The Fiscal Cost of Hurricanes: Disaster Aid Versus Social Insurance

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Online Appendix

Contents

1 Calculating Which Counties are Affected by Hurricanes

The width of a cyclone can vary substantially, even conditional on strength. An informative metric for measuring its spatial extent is the "maximum wind speed radius" (MWSR), which is the distance between a cyclone's center and the perimeter of the strongest winds.[1] The Extended Best Tracks dataset reports the estimated MWSR for cyclones that occurred between 1988 and 2012, in 6-hour increments.[2] The average MWSR is about 42 miles across all storms, including those that did not reach hurricane strength. As the maximum wind speed rises, the MWSR generally falls: a 1 mile per hour increase in the hurricane's wind speed is correlated with a 0.33 mile decrease in the MWSR. For observations with hurricane-strength winds, the MWSR averages only 30 miles.

For hurricanes occurring before 1988, the MWSR is not available. However, it can be approximated using maximum wind speed and pressure information. I use a flexible specification to estimate the relationship between MWSR and the maximum wind speed and central pressure for each data point in the Extended Best Tracks dataset. Specifically, I use 25 quantiles of pressure and 25 quantiles of maximum wind speeds to estimate the relationship between these and the MWSR. I then use wind speed and pressure information for earlier hurricanes to predict their MWSR. I also calculate the minimum observed MWSR for each wind speed quantile. If the predicted MWSR falls below this value, I replace it with the minimum MWSR. Although the MWSR also varies conditional on pressure and wind speed, as mentioned above, this procedure should capture a non-trivial amount of the overall variation.

For some hurricanes, pressure information is not available. In these cases, I predict the pressure using percentiles of the observed wind speeds. The overwhelming majority of observations missing pressure information precede the 1979-2000 time period of interest. Thus, any measurement error due to missing pressure information will mainly affect calculations of historic hurricane hits.

I then interpolate between the observed points by assuming that the hurricane path, changes in wind speed, and changes in the MWSR are linear between consecutive storm coordinates. I assume that all counties which fall in the maximum wind speed radius experience the reported maximum wind speed, which is what the MWSR implies, and that counties outside the MWSR are unaffected. Finally, I calculate the maximum wind speed a county is exposed to in each year. Damages rise convexly with the wind speed; therefore, focusing on the maximum wind speed provides the best proxy for the destructiveness of the storm.

This process will inevitably result in some measurement error. Some counties that are outside of the maximum wind speed radius may be significantly affected. Conversely, because the MWSR is unknown for some hurricanes, counties that are calculated to be affected may not be. Assuming

[1] The MWSR is also sometimes referred to as the "radius of maximum winds" (RMW).

[2] Available from `http://rammb.cira.colostate.edu/research/tropical_cyclones/tc_extended_best_track_dataset/`. Accessed February 2014.

no spillovers, this will attenuate my estimates, as some treated counties will be included in the control group and vice versa. However, my results are not very sensitive to the assumption about which counties are affected, as long as the counties through which the center of the storm passed are included in the treated group.

In their study of cyclones' national growth effects, Hsiang and Jina (2014) use an international cyclone database called IBTrACS, whose structure is similar to the two datasets I use.[3] Because IBTrACS also does not report the full wind distribution ("wind field") of a storm, the authors apply the Limited Information Cyclone Reconstruction and Integration for Climate and Economics (LICRICE) model, developed by Hsiang, which predicts each observation's wind field based on available intensity measures and the reported wind speed at the storm's center. Thus, a key difference between LICRICE and the prediction algorithm I use is that I only try to predict the MWSR, while Hsiang and Jina are predicting the entire wind field. However, the information used to make the predictions is ultimately very similar. Estimating the wind field requires additional assumptions about how the distribution of wind speeds varies with known and estimated parameters; Hsiang and Jina (2014) assume an idealized surface wind speed function whose parameters include the observable characteristics of the storm and the statistically estimated size of the cyclone's eye. Because their analysis is at the national level, having detailed spatial measures of cyclone strength (wind speed or energy) is necessary to account for the fact that large parts of a country may be unaffected. By contrast, an indicator for hurricane wind speeds exceeding a particular threshold is sufficient for my sub-national analysis.

2 Relative Damages Caused by Hurricanes

In this section, I assess the damages caused by hurricanes relative to other disasters. Data on damages and the occurrence of extreme weather events other than hurricanes are from the Spatial Hazard Events and Losses Database for the United States, also known as HAZUS (Hazards and Vulnerability Research Institute, 2009). These data are based on weather service reports by local government officials. Because the damage information is not based on careful *ex post* assessments, it should be viewed as a rough proxy for the true damages. Because hurricanes may be accompanied by flooding from rainfall and storm surges, I also look at their effect on flood insurance payments, as reported by the Consolidated Federal Funds Report (CFFR).

I regress three different damage statistics on measures of hurricane strength and other natural event indicators.

[3] IBTrACS stands for International Best Track Archive for Climate Stewardship (IBTrACS). See `http://www.ncdc.noaa.gov/ibtracs/` for a detailed description.

$$D_{ct} = a_c + a_t + \beta_1 Major\_hurricane_{ct} + \beta_2 Minor\_hurricane_{ct} + \gamma_1 Flood_{ct} + \gamma_2 Tornado_{ct} + \gamma_3 Severe\_storm_{ct} + \varepsilon_{ct} \tag{1}$$

$$D_{ct} = a_c + a_t + \sum_{k=1}^{5} \beta_k \mathbf{1}\left[Category_{ct} = k\right] + \gamma_1 Flood_{ct} + \gamma_2 Tornado_{ct} + \gamma_3 Severe\_storm_{ct} + \varepsilon_{ct} \tag{2}$$

where D_{ct} is log of property damages, property damages per capita or the log of flood insurance payments in county c in year t. All damage measures are in 2013 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 include droughts, wildfires, and heat. Thus, the reference category is a combination of more rare 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 21 states in the hurricane region.[4] The results are shown in Table A2. Column 1 compares the log of damages for different disasters. A major hurricane increases the reported property damages by 6 log points or 600%. In levels, this implies that a major hurricane increases the total damages in a county by about \$5.5 million dollars. The next most damaging event is a minor hurricane, which increases property damages by 2.3 log points or about \$118,000. In contrast, tornadoes, floods, and severe storms increase property damages by 2.2 (\$109,000), 1.2 (\$32,000), and 1.0 (\$23,000) log points (dollars), respectively. A similar pattern holds when the dependent variable is property damages per capita, except that the flood estimates become statistically insignificant.

Column 4 shows the effect of hurricanes broken down by category. As expected, Category 1 hurricanes are the least damaging, causing an extra 2.1 log points of damage, while Category 3, 4, and 5 storms are the most damaging, increasing property damages by 6.0-6.6 log points. The least damaging hurricane is about as damaging as a tornado, and more damaging than a flood or severe storm. Note that in per capita terms, Category 3 hurricanes are estimated to be more damaging than

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

Category 4 or 5 hurricanes. This is possibly because damages are assessed at the county level. As discussed in the previous section, Category 4 and 5 hurricanes tend to be less wide than Category 3 hurricanes. Thus, although their local destructiveness is greater than that of a Category 3 hurricane, the county-level damages may be smaller.

As mentioned above, the damage measures are estimates made by local officials soon after the occurrence of the event. Using hurricane-level damage data from the working paper version of Nordhaus (2010), I estimate the direct damages from hurricanes to be about $4 billion per year between 1970 and 2004, in 2013 dollars. Given that 1.5 hurricanes make landfall each year, on average, the estimates in this section appear to significantly 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. Here, I lag the hurricane variables because the fiscal year of the US government, which pays the flood claims, ends on September 30th, while the Atlantic hurricane season ends in November. Many hurricane-related flood insurance claims originating in August and September (the peak hurricane time) or later may not be appear in the data until the following fiscal year. Because some of the claims may be settled before the fiscal year ends and because wind damages are covered separately by homeowner's insurance, these estimates should be considered lower bounds.

Major hurricanes as estimated to increase flood claims by about 3.3 log points or about $1.7 million, while minor hurricanes increase them by 1.4 log points or about $204,000. Unsurprisingly, tornadoes have no significant impact on flood claims and the estimated effect of a severe storm is marginally negative. Floods increase claims by only about 0.7 percent.

When the effect of a hurricane on flood claims is broken down further, Category 3 storms are estimated to have the largest effect, raising flood insurance payments by about 3.4 log points. Category 1 and 2 hurricanes raise flood-related insurance payments by 1.2 and 2.4 log points, respectively. Category 4 and 5 storms increase them by 2.4 log points.

Overall, the estimates in Table A2 imply that hurricanes are the most destructive of the common US disasters, which makes them an important phenomenon to study.

3 Equation restrictions tests

In this section, I describe how I test whether the restrictions imposed by equation (2) and (3) are consistent with equation (1). Recall that equation (1) is based on the following flexible event study specification (see main text for explanation of notation):

$$O_{ct} = \sum_{\tau=-10,\tau\neq-1}^{10} \beta_\tau H_{c\tau} + \alpha_c + \alpha_t + \mathbf{X}'_{\mathbf{c,1969}}\alpha_t$$
$$+\beta_{-11}H_{c,-11} + \beta_{11}H_{c,11} + \varepsilon_{ct}.$$

When estimating the equation above, I combine hurricane indicators into two-year bins to increase power. In other words, I restrict certain coefficients to be equal to each other. The combined lags are $\tau = 1$ and 2, 3 and 4, 5 and 6, 7 and 8, and 9 and 10. The combined leads are the corresponding pairs of years prior to the hurricane. Below, I refer to these coefficients as $\widehat{\beta_{\tau-1,\tau}}$.

Recall that the specification of equation (2) is:

$$\begin{aligned} O_{ct} &= \gamma_1 H_{c,0\text{ to }4} + \gamma_2 H_{c,5\text{ to }10} + \alpha_c + \alpha_t + \mathbf{X}'_{\mathbf{c,1969}}\alpha_t \\ &\quad +\beta_{-11}H_{c,-11} + \beta_{11}H_{c,11} + \varepsilon_{ct} \end{aligned}$$

For equation (2), I test the hypothesis that (a) the pre-hurricane coefficients estimated by equation (1) are jointly equal to zero and (b) the post-hurricane coefficients estimated by equation (1) over the relevant time period (0-4 or 5-10 years) are equal to the respective coefficient from equation (2) (γ_1 or γ_2).

Finally, recall that the specification of equation (3) is as follows:

$$\begin{aligned} O_{ct} &= \theta_1 H_{c,0\text{ to }10} + \theta_2 H_{c,0\text{ to }10} * \tau + \gamma_1 H_{c,-10\text{ to }10} * \tau \\ &\quad +\alpha_c + \alpha_t + \mathbf{X}'_{\mathbf{c,1969}}\alpha_t + \beta_{-11}H_{c,-11} + \beta_{11}H_{c,11} + \varepsilon_{ct}. \end{aligned}$$

For equation (3), I test the hypothesis that (a) the coefficients estimated by equation (1) follow the linear trend estimated by equation (3), on average ($\widehat{\gamma_1} \times \tau$ in the pre-hurricane period and $(\widehat{\gamma_1} + \widehat{\theta_2}) \times \tau$ in the post-hurricane period) and (b) $\widehat{\beta_0}$, as estimated by equation (1), is equal to $1.5 \times \widehat{\gamma_1} + \widehat{\theta_1}$. Specifically, the restrictions (jointly tested) to assess the fit of equation (3) are:

1) $\widehat{\theta_1} + 1.5 \times \widehat{\gamma_1} = \widehat{\beta_0}$

2) $1.5 \times (\widehat{\theta_2} + \widehat{\gamma_1}) = \widehat{\beta_{1,2}} - \widehat{\beta_0}$

3) $2 \times (\widehat{\theta_2} + \widehat{\gamma_1}) = \widehat{\beta_{3,4}} - \widehat{\beta_{1,2}}$

4) $2 \times (\widehat{\theta_2} + \widehat{\gamma_1}) = \widehat{\beta_{5,6}} - \widehat{\beta_{3,4}}$

5) $2 \times (\widehat{\theta_2} + \widehat{\gamma_1}) = \widehat{\beta_{7,8}} - \widehat{\beta_{5,6}}$

6) $2 \times (\widehat{\theta_2} + \widehat{\gamma_1}) = \widehat{\beta_{9,10}} - \widehat{\beta_{7,8}}$

7) $2 \times \widehat{\gamma_1} = \widehat{\beta_{-5,-6}} - \widehat{\beta_{-3,-4}}$

8) $2 \times \widehat{\gamma_1} = \widehat{\beta_{-7,-8}} - \widehat{\beta_{-5,-6}}$

9) $2 \times \widehat{\gamma_1} = \widehat{\beta_{-9,-10}} - \widehat{\beta_{-7,-8}}$

Restriction 1 tests whether the estimated contemporaneous effect of the hurricane in the event study is consistent with the estimated mean shift. The term $1.5 \times \widehat{\gamma_1}$ is an adjustment to reflect that the reference category is 1.5 years before the hurricane. Restrictions 3-6 above capture the fact that if the trend break model is consistent with the event study, the difference between coefficients on neighboring post-hurricane years should be twice the estimated post-hurricane slope, which is $\widehat{\theta_2} + \widehat{\gamma_1}$. The difference is twice the slope because each coefficient in the event study accounts for two years of hurricane occurrence. Restriction 2 reflects that the year of the hurricane is not combined with any other years, so the difference between those two coefficients should be 1.5 times the slope rather than 2 times the slope. Finally, restrictions 7-9 are similar to restrictions 3-6 but reflect the pre-hurricane slope, which is $\widehat{\gamma_1}$.

