The Local Economic Impact of Natural Disasters*

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Abstract

We use county panel data to study the dynamic responses of local economies after natural disasters in the U.S. Specifically, we estimate disaster impulse response functions for personal income per capita and a broad range of other economic outcomes, using a panel version of the local projections estimator. In contrast to some recent cross-country studies, we find that disasters increase total and per capita personal income over the longer-run (as of 8 years out). The effect is driven initially largely by a temporary employment boost and in the longer run by an increase in average weekly wages. We then assess the heterogeneity of disaster impacts across several dimensions. We find that the longer-run increase in income per capita rises with disaster severity, as measured by monetary damages. Hurricanes, tornados, and fires yield longer run increases in income, while floods do not. The longer run increase in income tends to rise with recent disaster experience and is absent for counties with no recent experience. Finally, a spatial spillover analysis suggests that, while over the short- to medium-run, the regional and local impacts of disasters on personal income are similar, over the longer run the net regional effect may be negative, in contrast to the positive local effect.

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I. Introduction

Natural disasters have become more frequent and costly in recent decades. **Figure 1a** shows the number of counties in the U.S. with a Federal Emergency Management Agency (FEMA)-declared disaster and the associated inflation-adjusted disaster damages for each year from 1980 to 2017.[1] Both counts and damages have trended up over the past four decades.[2,3] While increased development and population growth in disaster-prone areas has played a role (Rappaport and Sachs 2003), climate change is often cited as an important driver of these trends (USGCRP 2017), and consensus climate change projections indicate that the frequency and severity of disasters like floods and fires are likely to rise even further in the decades ahead.[4]

Given these trends, understanding the economic impact that natural disasters have on affected local economies is critically important. Economic policymakers need to estimate and forecast the economic impacts of disasters, differentiating disaster-driven economic fluctuations from other sources. Changes in local employment, earnings, population, and property values after a disaster directly impact local tax revenues.[5] In addition, local and national fiscal policymakers need to understand the role of disaster aid and other government transfers in mitigating or amplifying the impacts of disasters.[6] Furthermore, natural disaster

[1] These counts exclude disasters without reported damages in the SHELDUS data as described in Section 4.

[2] These trends are not unique to FEMA and/or SHELDUS data on disasters. For instance, similar trends based on other measures of disasters have been noted in the recent Fourth National Climate Assessment (NCA4) as part of the U.S. Global Change Research Program (USGCRP 2017) and by the U.S. National Climatic Data Center (see https://www.ncdc.noaa.gov/billions/time-series).

[3] As can be seen in Appendix **Figure A1, t**he upward trend in damages is driven by hurricanes and floods, which together account for 75% of disasters. For fires, the frequency and costs show no clear trend, though it should be noted that these data do not yet include the extremely costly and record-breaking wildfires that have occurred in the western U.S. since 2017. For tornados, costs have trended up slightly, but the annual count of counties hit by tornado disasters appears to have fallen over time. This could be due to changes in categorization, if tornadoes are increasingly lumped together with other disaster types and categorized, for example, as floods or severe storms in our framework.

[4] For instance, the recent Climate Science Special Report (Fourth National Climate Assessment: Volume 1) from the Congressionally-mandated U.S. Global Change Research Program (USGCRP 2017) concludes that "*the frequency and intensity of extreme high temperature events are virtually certain to increase in the future as global temperature increases (high confidence). Extreme precipitation events will very likely continue to increase in frequency and intensity throughout most of the world (high confidence).*" The report goes on to note that these trends will result in increased frequency and severity of disaster types such as droughts, fires, and floods that are associated with high temperatures and swings in precipitation.

[5] See, for example, "Harvey-struck Texas counties face blow to property tax revenues" (Reuters 2017).

[6] See, for example, "Disaster Relief Bill at an Impasse Over Puerto Rico Aid" (New York Times 2019).

impulse responses can serve as an important input for macroeconomic climate change model calibrations.

Despite the importance for policymakers, there is little consensus among researchers on what the dynamic impacts of natural disasters are for local economic outcomes. As Botzen, Deschenes, and Sanders (2019) put it in a recent review of the literature, "more research is needed on long-term impacts (e.g., beyond 5 years) of natural disasters." An important recent paper by Hsiang and Jina (2014) presents in a schematic (which we reproduce in **Figure 2**) four commonly posited hypotheses on how economic activity might evolve following natural disasters. Using cross-country panel data they find that the impulse response function (IRF) of national GDP per capita with regard to cyclones/hurricanes is consistent with the "no recovery" hypothesis. However, studying earthquakes, Lackner (2019) finds positive effects at least 8 years after for high-income countries (though no recovery for low- to middle-income countries).

In this paper, we use U.S. county data to study the dynamic response of local economies following disasters. Given data limitations for county GDP, we focus on personal income, which is very highly correlated with GDP and is available back to 1980.[7] In contrast to prior studies, we also consider a broad range of other economic outcomes using a common methodology and data sample in order to provide a comprehensive picture. Using a panel-data version of the local projections estimator, we estimate IRFs out to eight years after disaster shocks. We consider outcomes that vary in frequency from monthly to quarterly to yearly. We further assess the heterogeneity of disaster impacts across different levels of monetary damages, disaster types, pre-disaster income, and local historical experience with disasters. Finally, we examine how natural disasters impact economic outcomes in counties of varying distances away from a directly affected county and estimate the net regional impact.

In contrast to the cross-country findings discussed above of long-lasting declines in national income per capita following disasters, we find robust evidence of long-lasting *increases* in local

[7] There are three main conceptual differences between GDP and personal income at the county level as defined by the U.S. Bureau of Economic Analysis: (1) personal income includes government transfers, while GDP does not, (2) GDP includes corporate income while personal income does not (though it does include corporate income distributed to shareholders via dividends and interest), and (3) GDP is based on place of work, while personal income is based on place of residence. One implication is that our results on personal income generally will not reflect any post-disaster losses (or gains) to corporate profits. For example, Kruttli, et al (2020) have found that firms affected by hurricanes experience significant uncertainty, with significant outperformance and underperformance in returns for affected firms several months after landfall.

personal income per capita following natural disasters within the U.S. Indeed, of the four hypotheses depicted in **Figure 2**, though none perfectly characterizes our estimate of the impulse response function, "build back better" comes closest. Specifically, our results point to an initial decline, followed by a recovery to a level of income per capita that is above the baseline trend at least 8 years after the disaster. Note that the "build back better" phrase, which we adopt from the prior literature, is not meant to be a statement about welfare. Our results are essentially agnostic on the impact of disasters on local welfare. Welfare considerations are beyond the scope of this paper and much more complicated due to unmeasured losses in wealth and capital stock and to post-disaster migration flows into and out of affected areas,[8] not to mention the non-pecuniary costs associated with injuries, fatalities and lost possessions.

