Online Appendix

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

Tatyana Deryugina

Contents

1 A Formal Model of the Role of Transfers in Capital Shocks

1.1 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 $F\left(K,\ L\right)$, 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 follows an iid distribution with the cdf $G\left(\varepsilon\right)$. 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.

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

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

where w is the prevailing wage rate in the location. It is straightforward to show that individual i will choose to work if $w^{1-\gamma} - \left(\theta\bar{w}\right)^{1-\gamma} \geq \varepsilon_i$. The labor supply function for the economy as a whole will be:

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

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

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

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,

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

which can be re-written as:

$$L = K_0 \left(\frac{w_0^*}{1-\alpha} \right)^{-\frac{1}{\alpha}} \tag{2}$$

Subtracting equation (1) from (2), we get the equilibrium relationship:

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

Given K_0, α, θ, and $\bar{w}$ this equation can be solved numerically for w_0^*, from which L_0^* can be computed.

1.2 Adjustment Following a Capital Shock

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^*.[1] 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 wage in other locations.[2]

Individual i 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. Assume that (a) m_i is iid with the distribution $F(m)$, (b) $m_i > 0$ for all

[1] The qualitative conclusions will hold with imperfect adjustment, as long as capital adjustment costs are not strictly smaller than individual moving costs.

[2] This was not the case with Hurricane Katrina evacuees, who appear to have had significant effects on other labor markets (McIntosh, 2008; De Silva et al., 2010). However, no other hurricane in the modern US has produced such an outflux of an area's population.

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 $(w_0^* - m^*)^{1-\gamma} - E[\varepsilon] = (w_1^*)^{1-\gamma} - E[\varepsilon]$. 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 $(w_1^*)^{1-\gamma} - \tilde{\varepsilon} = (\theta w_0^*)^{1-\gamma}$.

Total labor supply in the new equilibrium will be:

$$L_1^* = G(\tilde{\varepsilon})(1 - F(m^*)) = (1 - F(m^*))\, G\left((w_1^*)^{1-\gamma} - (\theta w_0^*)^{1-\gamma}\right) \tag{3}$$

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

$$L_1^* = K_1 \left(\frac{w_1^*}{1-\alpha}\right)^{-\frac{1}{\alpha}} \tag{4}$$

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^*. Next, 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 $(L_1^* - L_0^*)$, and the change in the population $(-F(m^*))$.

1.3 Simulation

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. This fraction remains unchanged after the shock.

To summarize the results, I plot the changes in wages, population, and total employment as a function of the transfer generosity. Figure A2 shows results for the fraction of the population leaving following the negative shock. 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$\%$. The reason the population drop does not approach 0 is because some individuals prefer working to taking transfers, all else equal.

Figure A1 shows the change in labor supply after the shock, expressed as a percentage of the pre-shock labor supply. With no transfers, labor supply is almost unchanged. Once wage replacement reaches 50%, labor supply falls by about 10$\%$. At the extreme, labor supply is 50$\%$ lower with full replacement. It does not fall below this because disutility of labor is assumed to be standard normal, so half of the population prefers working, all else equal. The same pattern would hold if absolute differences in labor supply were plotted.

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

Of course, this simulation is very stylized and not meant to make exact 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.

2 Calculating counties 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.[3] The Extended Best Tracks dataset reports the estimated MWSR for cyclones that occurred between 1988 and 2012, in 6-hour increments.[4] 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

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

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

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 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.

3 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.

$$\begin{aligned} D_{ct} &= a_c + a_t + \beta_1 Major\_hurricane_{ct} + \beta_2 Minor\_hurricane_{ct} \\ &\quad + \gamma_1 Flood_{ct} + \gamma_2 Tornado_{ct} + \gamma_3 Severe\_storm_{ct} + \varepsilon_{ct} \end{aligned} \tag{5}$$

$$\begin{aligned} D_{ct} &= a_c + a_t + \sum_{k=1}^{5} \beta_k \mathbf{1}\left[Category_{ct} = k\right] + \gamma_1 Flood_{ct} \\ &\quad + \gamma_2 Tornado_{ct} + \gamma_3 Severe\_storm_{ct} + \varepsilon_{ct} \end{aligned} \tag{6}$$

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 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 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.[5] 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 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 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 pay-

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

ments. 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 A1 imply that hurricanes are the most destructive of the common US disasters, which makes them an important phenomenon to study.

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.[6] 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.[7]

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

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

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

Epidemiology and End Results (SEER). Unlike REIS, SEER provides data by age, sex, and race. However, the underlying data are also from the Census Bureau, with minor modifications.[8] 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.[9]

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

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

[9] 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.