Because the restrictions above are tested jointly, they imply many other relationships than explicitly specified. For example, simple algebra shows that restrictions 1 and 2 imply that $\widehat{\theta_1} + 1.5 \times \widehat{\theta_2} + 3 \times \widehat{\gamma_1} = \widehat{\beta_{1,2}}$. As a result, it is not necessary to explicitly test that restriction (which needs to be met for the mean shift/trend break model to be consistent with the study).

The restrictions are jointly tested following the estimation of equation (1); $\widehat{\theta_1}$, $\widehat{\gamma_1}$, and $\widehat{\theta_2}$ enter these tests as constants. Taking into account the fact that these quantities themselves are uncertain would make the p-values larger (lower probability of rejection), as would testing the trend break model with a version of equation (1) that does not combine any leads or lags.

4 Population Data

Because population figures for years between the decennial Census are necessarily estimates, some discussion of their construction is in order. In this section, I briefly describe how these data are constructed. For more detail, see U.S. Bureau of the Census (1984), Byerly (1993), and the Census Bureau website.[5] Although U.S. Bureau of the Census (1984) and Byerly (1993) describe the methodology as applying to states, the same methodology is used to create county population estimates.[6]

I use two related population datasets in my analysis: Regional Economic Information System (REIS), which contains Census Bureau estimates, and Survey of Epidemiology and End Results

[5] `http://www.census.gov/popest/data/`

[6] Author's personal communication with the Census Bureau.

(SEER). Unlike REIS, SEER provides data by age, sex, and race. However, the underlying data are also from the Census Bureau, with minor modifications.[7] Both series span the period 1969-2010.

Every ten years, the Census Bureau's population data is composed of exact Census population counts, linearly projected to correspond to population as of July 1st. The in-between estimates are developed by using administrative records. Throughout my estimation period, the Census Bureau has used nearly the same data sources to create the intercensal estimates, although the way in which they are used has varied slightly.[8]

Specifically, the Census Bureau consistently uses registered birth and death data, international migration estimates, Federal tax return information (for ages 64 and under), and Medicare enrollment information (for ages 65 and over). In the 1970s-1990s, international migration estimates were reported by the Immigration and Naturalization Service. In the 2000s, international migration was estimated using the American Community Survey coupled with decennial Census information on the number of foreign-born people. Because the population is reported as of July 1st, a uniform distribution of events over the year (e.g., migration, people turning 65) is assumed.

Population estimates for previous years are updated whenever more recent or revised data, including decennial Census data, become available. The estimates used in the current paper were published in 2011 and reflect 2010 Census population estimates.

Although birth and death records should be very reliable, the use of tax returns for population estimates may miss people who do not file. The reliability of population estimates hinges on the assumption that the migration of the county's population is proportional to the migration patterns of the population for which migration data are available. If the hurricane alters the proportion of individuals who file taxes, for example, the population estimates may be biased.

The Census made special adjustments to the July 2006 population estimates in 62 counties and parishes in Alabama, Mississippi, Louisiana, and Texas because of the massive short-tern relocations caused by Hurricane Katrina. In addition, a January 2006 estimate was published. No special adjustments were made in subsequent years or for any other hurricane, however.

The fact that the Census Bureau did not make special adjustments or publish intra-year population estimates for other hurricanes does not rule out the possibility that those estimates are biased. The bias is much more likely to be problematic in the very short-term (i.e., 0-2 years after the hurricane) than longer time periods, on which I am focusing. Furthermore, the use of administrative datasets should significantly reduce any measurement error.

[7] For more details, see `http://seer.cancer.gov/popdata/methods.html`.

[8] An exception is that school enrollment data was used to create population estimates in the 1970s and 1980s, and the number of housing units was used in the 1970s.

5 Back-of-the-envelope calculations for Medicare and SSDI

Previous studies have shown that SSDI applications are positively correlated with the unemployment rate (Autor and Duggan, 2005), and evidence suggests that higher unemployment leads to greater SSDI enrollment (Black, Daniel and Sanders, 2002; Autor and Duggan, 2003; Duggan and Imberman, 2009).[9] A back-of-the-envelope calculation can help shed light on whether increased SSDI enrollment can explain the increase in Medicare payments. As Table 7 in the paper shows, retirement and disability payments, which include Social Security and thus SSDI, increase by at most 1.7% in the ten years after a hurricane. According to Autor and Duggan (2005), in 1985 about 10% of Social Security spending was devoted to SSDI. In turn, Social Security accounts for about 95% of all retirement and disability spending in my data. Thus, if the entire increase in retirement and disability spending is due to SSDI, this implies an upper bound of an 18% increase in SSDI spending per capita. By contrast, between 1979 and 2002, total SSDI spending doubled from about $40 to $80 billion.[10]

From 1974 to 2012, between 8.7% and 19.8% of Medicare spending was on the disabled under the age of 65, with the share increasing steadily over time (U.S. Department of Health and Human Services, 2013). In the mean shift/trend break estimates, annual Medicare payments per capita increase by as much as 8% relative to the year before a hurricane (corresponding estimates from equations (1) and (2) are smaller). The average Medicare payment per capita was around $875 during my sample period. Thus, the maximum Medicare increase roughly corresponds to an additional $70 per person per year. The average county in my sample has about 99,000 people, implying a maximum increase of $6.9 million per affected county per year. According to the Congressional Research Service (1997), in 1995 Medicare spent about $7,800 per non-elderly disabled beneficiary in real terms. Dividing $6.9 million by $7,800 suggests that an increase in the disability rolls of about 890 people per county per year (less than 1% of the average population) can account for the upper bound of the increase in Medicare spending.

6 Robustness Checks

Varying the geographic unit of observation. It is not obvious how large of an area a local labor market should encompass. Using county as the definition of the labor market is common in the labor literature, whether looking at the employment effects of Wal-Mart (Basker, 2005), agglomeration effects (Greenstone, Hornbeck and Moretti, 2010), or the wage effects of internet

[9]Unfortunately, it is not possible to obtain the number of SSDI recipients at the county level prior to 1999, and REIS does not report SSDI payments separately.

[10]Author's calculations using data from Social Security Administration (2015).

investment (Forman, Goldfarb and Greenstein, 2012).[11] However, a sizeable literature considers cities, metropolitan areas or Commuting Zones more natural definitions of labor markets (Bound and Holzer, 2000; Card, 2001; Cortes, 2008; Kahn and Mansur, 2010; Moretti, 2011; Autor, Dorn and Hanson, 2013).

Defining a local labor market too narrowly may bias estimates. For example, suppose a county that is not hit by a hurricane lies inside the same local labor market as an affected county. If workers respond by shifting to the unaffected county, I may overestimate the effect of hurricanes on employment. As a robustness test, I aggregate my data to the Core Based Statistical Area (CBSA) or the Commuting Zone (CZ) level (Tolbert and Sizer, 1996). I assume that if any county inside the CBSA or CZ is affected by a hurricane, the whole area is affected. The results for population, wages, and transfers are shown in Figures A8 and A9 and are similar to the main estimates. The employment rate results are slightly different. Specifically, at the commuting zone level, the employment rate is estimated to be (insignificantly) *higher* in the year of the hurricane and subsequently falls to pre-hurricane levels. At the CBSA level, however, the employment rate is estimated to continue decreasing throughout the post-hurricane period.

Varying the definition of employment and wages. Next, I test the robustness of my earnings and employment results by varying how these are measured. Figure A10 shows four different measures of the employment rate, including the preferred one used in the paper: County Business Patterns (CBP) employment as a percent of the population aged 15 and older. Alternatively, I look at CBP employment as a percent of the *entire* population and REIS employment as a percent of either the adult population or the entire population. The estimates using CBP employment are very similar. Estimates using REIS employment are insignificant. A key difference between the two series is that REIS reports the number of jobs rather than the number of employees. In addition, REIS includes public sector employment, which may be less responsive to shocks. Finally, I have also normalized employment by the working age population (ages 15-64) and obtained results very similar to the ones shown in Figure A10 (estimates available upon request).

Figure A11 shows different wage measures, including the preferred one used in the paper: average wage and salary per capita. In addition, I consider earnings per job, wage and salary per job, and per capita net earnings. In general, per capita outcomes exhibit pre-trends; however, the conclusion that earnings are unchanged holds throughout. The pre-trends are driven by about 30 counties. They do not appear to be due to pre-hurricane differences and remain present regardless of which controls are included. Excluding them eliminates the pre-trends but does not meaningfully change the transfer estimates.

Finally, Figure A12 shows the estimates using only counties that experience one hurricane

[11] Other examples where the county is used as the local labor market include Strobl (2011) and Gould, Weinberg and Mustard (2002).

between 1979 and 2002. The employment rate estimates cease to be significant at the 5% level, but are quantitatively similar to the main estimates. The per capita government transfer results are very similar.