Looking at other outcomes, we find that the recovery in personal income is initially fueled by a temporary boost in employment, especially in construction, as well as government support programs, including both direct disaster aid as well as automatic stabilizers like unemployment insurance and income maintenance programs. However, over the longer-run, the increase in personal income can be largely traced to higher earnings per worker. We also find a long-lasting increase in local house prices, measured by a repeat-sales house price index. This increase could reflect quality improvements – rebuilds and repairs – to the housing stock as well as rebuilt and improved local public infrastructure and amenities. Higher house prices may also contribute to higher personal income to local homeowners via rental income.

We also explore how post-disaster outcomes vary by disaster severity (measured by monetary damages), type of disaster (flood, hurricane, etc.), pre-disaster income, and the frequency with which individual counties have previously been hit. We find that the longer-run increase in personal income is robust across disasters of varying severities, but the magnitude of the effect strongly increases with severity. Highly damaging disasters are found to produce long-lasting increases in both employment and earnings per worker, though they also result in large population losses and, likely as a result, declines in house prices.

[8] With migration flows, the welfare consequences of a local area affected by a disaster become especially unclear because one must decide whether the focus is on the welfare of residents in the area at the time of the disaster or the residents in the area as of some later horizon. The welfare of out-migrants may differ substantially from the welfare of in-migrants.

In terms of other heterogeneities, we find the overall longer-run increase in income per capita following disasters stems primarily from hurricanes, fires, and tornados, with statistically insignificant longer-run impacts of floods, severe storms, and extreme winter weather. We find that the income boost in the first few years after a disaster appears to be concentrated in the richest half of counties based on initial (pre-disaster) income. However, by the end of eight years, per capita income increases across counties regardless of their initial income grouping. Lastly, we find that counties with more historical experience with disasters see larger increases in personal income over the longer-run.

Finally, we examine spatial spillovers to see how disaster effects propagate to other counties of varying distances away. Migration and recovery efforts could potentially boost nearby economies or strain them if there is competition over finite local resources. Using a spatial lag estimation methodology, we show that nearby counties (up to 199 miles away from disaster-hit county) experience a medium-run boost to personal income but are largely unaffected over the longer-run, consistent with residents of nearby counties participating in recovery efforts. Counties that are 200-399 miles away, on the other hand, see a decline in personal income over all horizons, which could be explained by resources being redirected to counties directly affected by disasters. Counties beyond that range (up to 599 miles away) experience some modest intermediate gains followed by a longer run decline. Aggregating the own-county effects with the spatial lag effects, we find that the longer-run income effect for a *region* – i.e., all counties within 600 miles of a disaster's epicenter – is modestly negative. This result may help explain the negative longer-run effects of disasters found in some prior studies based on country-level data.

Our findings have several important policy implications. For local policymakers, the finding that employment and personal income fall sharply immediately after a disaster, before eventually recovering, suggests they may need to plan ahead – for example, with larger rainy-day funds – in order to better deal with post-disaster declines in tax bases, which can be recouped after the recovery period. For national policymakers, these results highlight that different forms of disaster aid can have very different impacts on the local economy, and they relate to debates regarding place-based vs. people-based policies. Finally, the heterogeneity in outcomes suggests that we must exercise caution in extrapolating from results based on specific events, contexts, or time

frames, which is how much of the literature studying natural disaster effects has been focused thus far.

The remainder of this paper is organized as follows. In the next section, we discuss key findings from prior research. In section III, we discuss the economic channels by which disasters could impact local economies. Then in section IV, we describe the data we use both for disasters and to measure economic activity. We follow this with a discussion of our methodology in section V. In section VI, we present our baseline results. Section VII examines the heterogeneity of disaster effects across the dimensions discussed above as well as spatial spillovers and net regional effects. Finally, we conclude with a discussion of implications and suggestions for future work.

II. Literature

Previous research on the disasters' dynamic economic effects generally has focused on national aggregate outcomes, on quite specific outcomes, or on case studies of particular disasters.[9] As mentioned above, Hsiang and Jina (2014) uses cross-country panel data on cyclones to study their dynamic impact on national GDP per capita, finding a permanent (or at least long-lasting) decline.[10] Lackner (2019) shows that eight years after impact, earthquakes reduce per capita GDP for low- and middle-income countries, but may boost it for high-income countries. Similarly, von Peter, von Dahlen and Saxena (2012), also using cross-county panel data, find that while the average response of national GDP per capita to natural disasters is negative, the response to well-insured disasters (which are predominately in high-income countries) "can be inconsequential or positive for growth over the medium term as insurance payouts help fund reconstruction efforts." Another recent cross-country study, Sawada, et al. (2019), found that natural disasters and wars had positive long-run effects on per capita GDP growth.

There have also been a number of studies of disasters' impacts on local economies in the U.S., though these studies generally do not explore the full dynamics of the impacts. Strobl

[9] See Botzen, Deschenes, and Sanders (2019) for a recent literature review.

[10] See also Noy (2009), who shows that natural disasters contemporaneously reduce national GDP on average and more so in countries that are poorer, less open, or less educated.