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.

5 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 investment (Forman, Goldfarb and Greenstein, 2012).[10] 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

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

population, wages, and transfers are shown in Figures A4 and A5 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 *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 A6 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 either the adult population. 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 largely 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.

Figure A7 shows different wage measures, including the preferred one used in the paper: average wage and salary per job. In addition, I consider earnings per job, per capita wages, 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 (Figure A8).

Finally, Figure A9 shows the estimates using only counties that experience one hurricane between 1979 and 2000. 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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6 Appendix Figures

Figure A1: Change in labor supply following capital shock

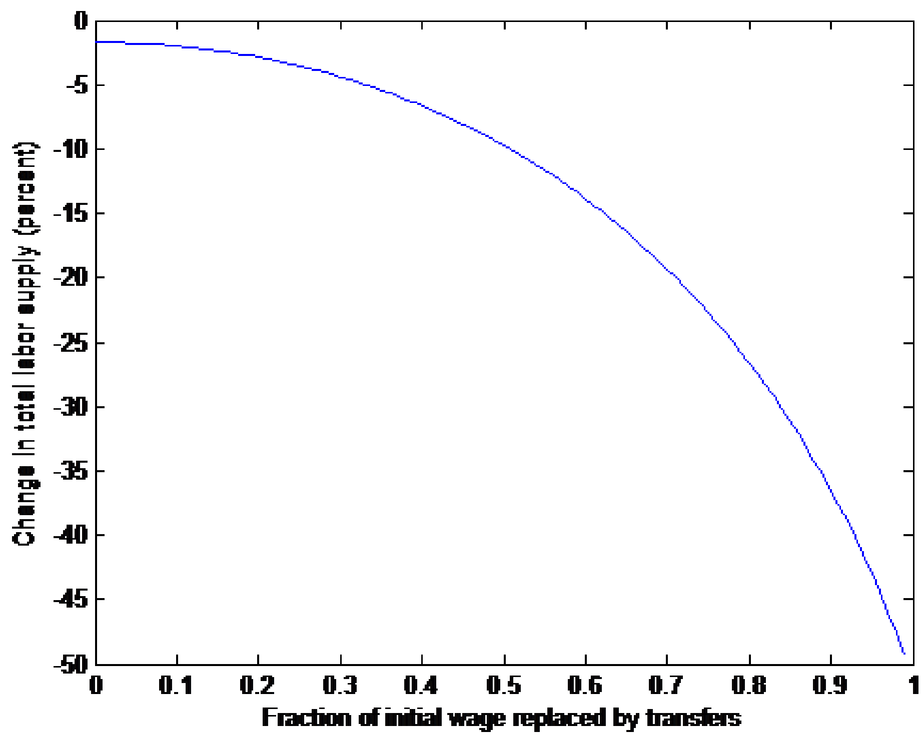


Figure A2: Change in population following capital shock

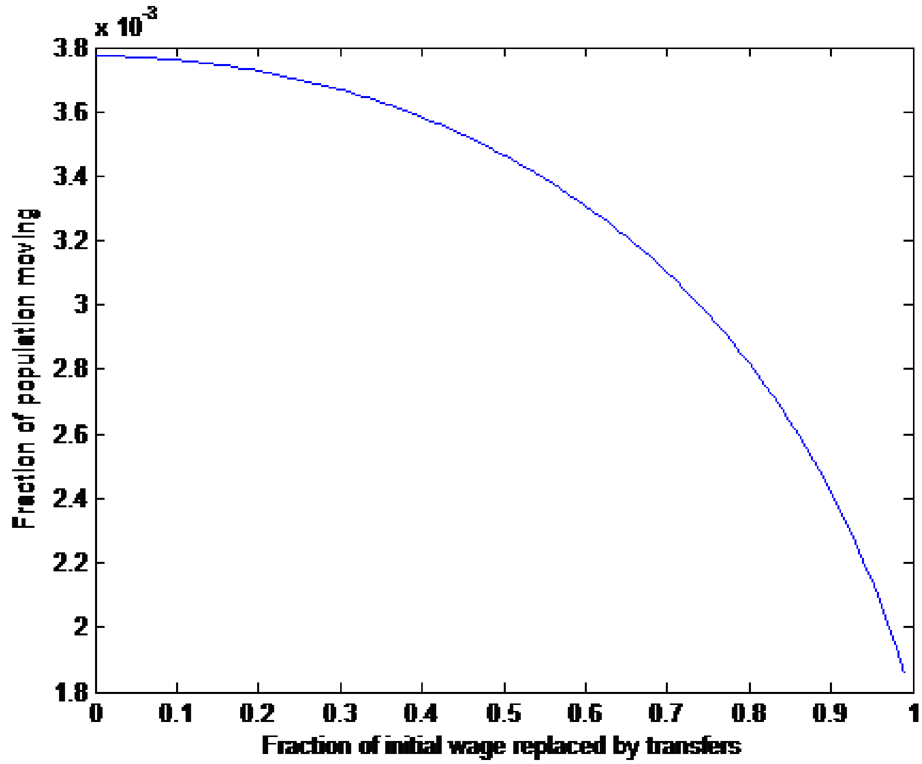


Figure A3: Change in wages following capital shock

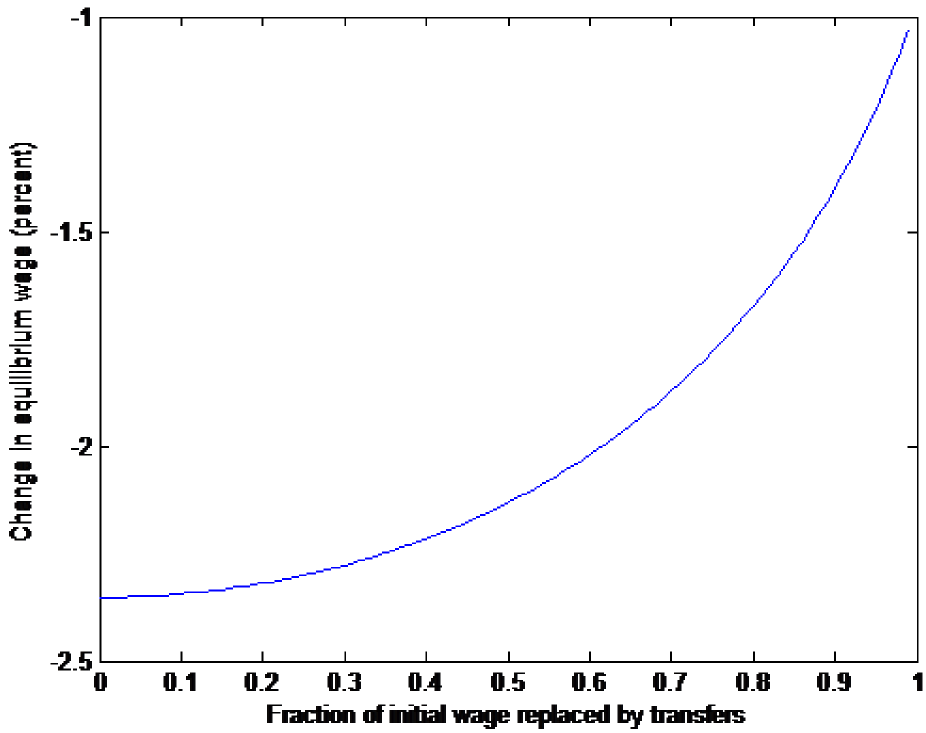
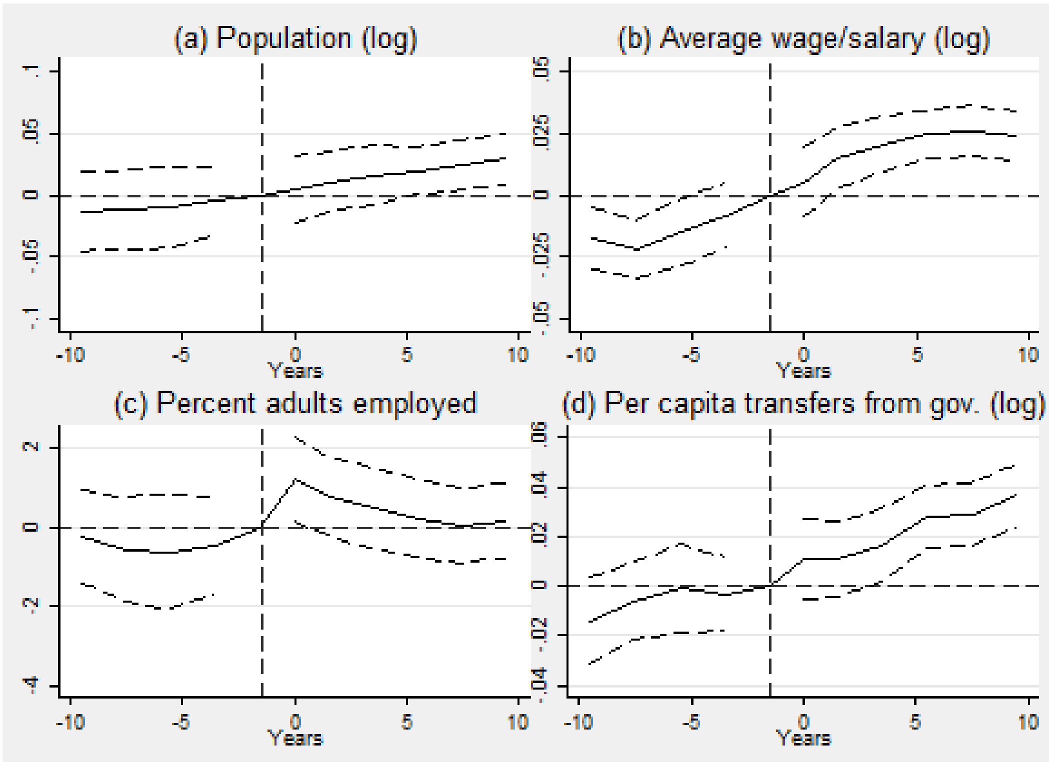
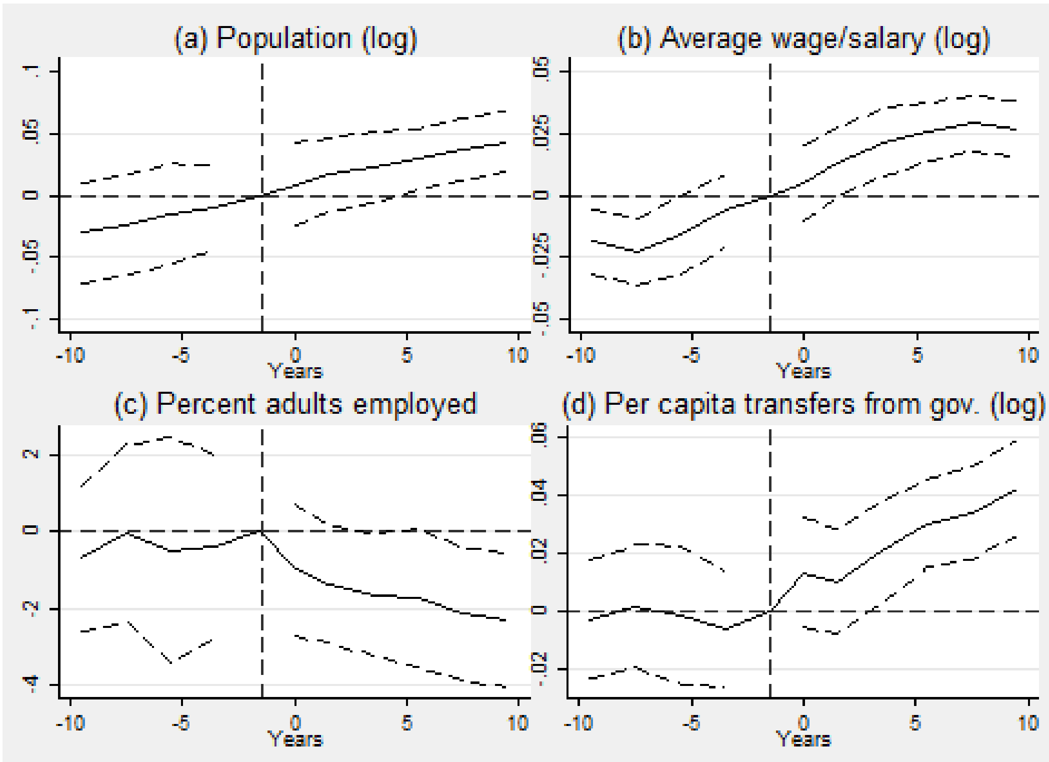