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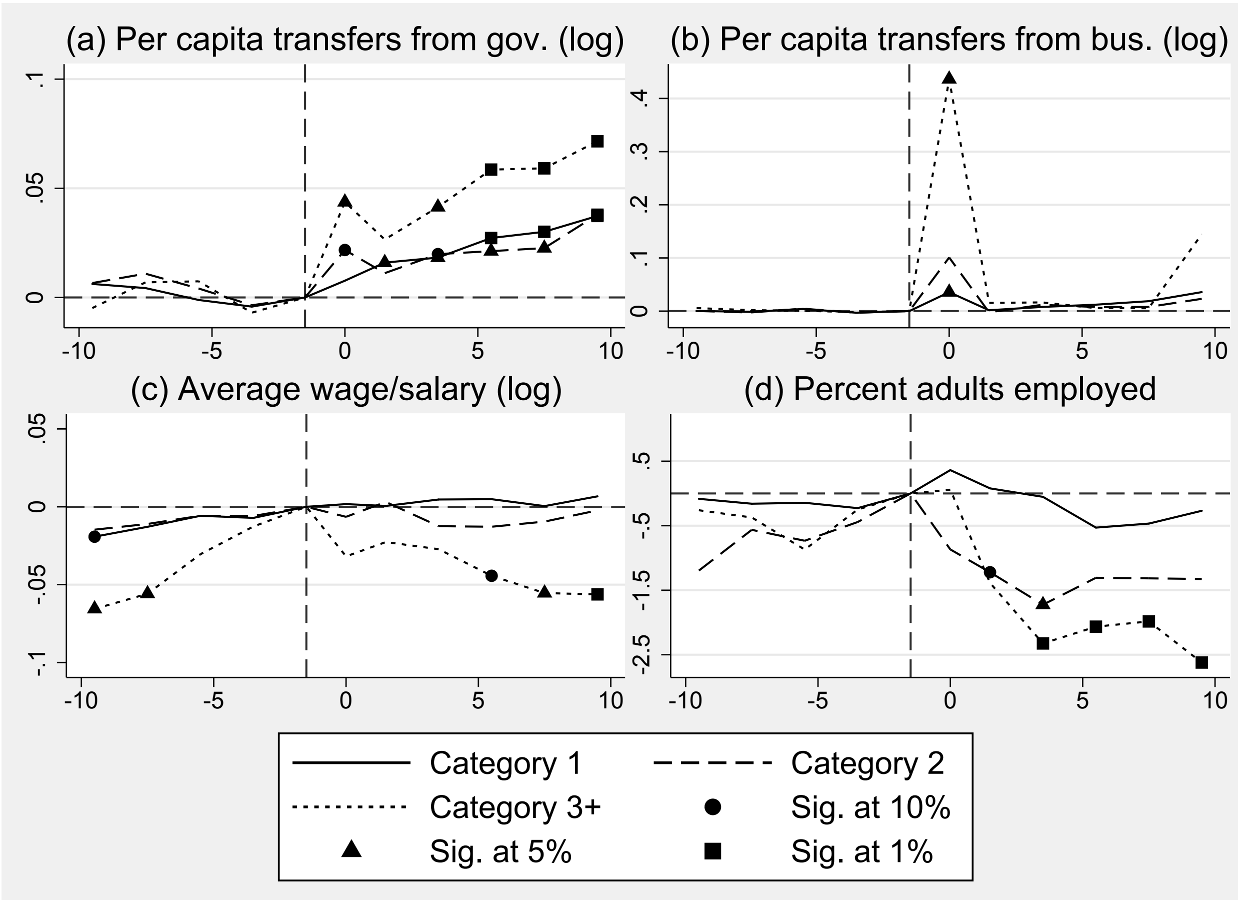
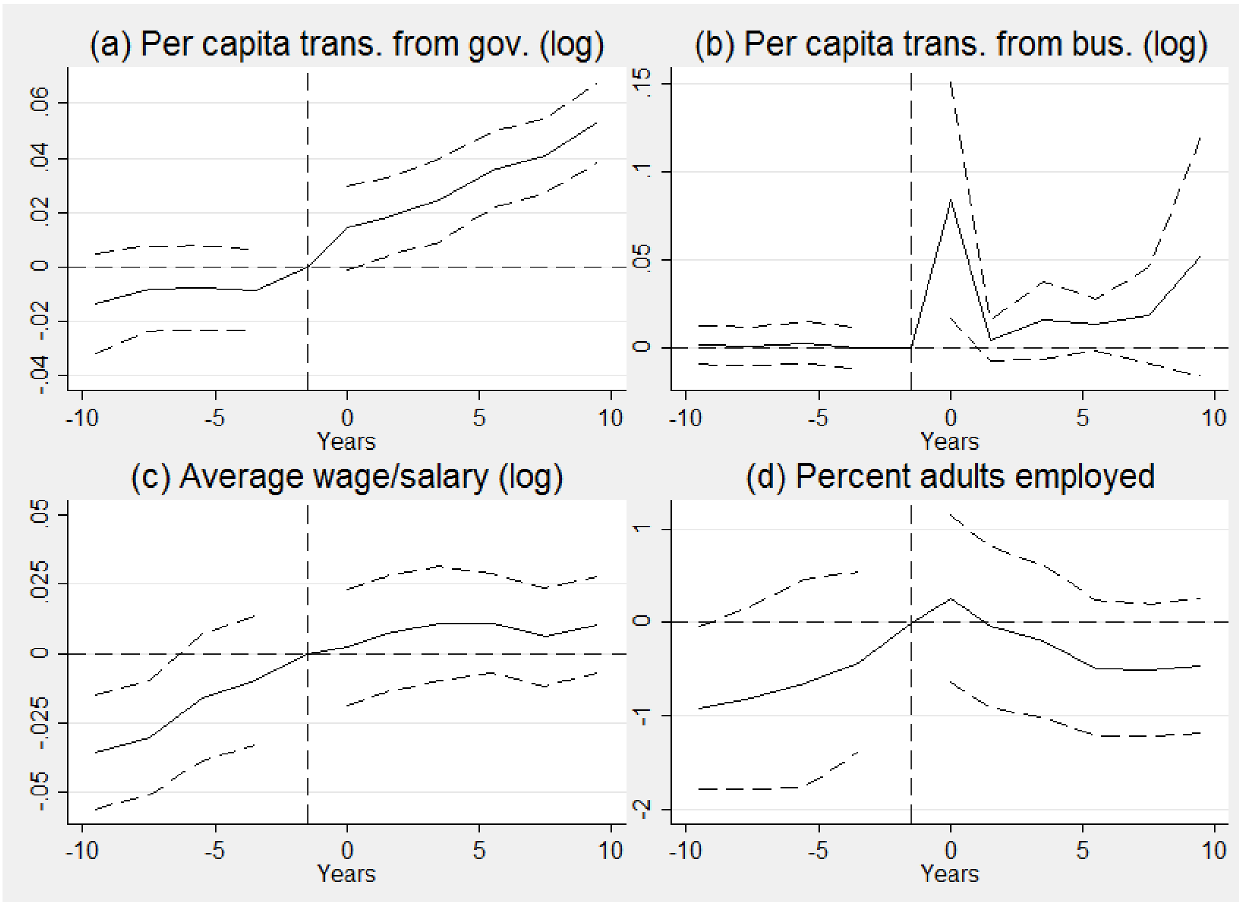
7 Appendix Figures

Figure A1: Heterogeneity by hurricane wind speed



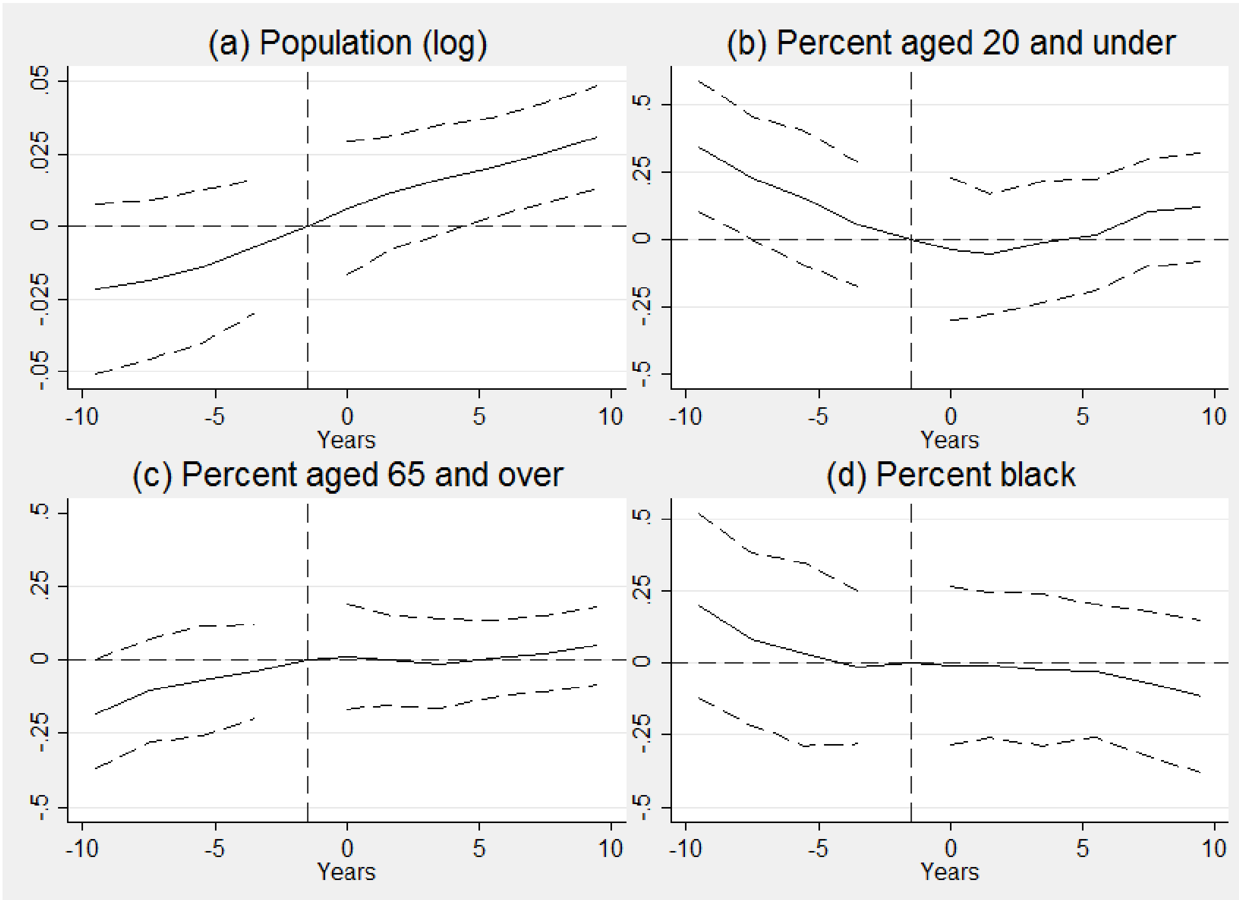
Outcome variable displayed above corresponding plot. The lines represent the point estimates for different hurricane categories, while the symbols represent significance levels, as described in the legend. Standard errors allow for spatial correlation of up to 200 kilometers around the county's centroid and for autocorrelation of order 5. Controls include county fixed effects, year fixed effects, year fixed effects linear in 1969 county characteristics, and indicators for hurricane occurrence outside of the time window of interest.

Figure A2: The effect of a hurricane on earnings and transfers, no county characteristics controls



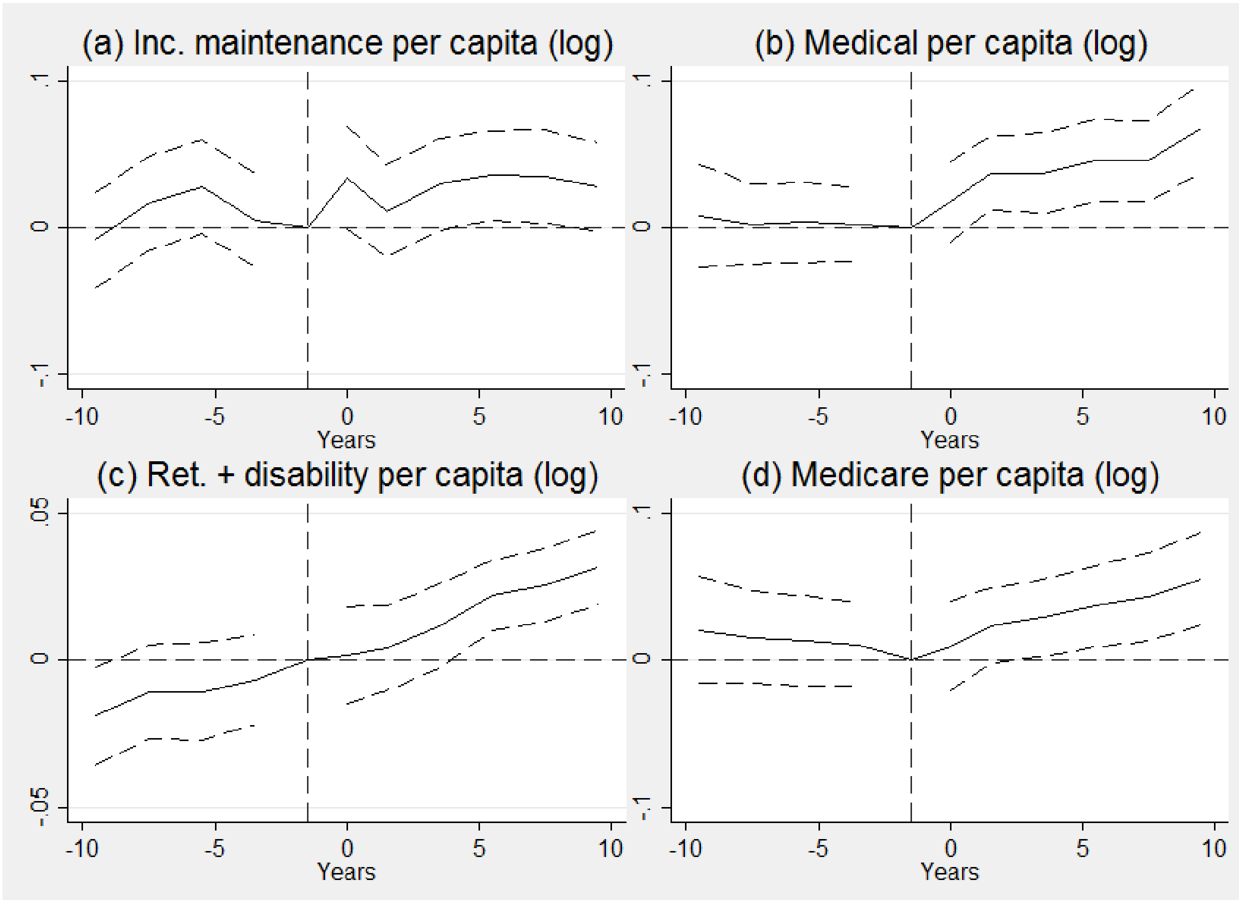
Point estimates from equation 2 and 95% confidence intervals shown. Outcome variable displayed above corresponding plot. Standard errors allow for spatial correlation of up to 200 kilometers around the county's centroid and for autocorrelation of order 5. Controls include county fixed effects, year fixed effects, and indicators for hurricane occurrence outside of the time window of interest.