(2011) focuses on coastal U.S. counties and finds that annual per capita income growth falls significantly in the year of the hurricane but returns to the pre-hurricane growth rate in the following year. In terms of the *level* of per capita income, which we look at (among other outcomes) below, this result implies that income in the long run grows at the same rate as before the disaster but the contemporaneous income loss is never recovered. This is consistent with the "no recovery" scenario depicted in **Figure 2** and found across countries by Hsiang and Jina (2014). By contrast, we find in this paper that after an initial drop following a disaster, personal income per capita more than recovers and is higher than it would have been absent the disaster at the end of our 8 year horizon. For very severe disasters, the positive effect begins immediately and is fairly large. For instance, we estimate that personal income per capita is about 3% higher 8 years after a disaster with damages per capita at the 99th percentile. This result is consistent with some case-study evidence of severe disasters in the U.S. In particular, Groen, et al. (2019) perform a careful longitudinal study of workers affected by Hurricanes Katrina and Rita in 2005, finding substantial long-term gains in earnings, driven largely by higher wages.

Another within-U.S. study that is closely related to ours is Boustan, et al. (2017). They find that counties affected by the most severe disasters experience higher out-migration, higher poverty rates, and lower house prices over the subsequent decade. In this paper, we similarly find significant longer-run (up to 8 years out) declines in population and house prices after very severe disasters. We also uncover two related results. First, there is actually a strong positive response of house prices after severe disasters in the *shorter-run*, lasting about 2-3 years.[11] This temporary boost in prices could be due to a temporary drop in housing supply caused by disaster destruction, combined with stable or increasing demand for workers in the area for recovery efforts, and lasting as long as it takes for the local area to rebuild. Second, we find a different pattern for less severe disasters – i.e., such as those with damages per capita below the 90th percentile for all disasters. For these disasters, the longer-run response of both population and house prices is slightly positive, yielding an average home price response that is positive in our 8-year horizon.

[11] This result is consistent with Graff Zivin et al (2020)'s finding that home prices are elevated for up to 3 years after hurricanes in Florida, though they do not look beyond 3 years.

Our results regarding the role of government transfers is related to Deryugina (2017), which studies the impact of hurricanes in the coastal areas of the U.S. on government transfers. Consistent with our findings, she finds that both disaster and non-disaster government transfers rise in affected counties in the first few years after a hurricane. This part of our analysis also relates to the body of work on the role of insurance in disaster recovery that is described in Kousky (2019).

There is a broad literature examining effects of specific types of natural disasters or even specific events on particular sets of outcomes, to which our paper relates. For example, examining the first three years thereafter, McCoy and Walsh (2017) find that wildfires in Colorado yield short-lived declines in house prices, while Bin and Landry (2013) find that hurricane flooding caused temporary declines in house prices in affected areas. Separately, there are a fairly large number of detailed case studies of specific disasters. Prominent examples include Vigdor (2008), Hornbeck (2012), Gallagher and Hartley (2017), and Deryugina, et al. (2018).

III. Economic Channels

The net impact of natural disasters on local economic outcomes is far from clear *a priori* because natural disasters combine, to various degrees, many types of economic shocks and affect outcomes through many separate channels. First, most disasters represent a negative shock to the productive capital stock and to household wealth, similar to war destruction. Second, disasters, especially severe disasters, can be a shock to the spatial equilibrium of population and economic activity (as modeled for example in Davis and Weinstein (2002) and Hornbeck (2012)). Third, they typically are at least temporary shocks to total factor productivityand production by disrupting electricity supply, materials supply, and other business operations. Fourth, they can temporarily reduce demand for local nontradables, such as leisure and hospitality services, discretionary retail spending, and entertainment. Fifth, disasters can reduce labor supply by hampering workers' abilities to commute and/or their willingness to leave behind damaged homes and families for work in the short run or through outmigration in the longer run. Moreover, these shocks to local product demand and labor supply translate into local income shocks with potential local multiplier effects.

In addition, natural disasters can trigger substantial disaster and non-disaster government transfers and loans. In terms of individual aid, in the U.S. FEMA provides grants to individuals for temporary housing and other needs through its Individual Assistance programs, which IHP is a component of. The SBA makes loans to qualified individuals, households, and businesses to help cover uninsured or underinsured property losses. However, these individual transfer and loan programs are relatively modest in dollar amounts, averaging about $370 million per year from 2006-2016.[12] FEMA's Public Assistance (PA) program, which issues grants to state and local governments to repair or rebuild public infrastructure,[13] averaged over $3.3 billion a year in grants over the same period,[14] while NFIP payouts averaged $2.2 billion a year.[15]

Disasters may also trigger significant transfer payments from non-disaster safety-net programs such as Unemployment Insurance, Temporary Assistance for Needy Families, Medicaid, and the Earned Income Tax Credit. Transfers from these programs increase after a disaster as more households in the affected area qualify, as found in Deryugina (2017) for hurricanes.

All of this direct and indirect aid could have positive or negative net effects on local economic activity. On the one hand, aid may spur economic activity through a government spending multiplier. While estimates of the size of the government spending multiplier vary widely, the literature generally has found large multipliers on employment and income in local areas from federal spending that is not financed by local taxation (i.e., local windfall spending). See, for example, Shoag (2013), Wilson (2012), and Chodorow-Reich, et al. (2012) for state-level evidence and Suarez, Serrato, and Wingender (2016) for county-level evidence. On the other hand, aid received by households displaced from their housing – especially aid that is not required to be used for rebuilding – may facilitate household relocation away from affected areas. In particular, while SBA disaster loans need to be repaid and rely on the homes that the funds are intended to repair as collateral, monies received by households from FEMA Individual Assistance aid and NFIP payouts have fewer strings attached.

[12] See March2017_OpenFEMAEdits_IADataset_IHPFloods_31317.xlsx, downloaded from FEMA at https://www.fema.gov/media-library/assets/documents/130225, downloaded on February 4, 2020.

[13] Though much smaller (in dollars), the Federal Highway Administration also provides funds for repair of federal-aid roads through its Emergency Relief Program.

[14] See https://www.fema.gov/data-visualization-summary-disaster-declarations-and-grants.

[15] See https://www.fema.gov/loss-dollars-paid-calendar-year.