Figure A4: The effect of a hurricane at the Commuting Zone level



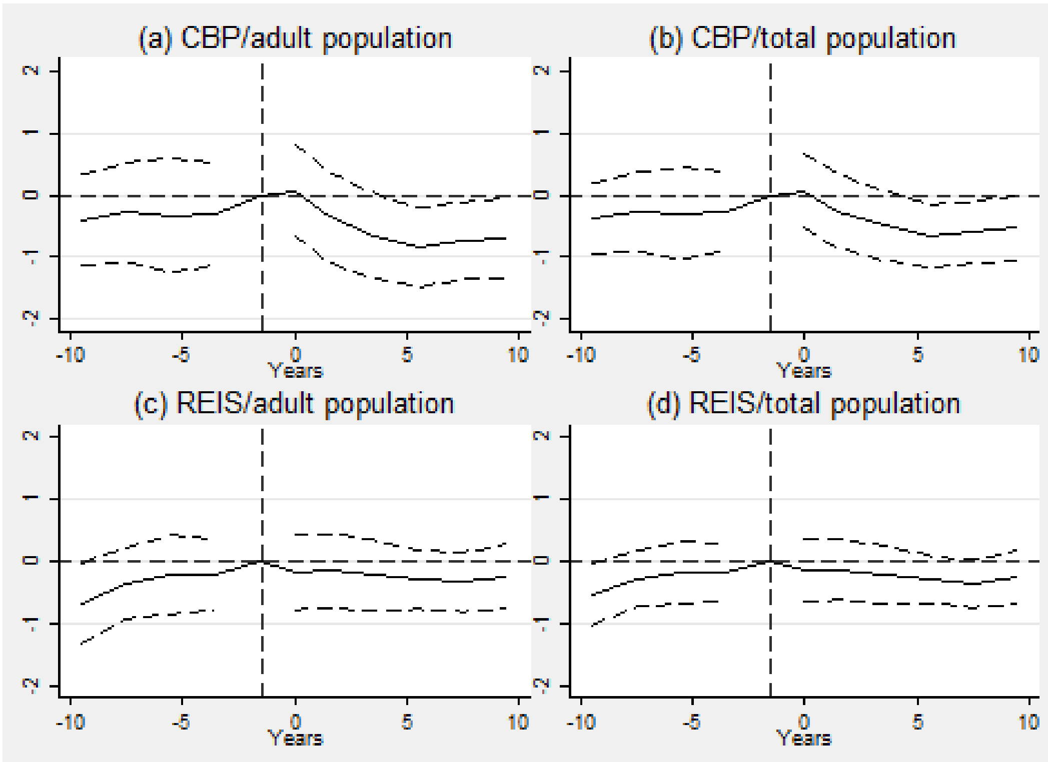
Outcome variable shown above corresponding plot. Point estimates from event study and 95% confidence intervals shown. Standard errors clustered spatially, allowing for spatial correlation of up to 200 kilometers around the Commuting Zone's centroid and for autocorrelation of order 5. Controls include 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 A5: The effect of a hurricane at the CBSA level



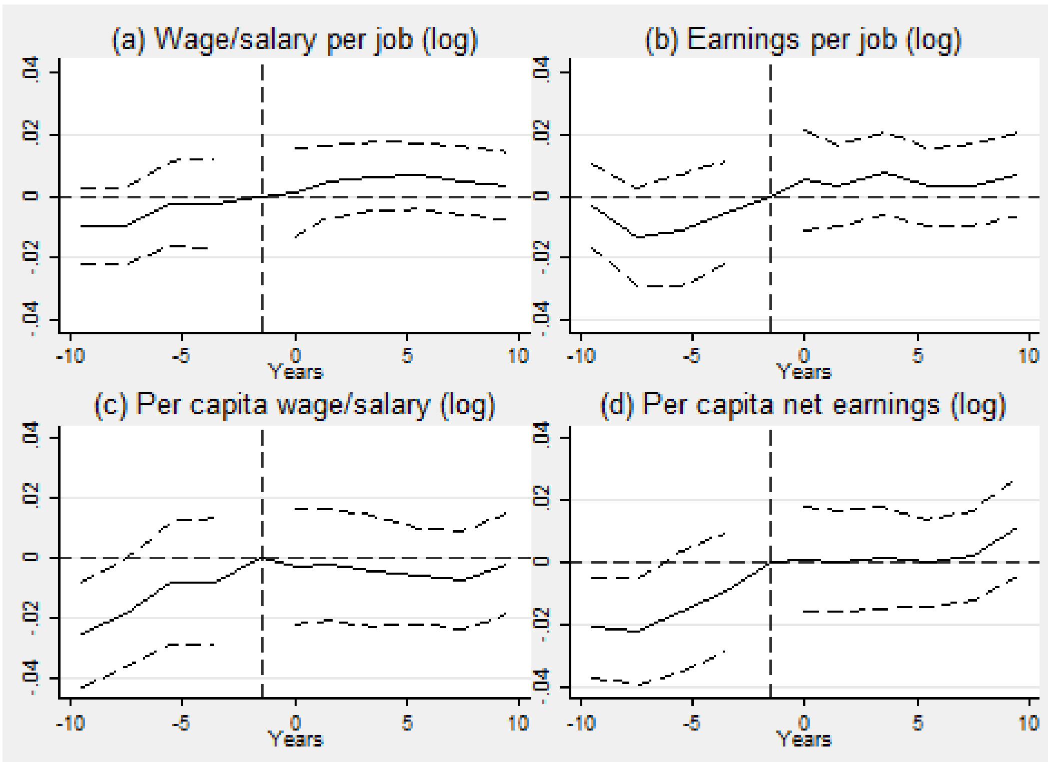
Outcome variable shown above corresponding plot. Point estimates from event study and 95% confidence intervals shown. Standard errors clustered spatially, allowing for spatial correlation of up to 200 kilometers around the CBSA's centroid and for autocorrelation of order 5. Controls include CBSA fixed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