Figure A3: The effect of a hurricane on demographics, no county characteristics controls



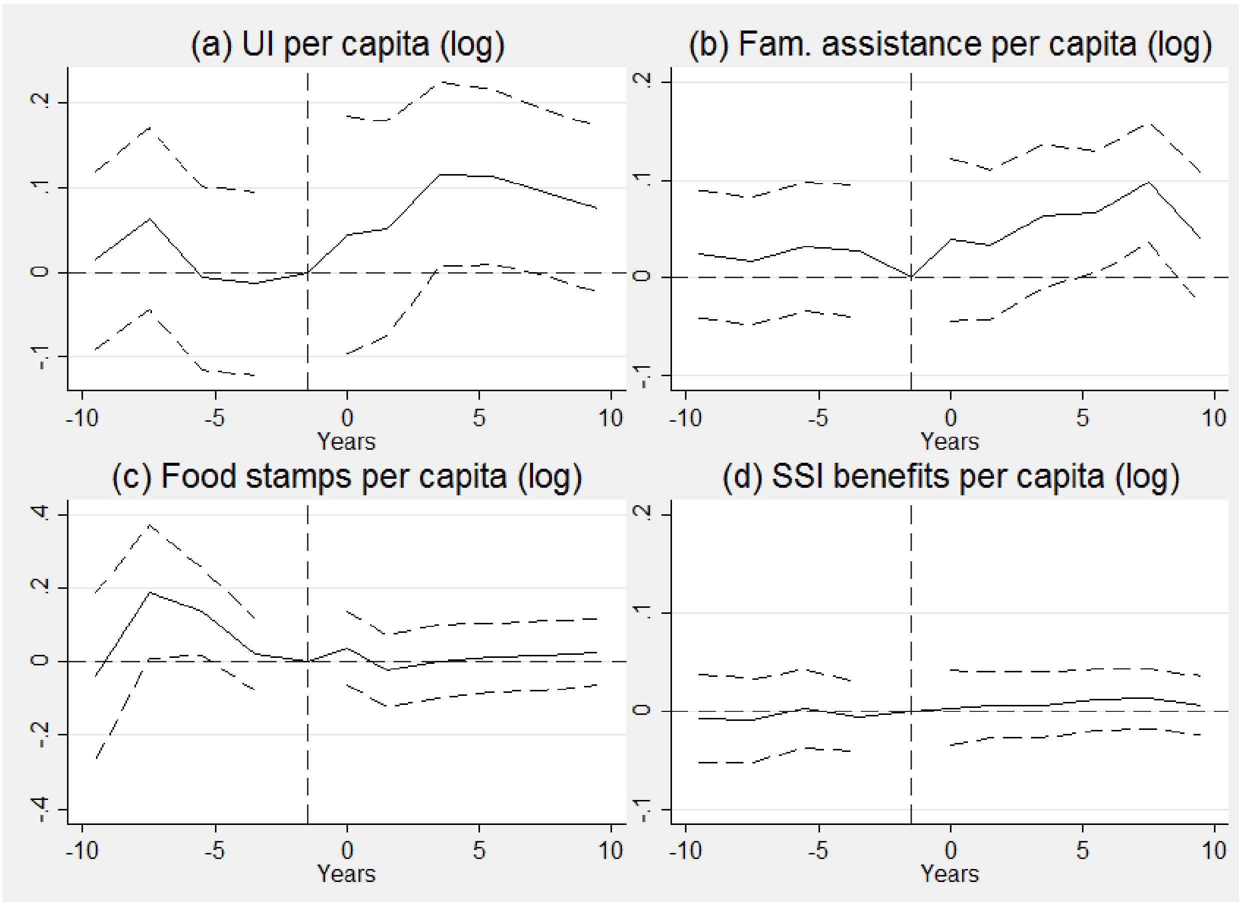
Point estimates from equation 2 and 95% confidence intervals shown. Outcome variable displayed above corresponding plot. Standard errors allow for spatial correlation of up to 200 kilometers around the county's centroid and for autocorrelation of order 5. Controls include county fixed effects, year fixed effects, and indicators for hurricane occurrence outside of the time window of interest.

Figure A4: The effect of a hurricane on transfer components, no county characteristics controls



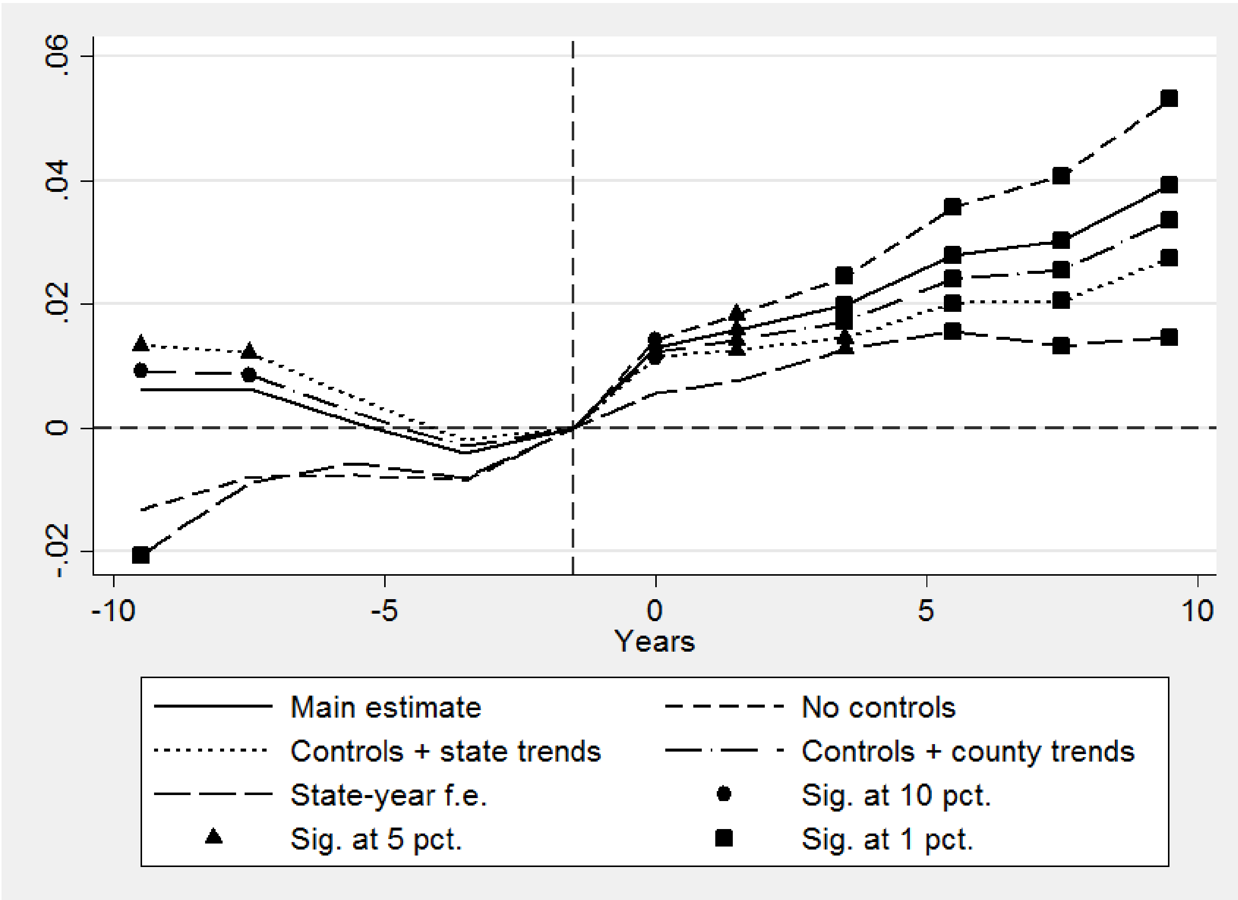
Point estimates from equation 2 and 95% confidence intervals shown. Outcome variable displayed above corresponding plot. Standard errors allow for spatial correlation of up to 200 kilometers around the county's centroid and for autocorrelation of order 5. Controls include county fixed effects, year fixed effects, and indicators for hurricane occurrence outside of the time window of interest.

Figure A5: The effect of a hurricane on transfer components, no county characteristics controls



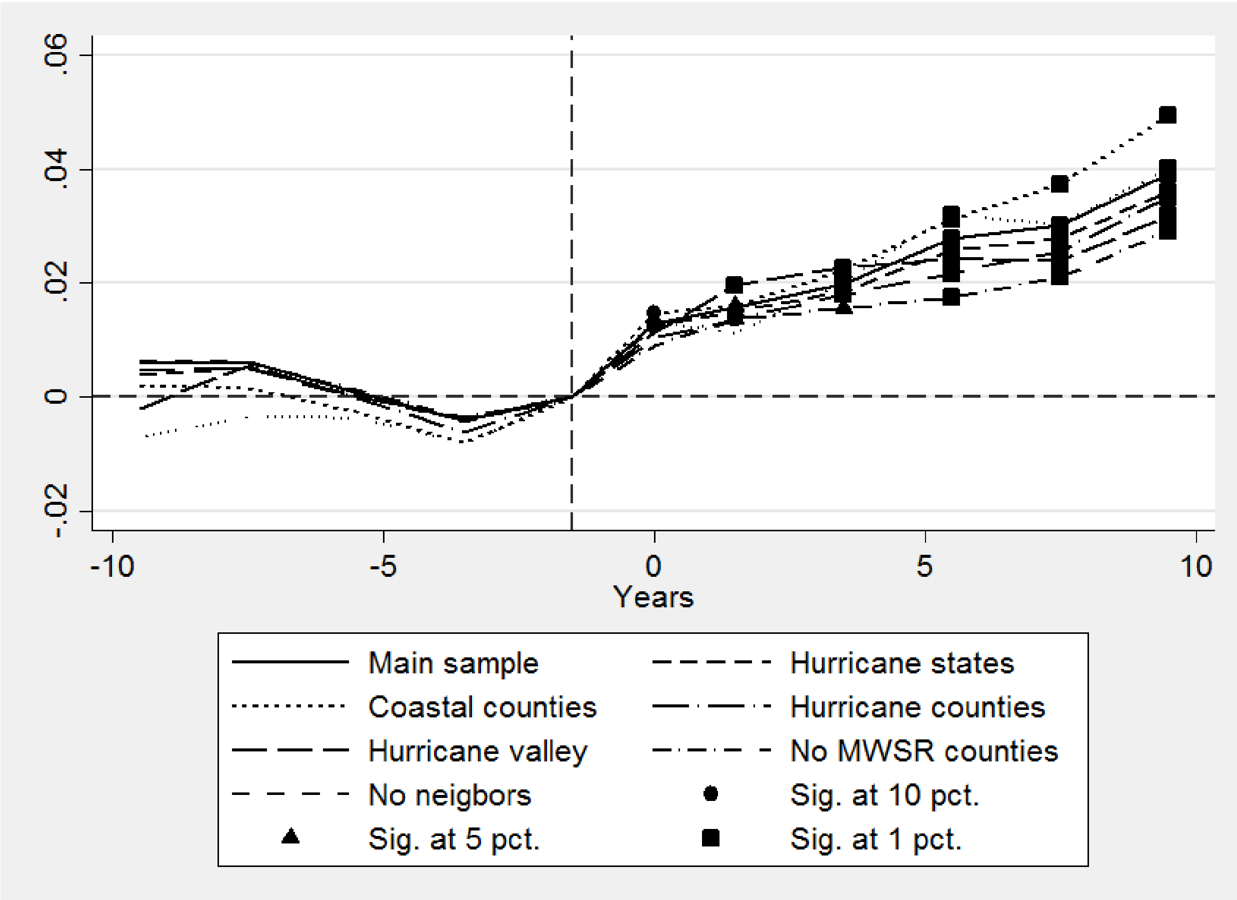
Point estimates from equation 2 and 95% confidence intervals shown. Outcome variable displayed above corresponding plot. Standard errors allow for spatial correlation of up to 200 kilometers around the county's centroid and for autocorrelation of order 5. Controls include county fixed effects, year fixed effects, and indicators for hurricane occurrence outside of the time window of interest.