The relative importance of these various economic channels likely evolves over time for any given disaster. In particular, the disruptions to production and labor supply – and resulting negative income shocks – may be short-lived, lasting just as long as it takes for local electricity and major transportation routes to be restored. Subsequently, to the extent that location fundamentals and agglomeration economies are important, the transition back to spatial equilibrium can lead to increased labor demand and resulting local multiplier effects (e.g., higher income and consumption; see Moretti 2010). Davis and Weinstein (2002), for example, studied the destruction of capital in Japanese cities due to Allied bombing in World War II and found complete transitions in affected areas back to the original spatial equilibrium. The transitional periods entail high levels of investment, construction, and employment in order to return the capital stock to steady state levels.

Yet, while war destruction seems not to permanently change spatial equilibria, natural disasters may be different. Natural disasters may be more geographically isolated, leaving many other areas as attractive alternatives for living, working, and producing, thereby leading to permanent shifts in economic activity away from the disaster area. Moreover, a natural disaster may increase the probability of future disasters as perceived by local producers and residents, reducing the attractiveness (location fundamentals) of the area.[16] If such factors negatively impact location fundamentals, natural disasters will lead to (a) permanently lower economic activity in the area and (b) a more rapid transition (e.g., investment, employment, and construction) to the new lower steady state.

Due to the presence of these multiple economic channels, each of which varies in their relative importance over time, we are agnostic *a priori* as to which channel dominates at any given horizon after a disaster. We empirically trace out the dynamic effect of disasters on local economic activity – that is, the net effect from all of these various channels – over time. We study a broad range of economic outcomes that should capture the effects of the shocks to local labor demand and supply and to household income.

[16] Changes to perceived risk of natural disasters may be more persistent than risk of military destruction, which can drop off when a conflict or war is resolved.

IV. Data

We use data on disasters and a variety of economic indicators, which we describe below. Table 1 summarizes the sources and treatment of the dependent variables, while summary statistics are shown in Table 2.

A. Natural Disasters

We use FEMA's real-time administrative Disaster Declarations Summary dataset in combination with the Spatial Hazard Events and Losses Database for the United States (SHELDUS) to measure U.S. county natural disasters. Although FEMA disaster declarations go back to 1953, due to the availability of our outcome data, we only estimate IRFs for disasters that occurred between 1980 and 2017. We focus on natural disasters that received a "Major Disaster" Presidential declaration according to the FEMA data and showed positive damages in the SHELDUS data.[17,18] We exclude FEMA-declared disasters with zero damages because we observe in the data many instances of FEMA declarations covering all counties in an affected state even when it is clear that only a portion of counties were physically affected.[19] Potential types of assistance include (1) Public Assistance (PA) for infrastructure repair; (2) Hazard Mitigation Grant Program (HMGP) grants to lessen the effects of future disaster incidents; and (3) Individual Assistance (IA) for aid to individuals and households.

FEMA disaster declarations are generally initiated when state governments issue requests to FEMA. FEMA sends a team to the disaster area to perform a Preliminary Damage Assessment, using drone, satellite, and civil air imagery as well as site visits to determine, for each affected county, whether the damage is extensive enough to warrant a major disaster designation and, if so, for what types of assistance the county is eligible.[20] FEMA disaster declarations cover much of the country, with 95 percent of counties experiencing at least one FEMA disaster declaration with positive damages between 1980 and 2017. **Figure 1b** maps the frequency of disaster

[17] We consider disasters where SHELDUS shows positive damages for the month of the incident begin date according to FEMA or the month thereafter if FEMA shows the incident end date in a month after the incident begin date.

[18] Given our focus on natural disasters, we exclude declarations due to terrorism or toxic substances.

[19] As detailed in Lindsay and Reese (2018) from the Congressional Research Service, "[e]ach presidential major disaster declaration includes a 'designation' listing the counties eligible for assistance as well as the types of assistance FEMA is to provide under the declaration.

[20] Source: author conversations with FEMA staff.

declarations by county from 1980 to 2017. The modal county experienced eight disasters during that period.

In addition to examining the effects of disasters in general, we use the SHELDUS data to examine how disasters' effects vary with severity as measured by monetary damages caused by the disaster. This database is based on data from the NOAA Storm Database, which in turn are based on reports from insurance companies, media, and other sources. SHELDUS separately reports county-level crop and property damages for a wide range of event types, such as floods, tornadoes, thunderstorms for years 1990 onward. We aggregate damages within the county over all events occurring during a month to estimate total disaster damages by county and month. We then use census population data to estimate per capita damages in 2017 dollars.

To our knowledge, SHELDUS is the most comprehensive source of monetary damages for natural disasters in the U.S., covering all types of natural disasters and the entire country at the county level. SHELDUS likely contains significant measurement error. A primary source of measurement error appears to stem from the fact that, when only total damages are known for a given disaster, SHELDUS allocates the total to all disaster-declared counties equally. Given that more populous counties are likely to have more property at risk of damage, we redistribute county damages to equate the per capita damages across affected counties. It should be noted that the distribution of per capital damages varies significantly across disaster types (see **Appendix Figure A2**). In particular, hurricanes tend to have the highest damages.

An alternative approach to measuring damages would be either to model damages as a function of physical disaster characteristics or to simply use physical characteristics as a reduced-form measure of damages.[21] Unfortunately, data on such physical characteristics is not readily available at the U.S. county level for a broad set of disaster types and not easily comparable across types. Moreover, using physical characteristics as a measure of damages when estimating economic impacts at the local level can be problematic. The monetary damages caused by a disaster – i.e., the magnitude of the "treatment" represented by the

[21] For example, Deryugina (2017) used FEMA's HAZUS-MH simulation model to estimate damages for major hurricanes in the U.S. as a function of wind speed and other storm characteristics. Hsiang and Jina (2014) use a reduced form approach to estimate the economic impact of major hurricanes around the world as a function of the wind speeds associated with each hurricane. Felbermayr and Groschl (2014) expand that approach to cover other types of disasters, using international geophysical and meteorological data. Similarly, Lackner (2019) estimates the impact of earthquakes, measuring their severity using spatially disaggregated data on ground shaking.

disaster shock – of a given physical strength can vary greatly from place to place depending on both local property values as well as construction quality and building codes and other differences in local resilience. For example, Bakkensen and Mendelsohn (2016) show that hurricane damages tend to be higher in the U.S. than in other OECD countries when examining responses to physical storm characteristics. By contrast, our approach amounts to estimating the response of various economic outcomes to a disaster of a given level of monetary damages (per capita). We consider both the mean level of damages (for our baseline results) as well as different percentiles of the damages distribution.