Figure A6: The effect of a hurricane on various employment measures



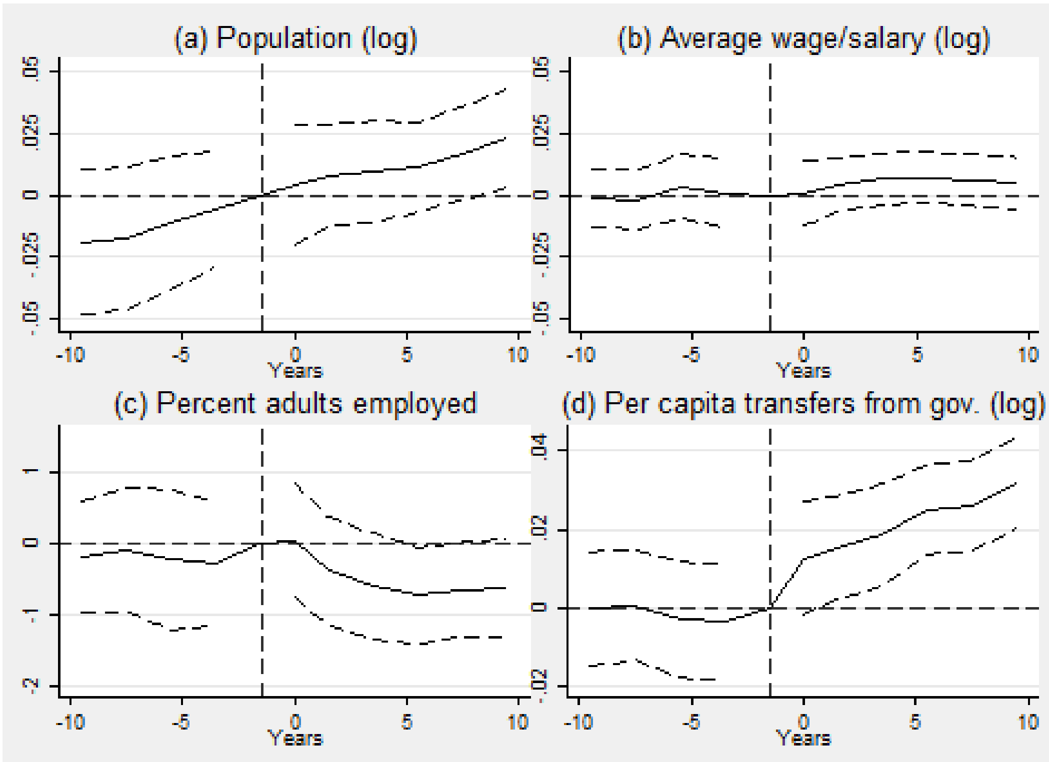
Outcome variable shown above corresponding plot. Point estimates from event study and 95% confidence intervals shown. Standard errors clustered spatially, allowing for spatial correlation of up to 200 kilometers around the county's centroid and for autocorrelation of order 5. Controls include county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