Figure A6: Robustness of transfer estimates to different controls



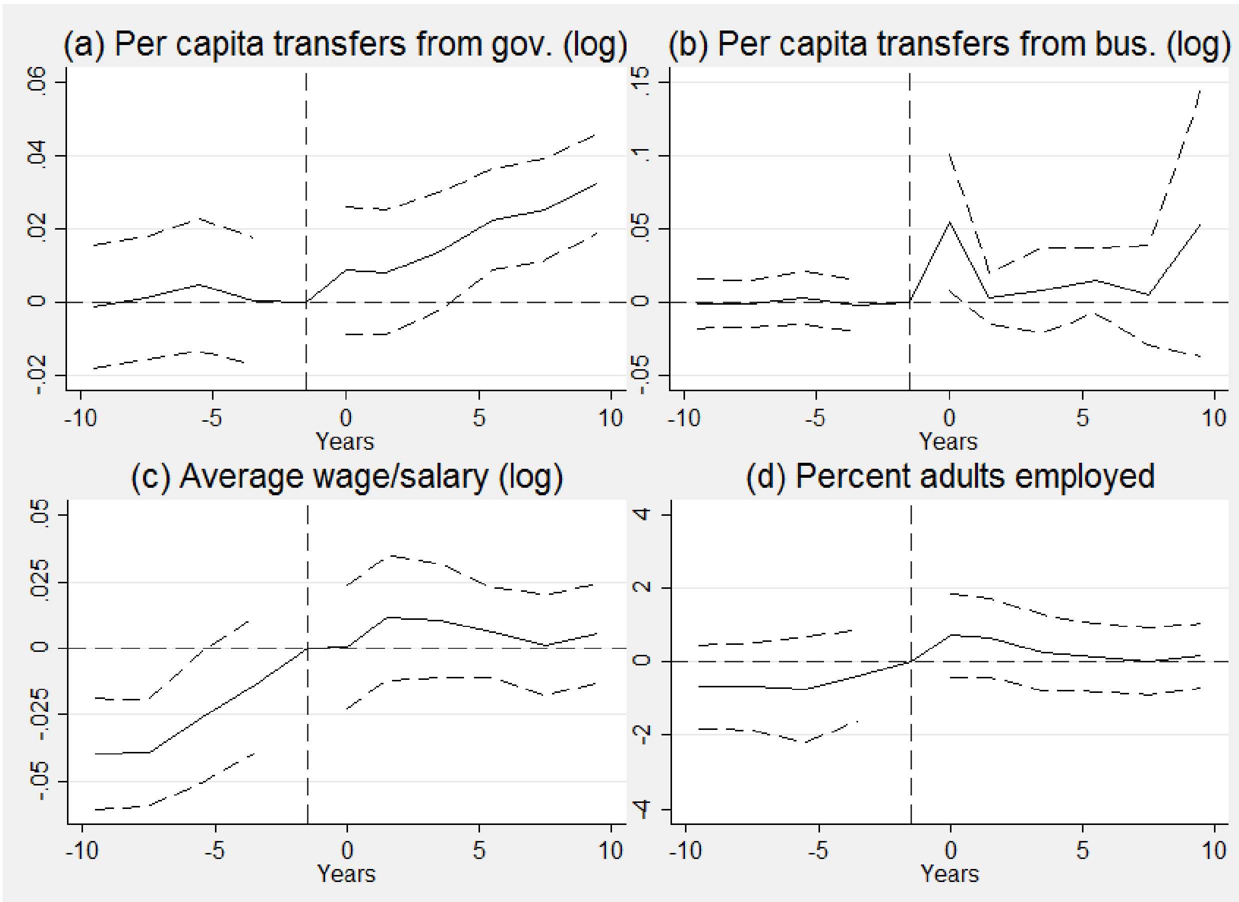
Outcome variable is log of total government transfers per capita. The lines represent point estimates from equation 2, while the symbols represent significance levels, as described in the legend. "Main estimate" includes year and county fixed effects and year fixed effects linear in 1969 county characteristics. "No controls" includes year and county fixed effects only. "Controls + state trends" includes year and county fixed effects, year fixed effects linear in 1969 county characteristics, and linear state-specific trends. "Controls + county trends" includes year and county fixed effects, year fixed effects linear in 1969 county characteristics, and linear county-specific trends. "State-year f.e." includes county fixed effects and state-by-year fixed effects. Standard errors allow for spatial correlation of up to 200 kilometers around the county's centroid and for autocorrelation of order 5. All regressions include indicators for hurricane occurrence outside of the time window of interest.

Figure A7: Robustness of transfer estimates to different samples



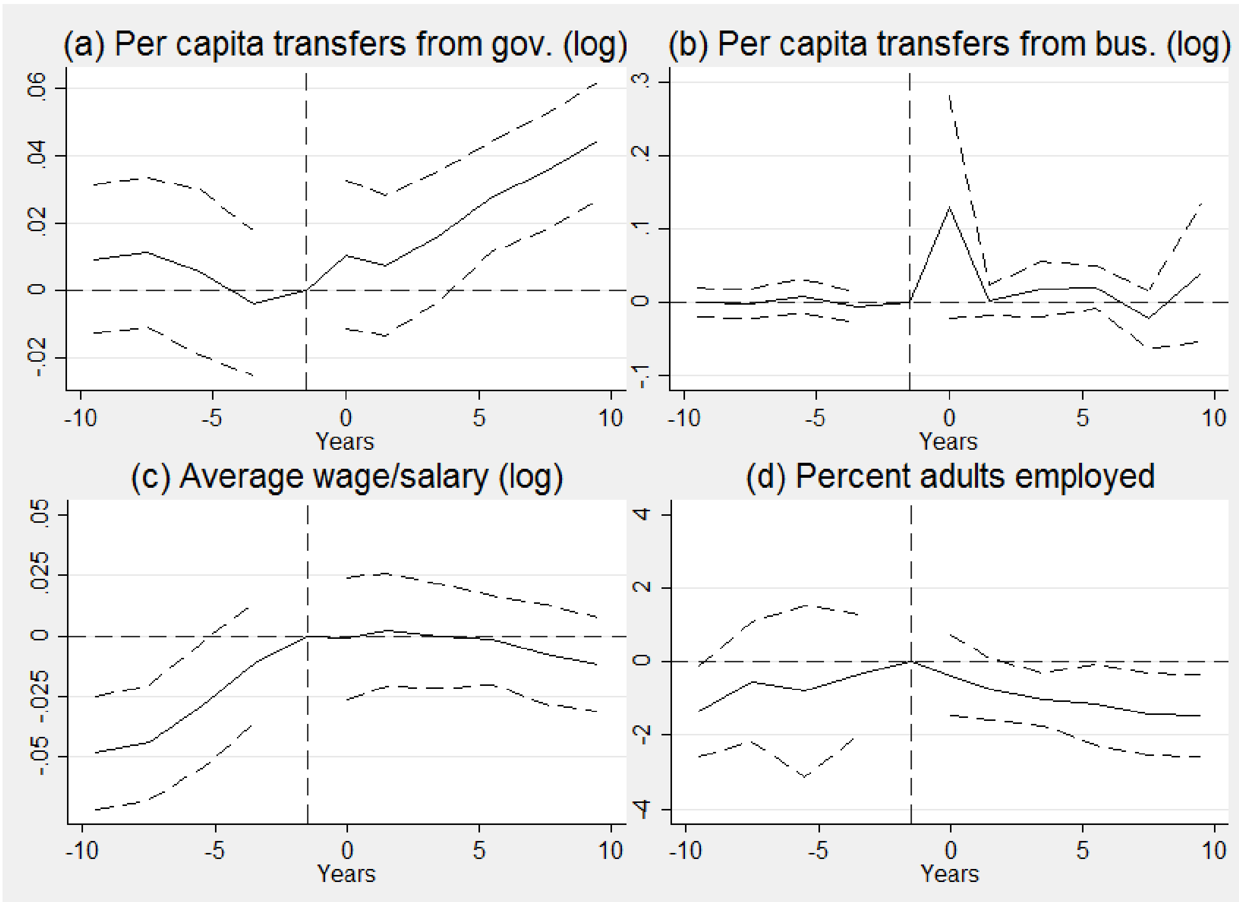
Outcome variable is log of total government transfers per capita. The lines represent the point estimates from equation 2, while the symbols represent significance levels, as described in the legend. “Main estimate” includes all counties in the hurricane-prone states and their neighbors. “Hurricane states” includes only counties located in states that experience hurricanes between 1979 and 2002. “Coastal counties” restricts the sample to coastal counties in the hurricane-prone states and their neighbors. “Hurricane counties” includes only counties that experience hurricanes between 1979 and 2002. “Hurricane valley” restricts the sample to South and Southeastern states that experience hurricanes: Alabama, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Texas, and Virginia. “No MWSR counties” excludes counties that fall inside the maximum wind speeds radius but are outside the path of the center of the hurricane. ”No neighbors” excludes unaffected counties that are adjacent to or located within 50 miles of counties that were affected by hurricanes. Standard errors allow for spatial correlation of up to 200 kilometers around the county’s centroid and for autocorrelation of order 5. Controls include county fixed effects, year fixed effects, year fixed effects linear in 1969 county characteristics, and indicators for hurricane occurrence outside of the time window of interest.

Figure A8: The effect of a hurricane at the Commuting Zone level



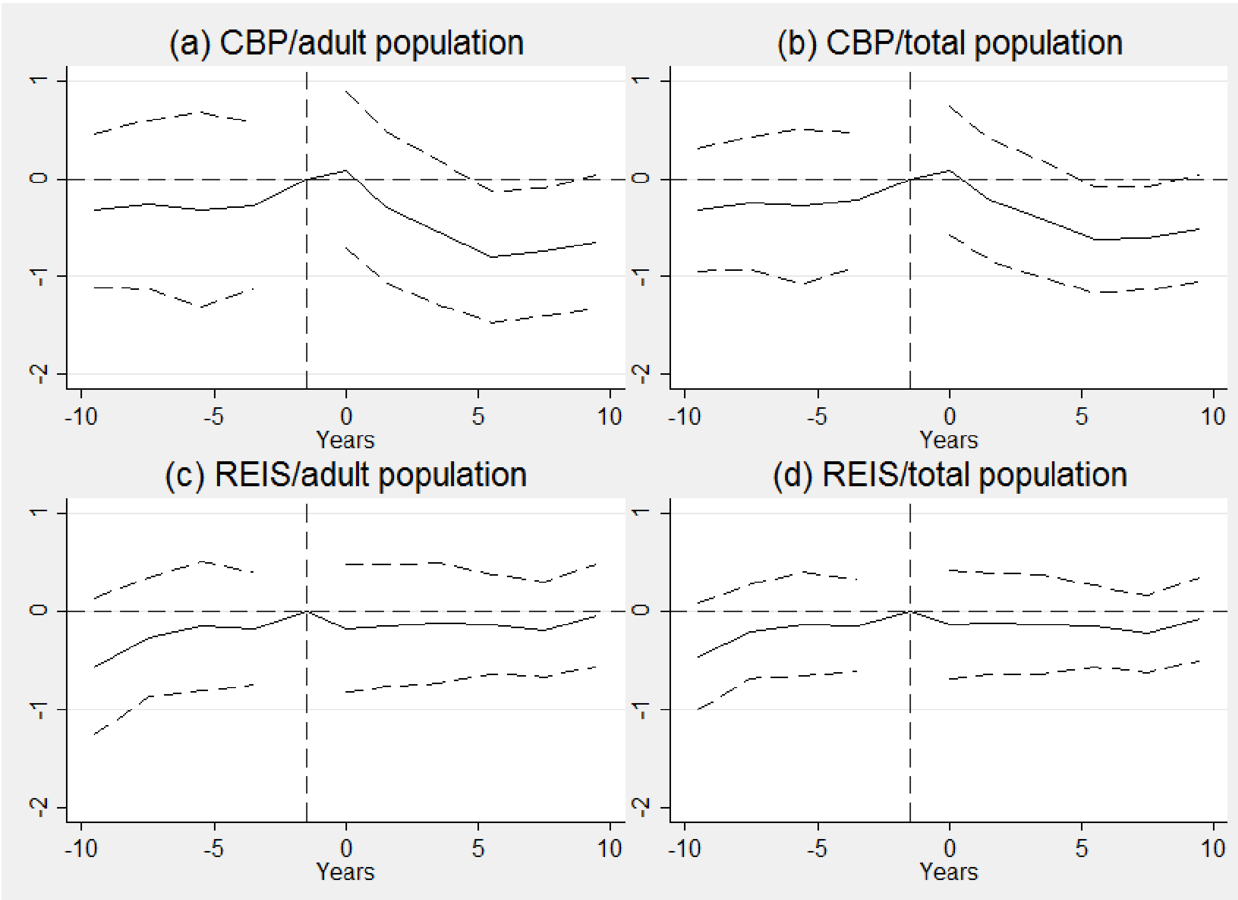
Outcome variable shown above corresponding plot. Point estimates from event study and 95% confidence intervals shown. Standard errors clustered spatially, allowing for spatial correlation of up to 200 kilometers around the Commuting Zone's centroid and for autocorrelation of order 5. Controls include Commuting Zone effects, year fixed effects linear in 1969 Commuting Zone characteristics, and indicators for hurricane occurrence outside of the time window of interest.