In addition to analyzing effects by disaster severity, we also examine heterogeneity of outcomes by disaster type. We designate as a hurricane any FEMA disaster declaration that is classified as hurricane type by FEMA *or* contains "hurricane" in the declaration title. To avoid overlap so that a disaster can only be counted as a flood or a hurricane, we have designated as a flood any remaining disaster that is classified as a flood or contains "flood" in its title.[22]

B. Income and government transfers

We use annual county level data on personal income and its components from the Regional Economic Information System (REIS) of the Bureau of Economic Analysis (BEA) for 1980 through 2016. In addition to total personal income, we examine wage and salary income as well as total government transfers, income maintenance, and unemployment insurance compensation. We adjust each of these variables to a per capita basis using Census population data.

C. Employment and Average Weekly Wages

Our data on employment and average weekly wages by county come from the Quarterly Census of Employment and Wages (QCEW), as used and described in detail in Wilson (2017). The QCEW is compiled by the Bureau of Labor Statistics (BLS) based on state Unemployment Insurance administrative records. Nearly all private nonfarm employers in the U.S. are required to report monthly employment counts and quarterly wages of their employees to their state Unemployment Insurance agencies. Employment covers "all full- and part-time workers who worked during or received pay (subject to Unemployment Insurance wages) for the pay period which includes the 12th day of the month." We separately examine effects for total nonfarm employment and construction employment (category 1012). Due to concerns about data quality,

[22] The geographic exposure to disasters varies significantly by disaster type (see **Appendix Figure A3**).

when estimating IRFs for the construction employment, we drop counties with more than 5 months of missing or zero construction employment. We use data on total (all-industry) employment from January 1990 through December 2015.[23]

The BLS calculates average weekly wages (AWW) "by dividing quarterly total wages by the average of the three monthly employment levels (all employees, as described above) and dividing the result by 13, for the 13 weeks in the quarter."[24] Note that AWW reflect both hourly wages and the number of hours worked per week.

D. House prices

We use the CoreLogic Home Price Index (HPI), available by county at a quarterly frequency from 1980Q1 to 2016Q4, to measure house prices. The index is based on transaction prices of repeated home sales. Repeated-sales price indices have the advantage that they reflect price changes of individual houses holding fixed all of the permanent characteristics of the house and are therefore independent of changes in the composition of houses in an area. However, a natural disaster can seriously affect the characteristics of a given house. For instance, unrepaired damage will negatively impact a house's value, while improvements made through renovations may increase its value. This potential for changing home characteristics should be kept in mind when interpreting our house price results.

E. Population

Estimates of annual population by county were obtained from the Census Bureau for 1980 through 2017 and reflect the population in each county as of July 1 of each year.

F. SBA Loans, IHP Aid, and NFIP Payouts

We collected data on SBA disaster loans for fiscal years 2001 through 2017 from the SBA website.[25] Data for years from 1989 through 2000 came from Bondonio and Greenbaum (2018) and were generously provided by Robert Greenbaum. The data provide dollar amounts of disbursements of SBA disaster loans, separately for households and for

[23] Our employment and wages data cover "nonfarm" employment and so exclude any employment in agriculture, ranching, fishing, and hunting.

[24] https://www.bls.gov/news.release/cewqtr.tn.htm.

[25] See https://www.sba.gov/offices/headquarters/oda/resources/1407821.

businesses, by county and fiscal year. We use data on county level IHP payments going back to 1990 that we obtained from FEMA via FOIA request.

We use the Federal Insurance & Mitigation Administration National Flood Insurance Program (FIMA NFIP) Redacted Claims Dataset (available at https://www.fema.gov/media-library/assets/documents/180374) to calculate NFIP payments associated with floods occurring each month in each county. Although we are able to observe the date of the incident to associate the payment amounts with our disaster observations, we are unable to observe when the payments are actually made.

V. Methodology

Throughout this paper, we estimate impulse response functions (IRFs) of various local economic outcomes with respect to FEMA-declared disaster shocks in order to see how economic activity responds over several years after a disaster. We use a variant of the Jordà (2005) local projection method, modified for panel data, as our baseline specification. We then build on that specification to explore heterogeneity in disaster effects and the contribution of government aid.

A. Baseline

In our baseline specification examining how disasters affect income and other outcomes, we estimate the following equation for a series of horizons $h \geq 0$:

$$y_{c,t+h} - y_{c,t-1} = \beta^h D_{c,t} + \boldsymbol{X'_{ct}\gamma^h} + \alpha^h_{r(c),t} + \alpha^h_{c,m(t)} + \epsilon_{c,t+h}\,. \qquad (1)$$

$y_{c,t}$ is an economic outcome of interest in county c in period t. Table 1 outlines how the outcome variables are modeled in our analyses. $D_{c,t}$ is the key treatment variable, equaling one if the county experienced a disaster in month t with positive damages and zero otherwise, as described in Section IV.A. The series of β^h are the IRF coefficients of interest. $\boldsymbol{X_{ct}}$ is a vector of control variables with parameters $\boldsymbol{\gamma^h}$. Specifically, $\boldsymbol{X'_{ct}\gamma^h}$ is defined as

$$\boldsymbol{X}'_{\boldsymbol{ct}}\boldsymbol{\gamma}^{\boldsymbol{h}} \equiv \sum_{\substack{\tau=-p,\\ \tau\neq 0}}^{h} \delta^{\tau h} D_{c,t+\tau} + \sum_{\tau=-p}^{h} \theta^{\tau h} D^{0}_{c,t+\tau} + \rho^{h} \Delta y_{c,t-1,t-k}. \quad (2)$$