Figure A7: The effect of a hurricane on various income measures



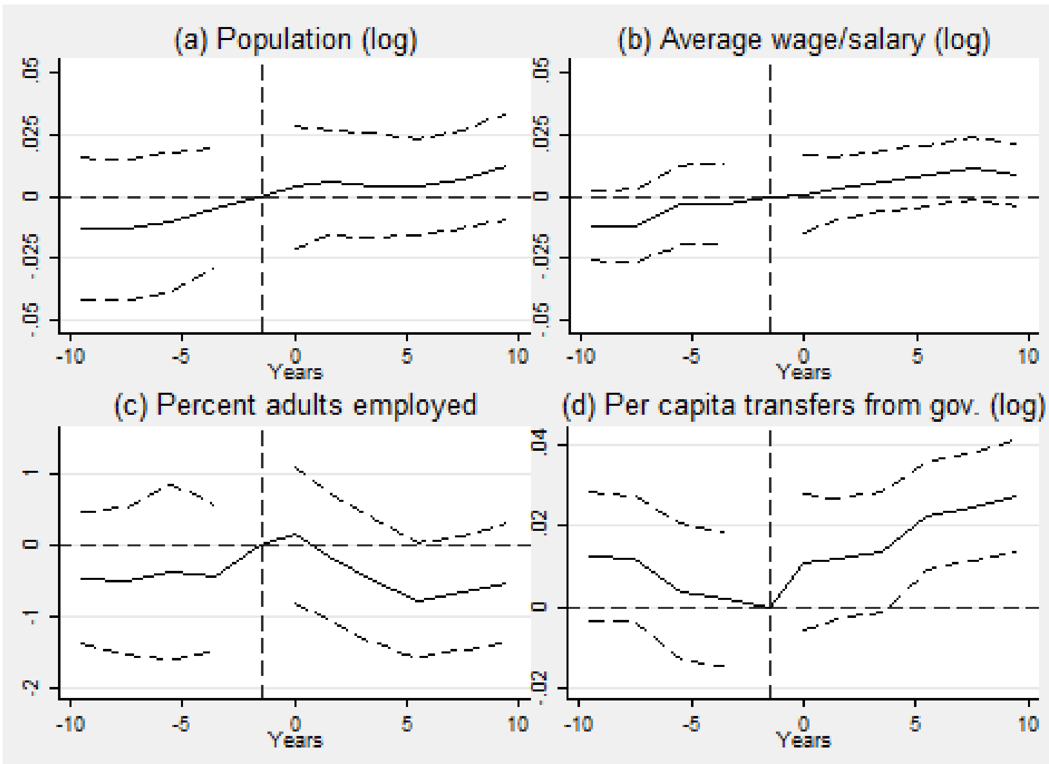
Outcome variable shown above corresponding plot. Point estimates from event study and 95% confidence intervals shown. Standard errors clustered spatially, allowing for spatial correlation of up to 200 kilometers around the county's centroid and for autocorrelation of order 5. Controls include county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

Figure A8: Estimates excluding counties with substantial pre-trends in wages.



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 A9: Counties that experience only one hurricane between 1979 and 2000.



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.

7 Appendix Tables

Table A1: 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***	30.42***	1.42***			
	(0.15)	(7.62)	(0.14)			
Major hurricane	6.01***	953.72***	3.34***			
	(0.39)	(359.18)	(0.29)			
Category = 1				2.07***	17.31***	1.19***
				(0.16)	(4.30)	(0.14)
Category = 2				3.07***	92.51**	2.39***
				(0.38)	(39.53)	(0.25)
Category = 3				6.06***	1111.82**	3.42***
				(0.50)	(442.01)	(0.30)
Category = 4 or 5				6.60***	379.32***	2.35***
				(0.70)	(20.95)	(0.64)
Tornado	2.20***	16.51***	0.03	2.20***	17.20***	0.02
	(0.05)	(2.26)	(0.06)	(0.05)	(2.19)	(0.06)
Flood	1.24***	0.40	0.73***	1.24***	0.51	0.73***
	(0.04)	(2.62)	(0.05)	(0.04)	(2.61)	(0.05)
Severe storm	1.04***	6.71***	-0.10*	1.04***	6.59***	-0.10*
	(0.04)	(2.53)	(0.06)	(0.04)	(2.53)	(0.06)
Dep. var. mean	9.52	9.52	11.11	9.52	11.92	11.11
Observations	23,539	25,618	12,335	23,539	25,618	12,335
R-squared	0.21	0.04	0.10	0.21	0.05	0.10

Standard errors (clustered by county) in parentheses. Significance levels: *10 percent, ** 5 percent, *** 1 percent. Damages and flood claims 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 A2: 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	-0.022	-0.062	-0.069	0.109
	(0.015)	(0.101)	(0.087)	(0.192)
T=-8 or -7	-0.020	-0.072	0.002	0.047
	(0.015)	(0.090)	(0.082)	(0.166)
T=-6 or -5	-0.013	-0.020	-0.006	0.007
	(0.014)	(0.091)	(0.088)	(0.170)
T=-4 or -3	-0.007	-0.017	-0.002	-0.011
	(0.012)	(0.077)	(0.072)	(0.139)
T=0	0.006	0.013	-0.010	-0.003
	(0.012)	(0.081)	(0.075)	(0.138)
T=1 or 2	0.010	0.048	-0.032	-0.008
	(0.010)	(0.071)	(0.067)	(0.126)
T=3 or 4	0.012	0.098	-0.050	-0.037
	(0.010)	(0.073)	(0.068)	(0.126)
T=5 or 6	0.014	0.146**	-0.059	-0.049
	(0.009)	(0.069)	(0.058)	(0.106)
T=7 or 8	0.020**	0.233***	-0.085	-0.110
	(0.009)	(0.069)	(0.059)	(0.113)
T=9 or 10	0.026***	0.253***	-0.115*	-0.160
	(0.010)	(0.069)	(0.062)	(0.120)
Observations	50,190	50,190	50,190	49,851
R-squared	1.000	0.999	0.994	0.992
p-value of F-test, leads 3-10	0.511	0.926	0.950	0.978
p-value of F-test, lags 0-4	0.647	0.588	0.902	0.990
p-value of F-test, lags 0-10	0.072	0.000	0.309	0.575