Figure A9: The effect of a hurricane at the CBSA level



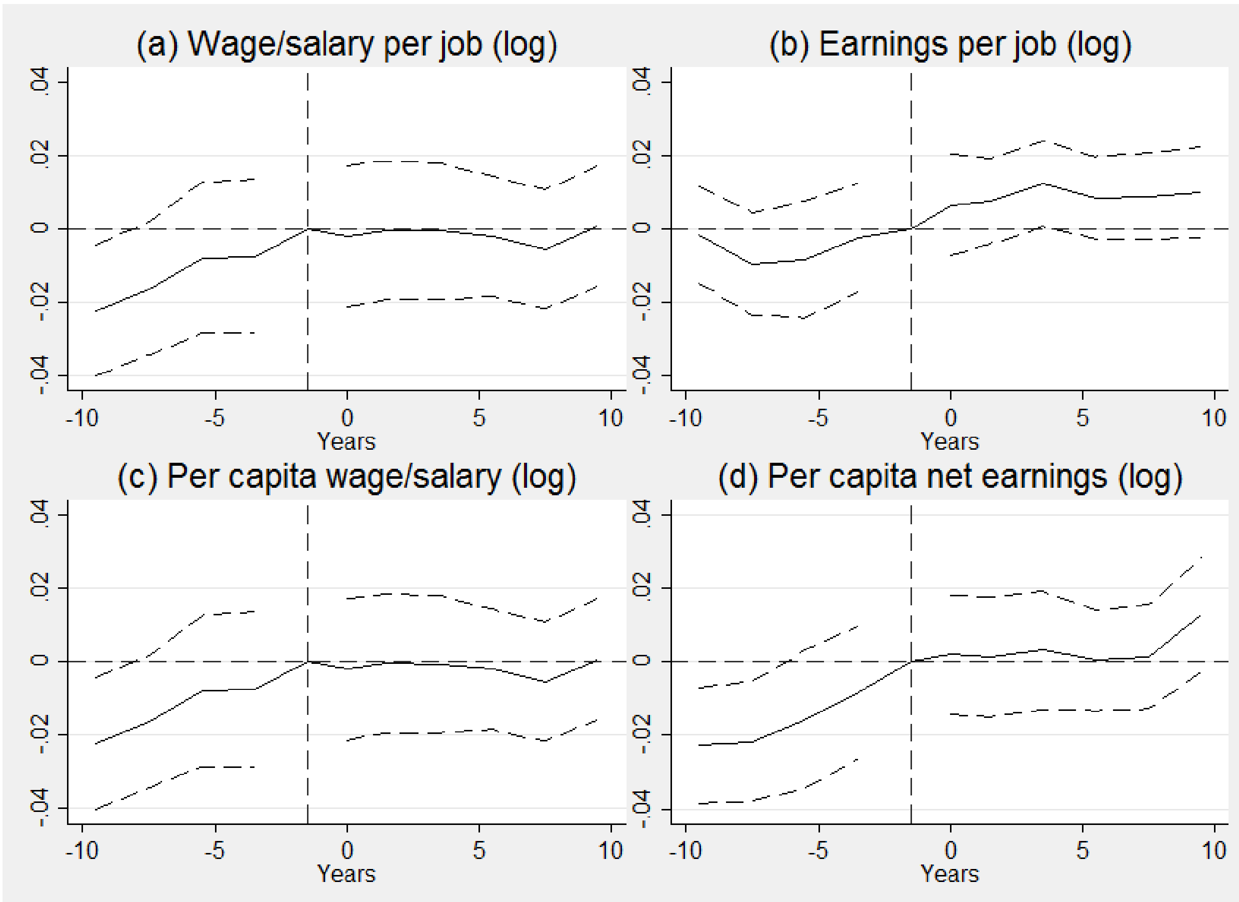
Outcome variable shown above corresponding plot. Point estimates from event study and 95% confidence intervals shown. Standard errors clustered spatially, allowing for spatial correlation of up to 200 kilometers around the CBSA's centroid and for autocorrelation of order 5. Controls include CBSA fixed effects, year fixed effects linear in 1969 CBSA characteristics, and indicators for hurricane occurrence outside of the time window of interest.

Figure A10: The effect of a hurricane on various employment measures



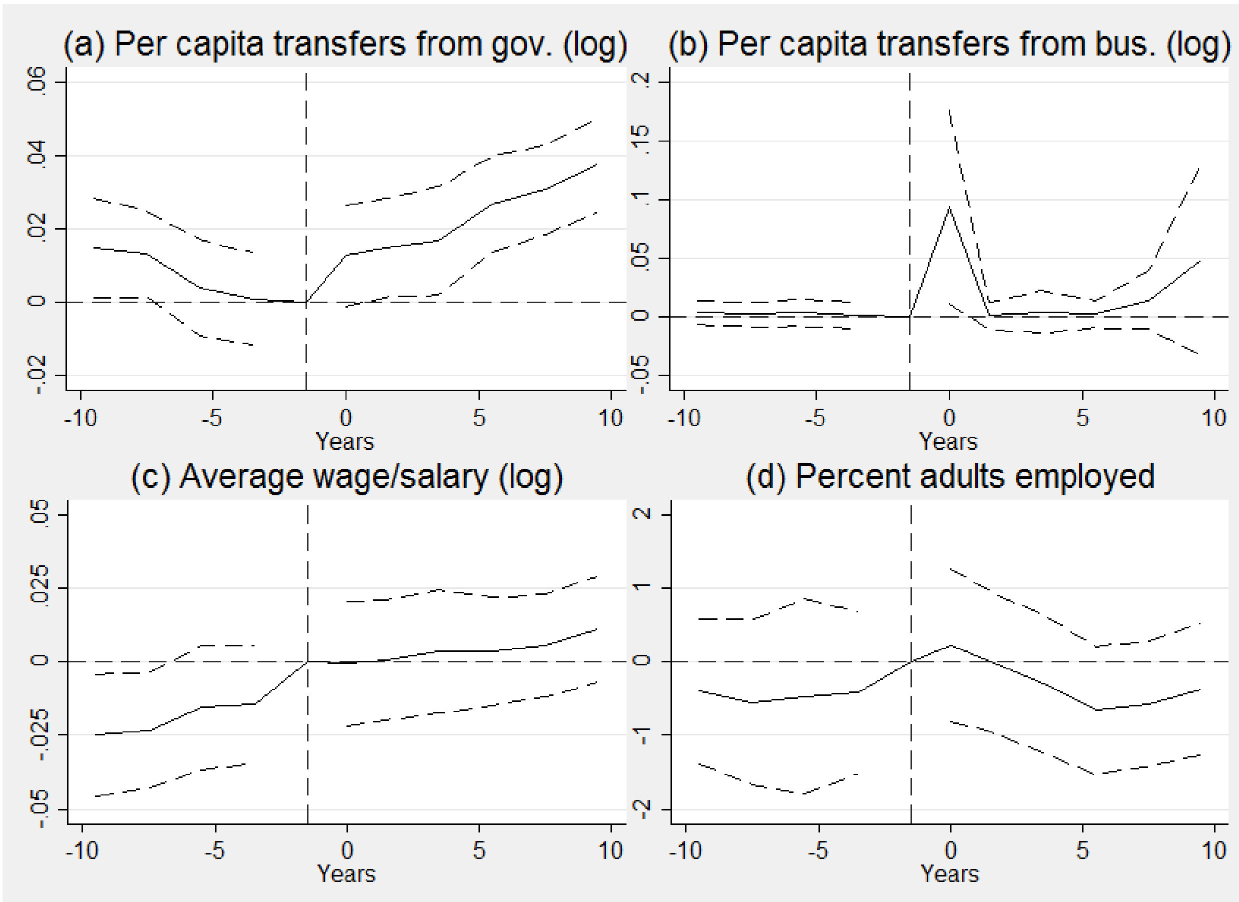
Outcome variable shown above corresponding plot. Point estimates from event study and 95% confidence intervals shown. Standard errors clustered spatially, allowing for spatial correlation of up to 200 kilometers around the county's centroid and for autocorrelation of order 5. Controls include county fixed effects, year fixed effects linear in 1969 county characteristics, and indicators for hurricane occurrence outside of the time window of interest.

Figure A11: The effect of a hurricane on various income measures



Outcome variable shown above corresponding plot. Point estimates from event study and 95% confidence intervals shown. Standard errors clustered spatially, allowing for spatial correlation of up to 200 kilometers around the county's centroid and for autocorrelation of order 5. Controls include county fixed effects, year fixed effects linear in 1969 county characteristics, and indicators for hurricane occurrence outside of the time window of interest.

Figure A12: Counties that experience only one hurricane between 1979 and 2002.



Outcome variable shown above corresponding plot. Point estimates from event study and 95% confidence intervals shown. Standard errors clustered spatially, allowing for spatial correlation of up to 200 kilometers around the county's centroid and for autocorrelation of order 5. Controls include county fixed effects, year fixed effects linear in 1969 county characteristics, and indicators for hurricane occurrence outside of the time window of interest.

8 Appendix Tables

Table A1: Total damage and disaster aid for major US hurricanes, 1979-2002

Hurricane (year)	Total damages	Disaster aid	Aid divided by total damages (percent)
Frederic (1979)	3,238	6,644	205
Allen (1980)	6,412	83.3	1.30
Alicia (1983)	4,521	81.0	1.79
Elena (1985)	1,473	66.7	4.53
Gloria (1985)	117	174	149
Hugo (1989)	9,978	786	7.87
Andrew (1992)	36,826	2,782	7.56
Fran (1996)	487	842	173
Bret (1999)	23.7	40.7	172
Floyd (1999)	706	1,335	189
Total	63,781	12,834	20.1

Notes: all amounts are in millions of 2008 dollars. Source for total damages is HAZUS-MH simulations. Source for disaster aid is PERI disaster declaration database.

Table A2: Determinants of property damages in the 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	2.27	30.53	1.42			
	(0.15)	(7.61)	(0.14)			
Major hurricane	6.01	953.73	3.34			
	(0.39)	(359.14)	(0.29)			
Category = 1				2.07	17.42	1.19
				(0.16)	(4.28)	(0.14)
Category = 2				3.07	92.58	2.39
				(0.38)	(39.53)	(0.25)
Category = 3				6.06	1111.89	3.42
				(0.50)	(442.00)	(0.30)
Category = 4 or 5				6.60	379.35	2.35
				(0.70)	(20.93)	(0.64)
Tornado	2.20	16.55	0.03	2.20	17.24	0.02
	(0.05)	(2.26)	(0.06)	(0.05)	(2.19)	(0.06)
Flood	1.24	0.43	0.73	1.24	0.54	0.73
	(0.04)	(2.63)	(0.05)	(0.04)	(2.62)	(0.05)
Severe storm	1.04	6.79	-0.10	1.04	6.67	-0.10
	(0.04)	(2.56)	(0.06)	(0.04)	(2.56)	(0.06)
Dep. var. mean	9.52	9.52	11.20	9.52	11.90	11.20
Observations	23,539	25,660	12,335	23,539	25,660	12,335
R-squared	0.21	0.04	0.10	0.21	0.05	0.10

Standard errors (clustered by county) in parentheses. All dollar amounts are in 2013 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 includes the states of Alabama, Connecticut, Delaware, Florida, Georgia, Louisiana, Maine, Maryland, Massachusetts, Mississippi, New Hampshire, New Jersey, New York, North Carolina, Pennsylvania, Rhode Island, South Carolina, Texas, Vermont, Virginia, and West Virginia.

Table A3: The effect of hurricanes on transfers, earnings, and the employment rate

	(1) Per capita transfers from government (log)	(2) Per capita transfers from business (log)	(3) Average wage/salary (log)	(4) Percent adults employed
T=-10 or -9	0.006	0.002	-0.022	-0.326
	(0.007)	(0.005)	(0.009)	(0.401)
T=-8 or -7	0.006	-0.001	-0.016	-0.265
	(0.006)	(0.005)	(0.009)	(0.439)
T=-6 or -5	0.001	0.003	-0.008	-0.316
	(0.006)	(0.006)	(0.011)	(0.507)
T=-4 or -3	-0.004	-0.002	-0.008	-0.271
	(0.006)	(0.006)	(0.011)	(0.438)
T=0	0.013	0.084	-0.002	0.091
	(0.007)	(0.032)	(0.010)	(0.409)
T=1 or 2	0.016	0.003	-0.000	-0.290
	(0.007)	(0.005)	(0.010)	(0.394)
T=3 or 4	0.020	0.009	-0.001	-0.548
	(0.007)	(0.011)	(0.010)	(0.378)
T=5 or 6	0.028	0.011	-0.002	-0.799
	(0.006)	(0.007)	(0.008)	(0.342)
T=7 or 8	0.030	0.015	-0.005	-0.746
	(0.006)	(0.012)	(0.008)	(0.334)
T=9 or 10	0.039	0.041	0.001	-0.649
	(0.006)	(0.036)	(0.008)	(0.349)
Observations	49,245	40,027	49,245	49,245
R-squared	0.961	0.861	0.958	0.216
p-value of F-test, leads 3-10	0.451	0.864	0.110	0.943
p-value of F-test, lags 0-4	0.017	0.017	0.997	0.365
p-value of F-test, lags 0-10	0.000	0.039	0.993	0.024

Estimated using equation 1 in the main paper. Standard errors (in parentheses) clustered spatially, allowing for spatial correlation of up to 200 kilometers around the county's centroid and for autocorrelation of order 5. Effect in years -2 and -1 assumed to be zero. Controls include year fixed effects, county fixed effects, trends linear in 1969 county characteristics, and indicators for hurricane occurrence outside of the time window of interest.

