.084	-63	0.075
Employment rate (fraction)	0.56	0.022	0.187	-0.001	0.946
Average earnings (log)	10.31	0.014	0.578	-0.001	0.964
Per capita transfers from gov. (log)	7.29	-0.083	0.017	-0.020	0.523
Per capita transfers from bus. (log)	4.05	0.001	0.922	-0.004	0.594
Fraction black	0.28	0.010	0.608	-0.014	0.487
Fraction 65 and over	0.09	-0.017	0.000	-0.002	0.622
Fraction 20 and under	0.41	0.014	0.006	-0.001	0.807
Panel B: 1970-1979 changes in characteristics					
Chg. population (log)	0.16	-0.034	0.106	-0.013	0.508
Chg. employment rate (fraction)	0.01	0.011	0.224	0.016	0.061
Chg. average earnings (log)	0.11	0.003	0.838	-0.021	0.120
Chg. per capita transfers from gov. (log)	0.50	0.024	0.206	0.008	0.641
Chg. per capita transfers from bus. (log)	0.31	0.001	0.854	0.004	0.159
Chg. fraction black	-0.02	0.002	0.539	-0.002	0.601
Chg. fraction 65 and over	0.02	0.000	0.812	0.000	0.785
Chg. fraction 20 and under	-0.06	-0.003	0.144	-0.001	0.533
Number of counties	127	154		160	

Source: 1970 and 1979 REIS. Monetary values are in 2008 dollars. Number of observations varies slightly because of missing values. Samples drawn from counties in Alabama, Georgia, Florida, Louisiana, Mississippi, North Carolina, South Carolina, Texas, and Virginia. Simple matching selects a subsample of control counties based on their similarity to the affected counties in historic hurricane risk. Complex matching selects a subsample of control counties based on their similarity to the affected counties in historic hurricane risk and 1970 characteristics. Sample excludes observations from unaffected counties within 25 miles of affected counties for ten years before and ten years after the hurricane.