The first term in equation (2) controls for other disasters that may have hit the same county either before the current disaster (up to p periods prior) or between the current disaster and the horizon of interest (h).[26] This ensures that the estimated IRF from a disaster is not contaminated by either lingering effects of past disasters or effects of other disasters that happen to occur between the current disaster and horizon h.[27] The second term controls for other minor disasters (i.e., without reported damages) occurring in the same county within the window from p periods before to h periods after period t.[28]

The third term in equation (2) ($y_{c,t-1} - y_{c,t-k}$) explicitly accounts for the potential of a pre-trend in the outcome variable. Because the dependent variable is the sum of period-by-period changes in the outcome over the post-disaster timeframe up until horizon h: $y_{c,t+h} - y_{c,t-1} \equiv \sum_{i=0}^{h} \Delta y_{c,t-i}$, this pre-trend term is a lag of the dependent variable with a different time horizon. We measure this pre-trend over the prior three years, so k equals 3, 12, or 36 depending on whether the outcome variable is annual, quarterly, or monthly.[29,30]

We include region-specific time fixed effects $\alpha^{h}_{r(c),t}$ to absorb any regional, or national shocks that may have coincided with disasters. Because this could absorb the effects of region-wide disasters, we are potentially underestimating the true impact of a disaster on a given county. To control for county-level heterogeneity and seasonality, we also include county-by-calendar month (quarter for quarterly frequency data) fixed effects $\alpha_{c,m(t+h)}$. For annual outcomes, this amounts to a simple county fixed effect.

[26] Though not shown in equation (2) for tractability, when $h < 0$ we still include the p lags indicating whether disasters occurred before period 0.

[27] We note that in practice in our sample, the inclusion/exclusion of these intervening disaster dummies has virtually no effect on our results, suggesting that intervening disasters are a very rare occurrence.

[28] $D^{0}_{c,t}$ can only equal one if $D_{c,t}$ is zero in a period.

[29] The choice of k involves a trade-off: higher values of k may provide a better forecast of the counterfactual no-disaster trend in the outcome between time *0* and h but will also reduce the sample size available for any given h regression.

[30] We could alternatively control for the counterfactual no-disaster trend by including a county-specific time trend, which would entail no loss of regression observations from the beginning of the sample. The downside of this approach is that a county's post-disaster time trend could itself be impacted by the disaster, making it a "bad control" (Angrist and Pischke 2009). Nonetheless, to assess robustness, in **Appendix Figure A4**, we provide alternative IRF results for each of our main outcome variables whereby we replace the pre-trend term in equation (2) with a county-specific time trend (i.e., an interaction between county fixed effects and the time variable).

B. *Heterogeneity in Disaster Treatment Effects*

The IRFs estimated using the baseline specification above are essentially average treatment effects (ATE). The true treatment effect of disasters is likely to be heterogeneous along a number of dimensions. We consider heterogeneity in terms of disaster severity (damages), disaster type, initial county income, and historical disaster experience.

To explore how the economic response to a disaster varies with the extent of its damages, we estimate an outcome's impulse response at a given horizon h to a polynomial function of the damages caused by the disaster:

$$\beta^h(s) = \sum_{p=0}^{P} \beta_p^h \, s_{c,t}^p \tag{3}$$

where $s_{c,t}$ denotes the per capita damages for county c in period t, as measured in SHELDUS. We use a third-order polynomial ($P = 3$) as our baseline case below. Substituting equation (3) into equation (*1*) yields the following specification:

$$\begin{aligned} y_{c,t+h} - y_{c,t-1} = \beta_0^h D_{c,t} + \beta_1^h D_{c,t} s_{c,t} + \beta_2^h D_{c,t} s_{c,t}^2 + \beta_3^h D_{c,t} s_{c,t}^3 \\ + \boldsymbol{X_{ct}'\gamma^h} + \alpha_{r(c),t}^h + \alpha_{c,m(t)}^h + \epsilon_{c,t+h} \end{aligned} \tag{4}$$

The estimated coefficients, $\hat{\beta}_p^h$ for $p = 0, \ldots, 3$, from this regression allow one to compute the impulse response, $\hat{\beta}^h(s)$, for any given level of damages (s) according to equation (3). In Section VI, we report the full impulse response function (from $h = 0$ to H) for selected percentiles of the distribution of $s_{c,t}$ across disasters in our sample.

To examine heterogeneity by disaster type, we estimate the following joint regression:

$$y_{c,t+h} - y_{c,t-1} = \sum_{d \in \mathcal{D}} \beta_d^h D_{c,t}^d + \boldsymbol{X_{ct}'\gamma^h} + \alpha_{r(c),t}^h + \alpha_{c,m(t)}^h + \epsilon_{c,t+h} \tag{5}$$

where $D_{c,t}^d$ is an indicator for a disaster of type d. The set of disaster types, $\mathcal{D}$, consists of hurricanes, floods, severe storms, extreme winter weather, fires, tornadoes, and other. The estimates of β_d^h trace out the IRF of the outcome variable with respect to a disaster of type d. For

these regressions, we modify the first term of the control vector so that the leads and lags of disasters are differentiated by type:[31]

$$\boldsymbol{X}'_{\boldsymbol{ct}}\boldsymbol{\gamma}^{\boldsymbol{h}} \equiv \sum_{d\in\mathcal{D}} \sum_{\substack{\tau=-p,\\ \tau\neq 0}}^{h} D^{d}_{c,t+\tau} + \sum_{\tau=-p}^{h} \theta^{\tau h} D^{0}_{c,t+\tau} + \rho^{h}\Delta y_{c,t-1,t-k}. \tag{6}$$

We also investigate heterogeneity in treatment effects in terms of two important county characteristics: initial income and previous disaster experience. For initial income, we split county*year observations into four groups based on their quartile of the distribution of prior-year $(t-1)$ personal income per capita. We then interact the disaster indicator with the income quartile variable, estimating the following specification:

$$y_{c,t+h} - y_{c,t-1} = \sum_{q=1}^{4} \beta^{h,q} M^{q}_{c,t-1} D_{c,t} + \sum_{q=1}^{4} \phi^{h,q} M^{q}_{c,t-1} + \boldsymbol{X}'_{\boldsymbol{ct}}\boldsymbol{\gamma}^{\boldsymbol{h}} + \alpha^{h}_{r(c),t} + \alpha^{h}_{c,m(t)} + \epsilon_{c,t+h} \tag{7}$$

where $M^{q}_{c,t-1}$ is one of four income quartile indicators indexed by q and $\boldsymbol{X}'_{\boldsymbol{ct}}\boldsymbol{\gamma}^{\boldsymbol{h}}$ is as defined earlier in equation (2). The $\beta^{h,q}$ coefficients trace out a separate impulse response function for each quartile q. We also include the four quartile indicators themselves as separate conditioning variables in the regression to ensure against possible "selection into treatment" – that is, the possibility that either higher or lower income counties are more likely to be hit by a disaster.