Table A4: The effect of hurricanes on demographics

	(1) Population (log)	(2) Percent 20 and under	(3) Percent 65 and older	(4) Percent black
T=-10 or -9	-0.021	-0.061	-0.072	0.197
	(0.014)	(0.090)	(0.081)	(0.177)
T=-8 or -7	-0.018	-0.075	-0.003	0.091
	(0.013)	(0.083)	(0.077)	(0.165)
T=-6 or -5	-0.012	-0.015	-0.019	0.046
	(0.013)	(0.086)	(0.084)	(0.176)
T=-4 or -3	-0.005	-0.018	-0.012	-0.009
	(0.011)	(0.074)	(0.068)	(0.149)
T=0	0.005	0.015	-0.004	-0.015
	(0.010)	(0.079)	(0.073)	(0.150)
T=1 or 2	0.007	0.043	-0.022	-0.028
	(0.009)	(0.069)	(0.066)	(0.134)
T=3 or 4	0.009	0.098	-0.039	-0.053
	(0.009)	(0.071)	(0.068)	(0.134)
T=5 or 6	0.010	0.142	-0.044	-0.063
	(0.008)	(0.066)	(0.057)	(0.112)
T=7 or 8	0.014	0.223	-0.070	-0.122
	(0.008)	(0.065)	(0.056)	(0.116)
T=9 or 10	0.019	0.239	-0.092	-0.175
	(0.009)	(0.065)	(0.058)	(0.120)
Observations	49,245	49,245	49,245	49,245
R-squared	0.402	0.929	0.600	0.197
p-value of F-test, leads 3-10	0.454	0.891	0.930	0.801
p-value of F-test, lags 0-4	0.780	0.568	0.944	0.983
p-value of F-test, lags 0-10	0.231	0.000	0.466	0.539

Estimated using equation 1 in the main paper. Standard errors (in parentheses) clustered spatially, allowing for spatial correlation of up to 200 kilometers around the county's centroid and for autocorrelation of order 5. Effect in years -2 and -1 assumed to be zero. Controls include year fixed effects, county fixed effects, trends linear in 1969 county characteristics, and indicators for hurricane occurrence outside of the time window of interest.

Table A5: The effect of hurricanes on specific transfers

	(1) Per capita income maintenance (log)	(2) Per capita public medical (log)	(3) Per capita ret. + disability (log)	(4) Per capita Medicare (log)
T=-10 or -9	0.003	0.026	-0.004	0.043
	(0.016)	(0.014)	(0.007)	(0.014)
T=-8 or -7	0.018	0.013	0.002	0.027
	(0.016)	(0.012)	(0.006)	(0.012)
T=-6 or -5	0.019	0.005	-0.002	0.019
	(0.016)	(0.012)	(0.007)	(0.013)
T=-4 or -3	0.003	0.003	-0.004	0.012
	(0.016)	(0.011)	(0.006)	(0.012)
T=0	0.031	0.015	0.002	0.004
	(0.017)	(0.013)	(0.007)	(0.014)
T=1 or 2	0.017	0.032	0.004	0.015
	(0.015)	(0.012)	(0.006)	(0.012)
T=3 or 4	0.040	0.032	0.009	0.018
	(0.015)	(0.012)	(0.006)	(0.012)
T=5 or 6	0.049	0.045	0.016	0.029
	(0.015)	(0.012)	(0.005)	(0.012)
T=7 or 8	0.046	0.048	0.015	0.032
	(0.016)	(0.011)	(0.005)	(0.012)
T=9 or 10	0.040	0.072	0.014	0.043
	(0.015)	(0.012)	(0.005)	(0.012)
Observations	49,245	49,245	49,245	49,245
R-squared	0.791	0.962	0.917	0.964
p-value of F-test, leads 3-10	0.696	0.402	0.895	0.013
p-value of F-test, lags 0-4	0.045	0.019	0.534	0.435
p-value of F-test, lags 0-10	0.004	0.000	0.000	0.002

Estimated using equation 1 in the main paper. Standard errors (in parentheses) clustered spatially, allowing for spatial correlation of up to 200 kilometers around the county's centroid and for autocorrelation of order 5. Effect in years -2 and -1 assumed to be zero. Controls include year fixed effects, county fixed effects, trends linear in 1969 county characteristics, and indicators for hurricane occurrence outside of the time window of interest.

Table A6: The effect of hurricanes on specific transfers

	(1) Per capita unemployment insurance (log)	(2) Per capita family assistance (log)	(3) Per capita food stamps (log)	(4) Per capita SSI (log)
T=-10 or -9	0.004	0.025	-0.077	0.012
	(0.046)	(0.030)	(0.099)	(0.019)
T=-8 or -7	0.032	0.004	0.119	0.012
	(0.046)	(0.029)	(0.077)	(0.016)
T=-6 or -5	0.009	0.014	0.075	0.011
	(0.048)	(0.029)	(0.055)	(0.015)
T=-4 or -3	0.012	0.024	0.006	0.000
	(0.047)	(0.029)	(0.045)	(0.013)
T=0	0.064	0.040	0.039	-0.001
	(0.056)	(0.035)	(0.047)	(0.015)
T=1 or 2	0.079	0.053	-0.001	-0.004
	(0.053)	(0.031)	(0.045)	(0.014)
T=3 or 4	0.125	0.092	0.028	-0.008
	(0.048)	(0.029)	(0.046)	(0.014)
T=5 or 6	0.099	0.107	0.041	-0.007
	(0.044)	(0.026)	(0.043)	(0.014)
T=7 or 8	0.075	0.140	0.046	-0.008
	(0.041)	(0.026)	(0.043)	(0.015)
T=9 or 10	0.047	0.078	0.051	-0.020
	(0.042)	(0.030)	(0.041)	(0.015)
Observations	49,245	46,376	49,098	49,157
R-squared	0.627	0.541	0.565	0.513
p-value of F-test, leads 3-10	0.957	0.891	0.286	0.857
p-value of F-test, lags 0-4	0.072	0.015	0.742	0.948
p-value of F-test, lags 0-10	0.136	0.000	0.720	0.885

Estimated using equation 1 in the main paper. Standard errors (in parentheses) clustered spatially, allowing for spatial correlation of up to 200 kilometers around the county's centroid and for autocorrelation of order 5. Effect in years -2 and -1 assumed to be zero. Controls include year fixed effects, county fixed effects, trends linear in 1969 county characteristics, and indicators for hurricane occurrence outside of the time window of interest.

Table A7: The effect of hurricanes on demographics and transfer components, model (3) estimates

	(1) Population (log)	(2) Percent 20 and under	(3) Percent 65 and older	(4) Percent black
Post-hurricane indicator	0.000	-0.005	-0.021	0.075
	(0.010)	(0.067)	(0.064)	(0.134)
Post-hurricane trend difference	-0.001	0.017	-0.015	0.008
	(0.002)	(0.011)	(0.009)	(0.020)
Overall trend	0.003	0.009	0.007	-0.025
	(0.002)	(0.010)	(0.009)	(0.019)
Observations	49,245	49,245	49,245	49,245
R-squared	0.402	0.929	0.600	0.197
	Per capita UI (log)	Per capita family assistance (log)	Per capita food stamps (log)	Per capita SSI (log)
Post-hurricane indicator	0.095	0.052	-0.027	0.002
	(0.041)	(0.027)	(0.049)	(0.013)
Post-hurricane trend difference	-0.003	0.007	0.001	0.000
	(0.006)	(0.004)	(0.010)	(0.002)
Overall trend	-0.001	-0.001	0.003	-0.002
	(0.005)	(0.003)	(0.010)	(0.002)
Observations	49,245	46,376	49,098	49,157
R-squared	0.626	0.541	0.565	0.513
	Per capita income maintenance (log)	Per capita medical (log)	Per capita disability/soc. sec. (log)	Per capita Medicare (log)
Post-hurricane indicator	0.023	0.025	0.005	0.015
	(0.014)	(0.011)	(0.006)	(0.011)
Post-hurricane trend difference	0.003	0.008	0.001	0.009
	(0.002)	(0.002)	(0.001)	(0.002)
Overall trend	-0.001	-0.003	0.000	-0.005
	(0.002)	(0.002)	(0.001)	(0.001)
Observations	49,245	49,245	49,245	49,245
R-squared	0.791	0.962	0.917	0.964

Estimated using equation 3. Standard errors (in parentheses) clustered spatially, allowing for spatial correlation of up to 200 kilometers around the county's centroid and for autocorrelation of order 5. Controls include year fixed effects, county fixed effects, trends linear in 1969 county characteristics, and dummies for hurricane occurrence outside of the time window of interest.

Table A8: The effect of hurricanes by wind speed, combined hurricane indicators (model 2)

	(1) Per capita transfers from government (log)	(2) Per capita transfers from business (log)	(3) Average wage/salary (log)	(4) Percent adults employed
0-4 years after hurricane, category 1	0.014	0.011	0.011	0.002
	(0.004)	(0.006)	(0.005)	(0.002)
5-10 years after hurricane, category 1	0.031	0.022	0.013	-0.003
	(0.003)	(0.012)	(0.003)	(0.001)
0-4 years after hurricane, category 2	0.013	0.024	0.002	-0.008
	(0.005)	(0.014)	(0.008)	(0.004)
5-10 years after hurricane, category 2	0.024	0.013	-0.001	-0.007
	(0.004)	(0.015)	(0.004)	(0.004)
0-4 years after hurricane, category 3	0.036	0.099	0.005	-0.011
	(0.007)	(0.048)	(0.011)	(0.003)
5-10 years after hurricane, category 3	0.063	0.051	-0.020	-0.019
	(0.003)	(0.052)	(0.004)	(0.006)
Mean of dep. var.	8.162	4.659	1.650	0.344
Observations	49,245	40,027	49,245	49,245
R-squared	0.961	0.861	0.958	0.216

Standard errors (in parentheses) clustered spatially, allowing for spatial correlation of up to 200 kilometers around the county's centroid and for autocorrelation of order 5. All regressions include year and county fixed effects and indicators for hurricane occurrence outside of the time window of interest. Overall trend estimates by category not shown.

Table A9: Total change in transfer components by hurricane category (present discounted value), equation 1

	(1) Category 1	(2) Category 2	(3) Category 3+
Average wage/salary	159	-328	-1902
	(359)	(721)	(906)
Transfers from businesses (private insurance)	17	19	91
	(8)	(12)	(48)
All non-disaster transfers from government =	789	739	1698
	(166)	(295)	(468)
Unemployment payments +	53	118	223
	(43)	(52)	(61)
Public medical benefits +	402	374	467
	(91)	(137)	(163)
Medicare benefits +	123	145	237
	(57)	(91)	(132)
Retirement and disability insurance benefits +	138	119	622
	(79)	(147)	(247)
Federal educational assistance +	-21	-19	-7
	(10)	(19)	(31)
Income maintenance =	173	-63	595
	(49)	(79)	(161)
SSI benefits +	-4	-38	-7
	(14)	(23)	(32)
Food stamps +	34	-4	145
	(23)	(33)	(73)
Family assistance	57	33	109
	(16)	(21)	(48)

Table shows present discounted value of additional inflows of various transfers 0-10 years after the hurricane by hurricane category. Standard errors (in parentheses) clustered spatially, allowing for spatial correlation of up to 200 kilometers around the county's centroid and for autocorrelation of order 5. Assumed interest rate is 3 percent. Estimated with a nonlinear combination of coefficients from Equation 1.

Table A10: Total change in transfer components by hurricane category (present discounted value), equation 2

	(1) Category 1	(2) Category 2	(3) Category 3+
Average wage/salary	600	13	-363
	(156)	(235)	(230)
Transfers from businesses (private insurance)	17	19	78
	(7)	(11)	(38)
All non-disaster transfers from government =	760	628	1699
	(75)	(122)	(149)
Unemployment payments +	32	122	332
	(18)	(23)	(33)
Public medical benefits +	338	242	332
	(49)	(63)	(74)
Medicare benefits +	11	52	225
	(28)	(38)	(47)
Retirement and disability insurance benefits +	161	195	686
	(24)	(37)	(75)
Federal educational assistance +	-30	3	30
	(5)	(9)	(13)
Income maintenance =	153	-161	583
	(26)	(36)	(59)
SSI benefits +	6	-93	-76
	(9)	(10)	(16)
Food stamps +	-11	-62	15
	(13)	(16)	(21)
Family assistance	60	-6	69
	(9)	(10)	(18)

Table shows present discounted value of additional inflows of various transfers 0-10 years after the hurricane by hurricane category. Standard errors (in parentheses) clustered spatially, allowing for spatial correlation of up to 200 kilometers around the county's centroid and for autocorrelation of order 5. Assumed interest rate is 3 percent. Estimated with a nonlinear combination of coefficients from Equation 2.