Estimated using equation 1 in the main paper. Significance levels: * 10 percent, ** 5 percent, *** 1 percent. 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 A3: The effect of hurricanes on earnings, the employment rate, and transfers

	(1) Average wage/salary (log)	(2) Percent adults employed	(3) Per capita transfers from government (log)	(4) Per capita transfers from business (log)
T=-10 or -9	-0.010	-0.398	0.003	0.002
	(0.006)	(0.372)	(0.008)	(0.005)
T=-8 or -7	-0.009	-0.279	0.004	-0.000
	(0.006)	(0.408)	(0.007)	(0.005)
T=-6 or -5	-0.002	-0.324	0.000	0.004
	(0.007)	(0.475)	(0.007)	(0.006)
T=-4 or -3	-0.002	-0.306	-0.003	-0.001
	(0.007)	(0.412)	(0.008)	(0.006)
T=0	0.001	0.071	0.012	0.079**
	(0.007)	(0.378)	(0.008)	(0.031)
T=1 or 2	0.005	-0.347	0.013*	0.003
	(0.006)	(0.371)	(0.007)	(0.005)
T=3 or 4	0.006	-0.646*	0.018***	0.009
	(0.006)	(0.355)	(0.007)	(0.011)
T=5 or 6	0.007	-0.842***	0.025***	0.011
	(0.005)	(0.323)	(0.006)	(0.007)
T=7 or 8	0.005	-0.737**	0.026***	0.015
	(0.006)	(0.316)	(0.006)	(0.011)
T=9 or 10	0.003	-0.679**	0.031***	0.038
	(0.006)	(0.332)	(0.006)	(0.034)
Observations	50,190	49,855	50,190	41,847
R-squared	1.000	0.972	1.000	0.999
p-value of F-test, leads 3-10	0.355	0.875	0.947	0.903
p-value of F-test, lags 0-4	0.655	0.192	0.061	0.019
p-value of F-test, lags 0-10	0.881	0.011	0.000	0.043

Estimated using equation 1 in the main paper. Significance levels: * 10 percent, ** 5 percent, *** 1 percent. 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 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	0.033	0.011	-0.025	0.038***
	(0.047)	(0.018)	(0.029)	(0.014)
T=-8 or -7	0.046	0.023	-0.010	0.023*
	(0.046)	(0.017)	(0.023)	(0.013)
T=-6 or -5	0.014	0.023	-0.014	0.019
	(0.049)	(0.018)	(0.022)	(0.014)
T=-4 or -3	0.022	0.007	0.002	0.013
	(0.048)	(0.018)	(0.019)	(0.012)
T=0	0.067	0.027	0.021	0.007
	(0.054)	(0.018)	(0.023)	(0.013)
T=1 or 2	0.076	0.012	0.035*	0.014
	(0.050)	(0.016)	(0.021)	(0.011)
T=3 or 4	0.134***	0.038**	0.026	0.021*
	(0.048)	(0.016)	(0.021)	(0.011)
T=5 or 6	0.100**	0.041***	0.029	0.031***
	(0.043)	(0.015)	(0.020)	(0.011)
T=7 or 8	0.082**	0.033**	0.034	0.028**
	(0.040)	(0.016)	(0.021)	(0.011)
T=9 or 10	0.060	0.026	0.075***	0.029***
	(0.040)	(0.016)	(0.021)	(0.011)
Observations	50,137	50,028	49,179	50,143
R-squared	0.993	0.999	0.998	1.000
p-value of F-test, leads 3-10	0.871	0.634	0.838	0.072
p-value of F-test, lags 0-4	0.046	0.065	0.355	0.313
p-value of F-test, lags 0-10	0.123	0.066	0.027	0.017

Estimated using equation 1 in the main paper. Significance levels: * 10 percent, ** 5 percent, *** 1 percent. 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.