Similarly, we estimate separate IRFs for four different categories of local disaster experience. We again split observations into four categories and then interact the category indicators with the disaster indicator (as well as including the category indicators as separate regressors). We divide county- and time-specific disaster experience based on whether the county experienced (a) no periods, (b) 1 period, (c) 2-3 periods, or (d) 4 or more periods with disasters in the previous 10 years, where periods are monthly, quarterly, or annual, based on the outcome of interest.

[31] For monthly outcomes, due to computational demands, we control for 12-month aggregate indicators for the leads and lags of each disaster type.

C. *Spatial Lags*

To examine how natural disaster impacts propagate to neighboring regions, we build on our baseline specification in equation (*1*) by adding continuous treatment variables $D_{c,t}^{b}$ measuring the occurrence of disasters in other counties of varying distances away from county *c*:

$$y_{c,t+h} - y_{c,t-1} = \sum_{b \in B} \pi^{h,b} D_{c,t}^{b} + \beta^{h} D_{c,t} + \boldsymbol{X_{ct}'\gamma^{h}} + \alpha_{r(c),t}^{h} + \alpha_{c,m(t)}^{h} + \epsilon_{c,t+h} \qquad (8)$$

For any given focal county, *c*, we split all other counties into B separate distance bands ("donuts") indexed by b, which we identify by the band's lower bound. We consider distance bands of 50 – 199 miles (b = 50), 200 – 399 miles (b = 200), and 400 – 599 miles (b = 400).

The treatment variable $D_{c,t}^{b}$ is then defined as the share of population within distance band b from county c that was in counties that experienced a disaster in period t:

$$D_{ct}^{b} \equiv \sum_{i \neq c} 1[b \leq d_{ci} < b'] \omega_{ci} D_{it}, \qquad (9)$$

where

$$\omega_{ci} \equiv \frac{pop_i}{\sum_i 1[b \leq d_{ci} < b'] pop_i}, \qquad (10)$$

and pop_i denotes population of county *i* and d_{ci} denotes the distance between the population centroids of counties *c* and *i*. For example, if county c has 10 million people living within 200-399 miles of it, and there is a disaster in year t in a county or counties in that band covering a population of 2 million, then $D_{c,t}^{200}$ would be 0.2.

VI. Baseline Results

We now present our baseline IRF estimates, which come from estimating β^{h} in equation (1) above. The results are shown in **Figure 3**. The shaded areas around the coefficient estimates represent 90 and 95 percent confidence intervals, calculated based on errors that are robust to

heteroscedasticity and clustering by county (to account for serial correlation). Recall that these IRFs should be interpreted – in line with an average treatment effect interpretation – as estimates of the average cumulative difference between the actual outcome for a county hit by a disaster and the counterfactual outcome for that county had it not been hit by a disaster. In other words, a point estimate on the horizontal zero line in the IRF graphs does *not* mean that the level of the outcome variable is equal to its pre-disaster ($t - 1$) level, but rather that it is equal to our estimate of what it would have been in a no-disaster counterfactual. This no-disaster counterfactual reflects region-by-time and county-by-calendar month (or quarter) fixed effects as well as the controls in equation (2).

A. Personal Income Per Capita

Panel (a) shows the estimated IRF for personal income per capita (p.c.). We find a sharp drop, equal to roughly –0.1%, in income p.c. in the year the disaster hits. To put this magnitude in perspective, note that average annual growth in income p.c. in our sample is 1.9%. Thus, a county hit by a disaster tends to experience about 5% lower income p.c. growth in that initial year than they would have experienced otherwise. However, after this initial drop, we find that income p.c. not only recovers to the no-disaster counterfactual but actually rises well above it. As of one year out, income p.c. is nearly 0.2% higher. Income p.c. remains about that much higher for the next several years and then increases more around 6 to 7 years out. As of 8 years out, income p.c. is estimated to be a little over 0.6% above where it otherwise would have been. Recalling the hypothetical scenarios in **Figure 2**, these baseline results on income p.c. seem most consistent with the "build back better" scenario. To explore what is driving this increase in personal income, we next examine IRFs for employment and wages.

B. Related Outcomes

To help understand the mechanisms driving the longer-run positive response of income per capita to disasters, we next estimate the disaster IRFs for several other outcomes. We start with the estimated IRF for total nonfarm employment, which is estimated at a monthly frequency. The results are shown in panel (b) of **Figure 3**. Consistent with an initial disruption in activity, employment falls sharply, by about 0.09%, in the month of the disaster. Average monthly employment growth in our sample is approximately 0.16%, so this initial

impact amounts to cutting that month's employment growth by more than half. The initial decline carries over into the next month, but then rises significantly over subsequent months for an extended recovery period, with employment peaking around one year out. After this recovery period, employment gradually returns to the no-disaster counterfactual. As of eight years out, the point estimate suggests modestly higher employment of about 0.2% but it is not statistically significant.

To get a better sense of the extent to which the overall employment response is driven by recovery and rebuilding efforts, we look at the response of construction employment in Panel (c). As with total employment, there is a sharp decline in the month of the disaster, followed by a recovery period with local construction employment peaking about a year out, when construction employment is estimated to be roughly 1.2% higher than in the no-disaster counterfactual. This is about six times larger than the total employment response at that horizon. The IRF of construction employment beyond one year flattens out somewhat but then, unlike total employment, steadily rises over the medium to longer run. As of eight years out, construction employment is estimated to be over 3% higher than it would have been in absence of the disaster. This suggests that the process of repairing and rebuilding public and private structures is, on average, quite long-lasting.