Table A11: The effect of hurricanes on transfers, earnings, and the employment rate, no characteristics controls

	(1) Per capita transfers from government (log)	(2) Per capita transfers from business (log)	(3) Average wage/salary (log)	(4) Percent adults employed
T=-10 or -9	-0.013	0.001	-0.036	-0.914
	(0.009)	(0.006)	(0.010)	(0.444)
T=-8 or -7	-0.008	0.001	-0.031	-0.805
	(0.008)	(0.006)	(0.011)	(0.502)
T=-6 or -5	-0.008	0.003	-0.016	-0.650
	(0.008)	(0.006)	(0.012)	(0.569)
T=-4 or -3	-0.008	-0.001	-0.010	-0.428
	(0.008)	(0.006)	(0.012)	(0.495)
T=0	0.014	0.084	0.002	0.257
	(0.008)	(0.034)	(0.011)	(0.457)
T=1 or 2	0.018	0.004	0.007	-0.045
	(0.007)	(0.006)	(0.011)	(0.441)
T=3 or 4	0.024	0.015	0.011	-0.201
	(0.008)	(0.011)	(0.011)	(0.417)
T=5 or 6	0.036	0.013	0.011	-0.490
	(0.007)	(0.008)	(0.009)	(0.373)
T=7 or 8	0.041	0.018	0.006	-0.507
	(0.007)	(0.014)	(0.009)	(0.362)
T=9 or 10	0.053	0.052	0.010	-0.464
	(0.007)	(0.035)	(0.009)	(0.372)
Observations	49,698	40,217	49,698	49,698
R-squared	0.948	0.848	0.951	0.158
p-value of F-test, leads 3-10	0.602	0.982	0.003	0.307
p-value of F-test, lags 0-4	0.013	0.032	0.759	0.802
p-value of F-test, lags 0-10	0.000	0.062	0.863	0.196

Estimated using equation 1 in the main paper. Standard errors (in parentheses) clustered spatially, allowing for spatial correlation of up to 200 kilometers around the county's centroid and for autocorrelation of order 5. Effect in years -2 and -1 assumed to be zero. Controls include year fixed effects, county fixed effects, and indicators for hurricane occurrence outside of the time window of interest.

Table A12: The effect of hurricanes on demographics, no characteristics controls

	(1) Population (log)	(2) Percent 20 and under	(3) Percent 65 and older	(4) Percent black
T=-10 or -9	-0.022	0.343	-0.182	0.196
	(0.015)	(0.124)	(0.095)	(0.163)
T=-8 or -7	-0.018	0.228	-0.104	0.080
	(0.014)	(0.116)	(0.089)	(0.153)
T=-6 or -5	-0.014	0.151	-0.070	0.030
	(0.013)	(0.127)	(0.096)	(0.162)
T=-4 or -3	-0.007	0.056	-0.040	-0.016
	(0.012)	(0.117)	(0.082)	(0.135)
T=0	0.006	-0.037	0.012	-0.011
	(0.012)	(0.135)	(0.091)	(0.139)
T=1 or 2	0.011	-0.054	0.002	-0.008
	(0.010)	(0.115)	(0.078)	(0.129)
T=3 or 4	0.016	-0.011	-0.011	-0.023
	(0.010)	(0.115)	(0.078)	(0.134)
T=5 or 6	0.020	0.017	0.006	-0.030
	(0.009)	(0.105)	(0.067)	(0.118)
T=7 or 8	0.025	0.100	0.024	-0.073
	(0.009)	(0.102)	(0.066)	(0.128)
T=9 or 10	0.031	0.117	0.050	-0.116
	(0.009)	(0.102)	(0.068)	(0.135)
Observations	49,698	49,698	49,698	49,698
R-squared	0.348	0.879	0.470	-0.010
p-value of F-test, leads 3-10	0.508	0.034	0.344	0.764
p-value of F-test, lags 0-4	0.391	0.964	0.995	0.998
p-value of F-test, lags 0-10	0.001	0.502	0.971	0.958

Estimated using equation 1 in the main paper. Standard errors (in parentheses) clustered spatially, allowing for spatial correlation of up to 200 kilometers around the county's centroid and for autocorrelation of order 5. Effect in years -2 and -1 assumed to be zero. Controls include year fixed effects, county fixed effects, and indicators for hurricane occurrence outside of the time window of interest.

Table A13: The effect of hurricanes on specific transfers, no characteristics controls

	(1) Per capita income maintenance (log)	(2) Per capita public medical (log)	(3) Per capita ret. + disability (log)	(4) Per capita Medicare (log)
T=-10 or -9	-0.008	0.008	-0.019	0.021
	(0.017)	(0.018)	(0.009)	(0.019)
T=-8 or -7	0.017	0.002	-0.011	0.016
	(0.016)	(0.014)	(0.008)	(0.016)
T=-6 or -5	0.028	0.004	-0.011	0.013
	(0.016)	(0.014)	(0.008)	(0.016)
T=-4 or -3	0.006	0.002	-0.007	0.011
	(0.016)	(0.013)	(0.008)	(0.015)
T=0	0.034	0.018	0.002	0.010
	(0.018)	(0.014)	(0.008)	(0.016)
T=1 or 2	0.011	0.037	0.004	0.024
	(0.016)	(0.013)	(0.007)	(0.013)
T=3 or 4	0.030	0.037	0.012	0.029
	(0.016)	(0.014)	(0.007)	(0.013)
T=5 or 6	0.036	0.046	0.022	0.037
	(0.016)	(0.014)	(0.006)	(0.014)
T=7 or 8	0.035	0.046	0.026	0.043
	(0.016)	(0.014)	(0.006)	(0.015)
T=9 or 10	0.028	0.068	0.032	0.056
	(0.016)	(0.016)	(0.007)	(0.016)
Observations	49,698	49,698	49,698	49,698
R-squared	0.762	0.956	0.884	0.953
p-value of F-test, leads 3-10	0.286	0.994	0.215	0.771
p-value of F-test, lags 0-4	0.131	0.014	0.370	0.133
p-value of F-test, lags 0-10	0.124	0.000	0.000	0.003

Estimated using equation 1 in the main paper. Standard errors (in parentheses) clustered spatially, allowing for spatial correlation of up to 200 kilometers around the county's centroid and for autocorrelation of order 5. Effect in years -2 and -1 assumed to be zero. Controls include year fixed effects, county fixed effects, and indicators for hurricane occurrence outside of the time window of interest.

Table A14: The effect of hurricanes on specific transfers, no characteristics controls

	(1) Per capita unemployment insurance (log)	(2) Per capita family assistance (log)	(3) Per capita food stamps (log)	(4) Per capita SSI (log)
T=-10 or -9	0.014	0.024	-0.039	-0.008
	(0.053)	(0.033)	(0.116)	(0.023)
T=-8 or -7	0.063	0.018	0.190	-0.010
	(0.054)	(0.033)	(0.093)	(0.022)
T=-6 or -5	-0.007	0.032	0.138	0.002
	(0.055)	(0.034)	(0.061)	(0.020)
T=-4 or -3	-0.014	0.027	0.021	-0.006
	(0.055)	(0.034)	(0.050)	(0.018)
T=0	0.043	0.039	0.039	0.003
	(0.071)	(0.042)	(0.051)	(0.019)
T=1 or 2	0.051	0.034	-0.024	0.006
	(0.065)	(0.039)	(0.049)	(0.017)
T=3 or 4	0.115	0.064	0.003	0.006
	(0.055)	(0.037)	(0.051)	(0.017)
T=5 or 6	0.113	0.067	0.012	0.011
	(0.052)	(0.032)	(0.048)	(0.016)
T=7 or 8	0.094	0.098	0.018	0.013
	(0.050)	(0.032)	(0.048)	(0.016)
T=9 or 10	0.074	0.040	0.028	0.005
	(0.050)	(0.035)	(0.046)	(0.015)
Observations	49,698	46,672	49,522	49,586
R-squared	0.582	0.493	0.515	0.333
p-value of F-test, leads 3-10	0.527	0.907	0.059	0.978
p-value of F-test, lags 0-4	0.188	0.399	0.655	0.981
p-value of F-test, lags 0-10	0.277	0.068	0.892	0.988

Estimated using equation 1 in the main paper. Standard errors (in parentheses) clustered spatially, allowing for spatial correlation of up to 200 kilometers around the county's centroid and for autocorrelation of order 5. Effect in years -2 and -1 assumed to be zero. Controls include year fixed effects, county fixed effects, and indicators for hurricane occurrence outside of the time window of interest.

Table A15: The robustness of transfer estimates to various controls

	(1) Main estimate	(2) No controls	(3) Controls + state trends	(4) Controls + county trends	(5) Controls + state-year f.e.
T=-10 or -9	0.006	-0.013	0.013	0.009	-0.021
	(0.007)	(0.009)	(0.006)	(0.005)	(0.007)
T=-8 or -7	0.006	-0.008	0.012	0.009	-0.009
	(0.006)	(0.008)	(0.006)	(0.005)	(0.006)
T=-6 or -5	0.001	-0.008	0.005	0.002	-0.006
	(0.006)	(0.008)	(0.006)	(0.005)	(0.006)
T=-4 or -3	-0.004	-0.008	-0.002	-0.003	-0.008
	(0.006)	(0.008)	(0.006)	(0.005)	(0.006)
T=0	0.013	0.014	0.011	0.012	0.006
	(0.007)	(0.008)	(0.006)	(0.006)	(0.006)
T=1 or 2	0.016	0.018	0.013	0.014	0.008
	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
T=3 or 4	0.020	0.024	0.015	0.017	0.013
	(0.007)	(0.008)	(0.006)	(0.006)	(0.006)
T=5 or 6	0.028	0.036	0.020	0.024	0.016
	(0.006)	(0.007)	(0.005)	(0.005)	(0.005)
T=7 or 8	0.030	0.041	0.020	0.025	0.013
	(0.006)	(0.007)	(0.005)	(0.005)	(0.005)
T=9 or 10	0.039	0.053	0.027	0.033	0.015
	(0.006)	(0.007)	(0.005)	(0.005)	(0.005)
Characteristics controls	Yes	No	Yes	Yes	No
Additional controls	None	None	Linear state trends	Linear county trends	State-year fixed effects
Observations	49,245	49,698	49,245	49,245	49,698
R-squared	0.961	0.948	0.965	0.981	0.960

Standard errors (in parentheses) clustered spatially, allowing for spatial correlation of up to 200 kilometers around the county's centroid and for autocorrelation of order 5. Effect in years -2 and -1 assumed to be zero. All regressions include year and county fixed effects and indicators for hurricane occurrence outside of the time window of interest.

Table A16: The robustness of transfer estimates to various samples

	(1) Main estimate	(2) Hurricane states	(3) Coastal counties	(4) Hurricane counties	(5) Hurricane valley	(6) No MWSR counties	(7) No neigbors
T=-10 or -9	0.006	0.004	0.002	0.005	-0.002	0.006	-0.007
	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.009)
T=-8 or -7	0.006	0.005	0.002	0.005	0.005	0.006	-0.004
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)
T=-6 or -5	0.001	0.000	-0.003	-0.000	0.000	0.001	-0.004
	(0.006)	(0.006)	(0.008)	(0.006)	(0.007)	(0.007)	(0.007)
T=-4 or -3	-0.004	-0.004	-0.008	-0.006	-0.004	-0.004	-0.008
	(0.006)	(0.006)	(0.008)	(0.006)	(0.007)	(0.007)	(0.008)
T=0	0.013	0.012	0.015	0.010	0.011	0.009	0.013
	(0.007)	(0.007)	(0.009)	(0.007)	(0.008)	(0.008)	(0.008)
T=1 or 2	0.016	0.015	0.016	0.014	0.020	0.014	0.011
	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)
T=3 or 4	0.020	0.019	0.022	0.018	0.023	0.016	0.020
	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	(0.008)
T=5 or 6	0.028	0.026	0.031	0.022	0.024	0.017	0.032
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)
T=7 or 8	0.030	0.028	0.037	0.026	0.024	0.021	0.030
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)
T=9 or 10	0.039	0.036	0.049	0.035	0.032	0.029	0.040
	(0.006)	(0.006)	(0.007)	(0.005)	(0.006)	(0.006)	(0.007)
Observations	49,245	43,924	17,240	15,723	36,642	11,388	30,961
R-squared	0.961	0.961	0.966	0.970	0.963	0.967	0.958

Standard errors (in parentheses) clustered spatially, allowing for spatial correlation of up to 200 kilometers around the county's centroid and for autocorrelation of order 5. Effect in years -2 and -1 assumed to be zero. All regressions include year and county fixed effects and indicators for hurricane occurrence outside of the time window of interest.