Panel (d) shows the quarterly IRF for average weekly wages (AWW) of local workers. AWW reflect the product of weekly hours and the hourly wage. AWW rise steadily after a disaster; by the end of the 8-year horizon, we estimate that AWW are about 0.4% higher than they would have been in absence of the disaster. This rise could be driven by an increase in hours worked per week, the hourly wage, or a combination of the two. There are at least two potential channels for the rise in AWW. First, disasters could increase local labor demand related to recovery efforts which, combined with a sluggish extensive-margin labor supply response (due, for example, to temporarily reduced housing stock and/or frictions on the in-migration of additional workers with the necessary skills for reconstruction work), could push up both hours and hourly wages. Second, there could also be a compositional shift in the types of workers in a county after a disaster – for example, a shift toward higher-wage construction workers and away from lower-wage workers in retail and leisure and hospitality. *A priori*, one might not expect either of these two channels to be as persistent as the AWW increase that we find. However, the

long-lasting increase in construction employment found in panel (c) suggests that both could be fairly persistent.

Panel (e) displays the estimated IRF for quarterly house prices, based on the CoreLogic repeat-sales house price index. We find that the house price index increases very modestly in the near-term and then more substantially over the longer term. As of eight years after a disaster, the local house price index is estimated to be about 1.4% higher than it would have been otherwise. While the initial modest increase likely reflects a reduction in housing supply due to disaster damage, the longer run positive price effect could be explained by a steady or increasing demand for housing – consistent with the AWW and employment responses – combined with a persistently reduced supply. It is also possible that the higher house price path reflects a higher quality of homes in the rebuilding process or a shift in the composition of houses being resold for the CoreLogic repeat sales index. That is, it is possible that homes are being rebuilt in more resilient locations or using better methods and materials, reflecting a shift in quality that won't be captured in a repeat-sales index.

The results for population are shown in panel (f). We find that, on average, the response of population to a disaster is small and generally statistically insignificant up to at least eight years out. This suggests that the positive response found for personal income per capita is indeed driven by an increase in the numerator, personal income, rather than a decrease in the denominator, population.[32,33]

C. Government Transfers

Lastly, we examine the impact of disasters on government transfer income, including disaster aid, and loans. As discussed in Section III, natural disasters can trigger substantial disaster and non-disaster government transfers and loans. Here, we consider direct disaster relief from FEMA's Individual and Household Program (IHP) aid, Small Business

[32] As shown in **Appendix Figure A4**, we obtain a somewhat different result if we use an alternative specification that replaces the county-specific pre-disaster linear time trend variable with a county-specific full-sample linear time trend variable (i.e., an interaction between the county fixed effect and year). As mentioned earlier, our preferred specification does not include the latter because it is potentially endogenous with respect to the disaster treatment. Nonetheless, using that specification yields results that are broadly similar to the baseline results for all outcomes except population. This specification yields an IRF for population that is steadily declining over time. As of eight year out, population is estimated to be a little over –0.1% below the no-disaster counterfactual.

[33] In **Appendix Figure A5**, we drill down into the population response by estimating the IRFs for in-migration and out-migration. We find that the near-zero population response is *not* due to a lack of migration responses. Rather, there are large negative responses over the longer-run of both in-migration and out-migration that roughly cancel each other out.

Administration (SBA) disaster loans (which can go to both households and businesses), and National Flood Insurance Program (NFIP) payouts. Note that IHP transfers and NFIP payouts are subcomponents of the BEA's measure of personal income, while SBA loans are not part of personal income but could potentially affect personal income over the medium to longer run.[34] Disasters may also trigger significant transfer payments from non-disaster safety-net programs, especially Unemployment Insurance (UI) and Income Maintenance programs (such as Temporary Assistance for Needy Families, Medicaid, and the Earned Income Tax Credit).

The results for these government programs are shown in **Figure 4**, panels (a)-(f). Panels (d) – (f) show the post-disaster increases for IHP aid, SBA loans and NFIP payouts, in log per capita terms.[35] As one would expect, each of these aid outcomes increases substantially after a natural disaster. The data on these variables do not record the timing of the payouts, so these responses should not be interpreted as occurring all in the initial year, but rather represent the cumulative increase over all post-disaster years. Panel (a) shows that overall government transfers increase substantially in the first few years after a disaster, but are actually reduced over the longer run. This longer run decline appears to be driven by lower income maintenance transfers, as shown in panel (b). UI transfers, on the other hand, are elevated for the first few years but are essentially unchanged over the longer run (see panel (c)). The lack of any longer run increase in these safety-net transfers is consistent with the results in **Figure 3**, namely that total employment is unchanged over the longer run while average weekly wages are higher, implying that over the longer run fewer local households are likely to qualify for safety-net programs. In addition, the increase in direct disaster aid appears to be too small and too short-lived to result in a longer run boost to total government transfers (as apparent by the decline seen in panel (a)).

D. Summary of Baseline Results

Our baseline results point to a longer-run increase in local personal income after a natural disaster. Given the longer-run decline in local government transfer income, the increase in personal income appears to stem from higher labor income, which in turn appears to stem from a

[34] IHP aid is included in the Other Transfers subcomponent of the Total Government Transfers component of Personal Income. Insurance payouts are included in the Current Transfer Receipts of Individuals from Businesses component of Personal Income. See BEA (2017).

[35] Because these disaster-specific aid variables yield many observations with zeros, we use the log of the observed per capita aid amount plus 1.

longer-run increase in labor earnings (average weekly wages) rather than employment.[36] This increase in earnings is consistent with a long-lasting process of recovery and rebuilding – as reflected by the long-run increase in construction employment – along with, potentially, productivity gains from improved local public and private capital stock. The hypothesis that the local capital stock is substantially improved is supported by our finding of higher house prices over the longer run.[37] A shift in composition to higher income individuals choosing to live in areas that have been built back better after disasters would also be consistent with these phenomena.

VII. Heterogeneity and Spatial Spillovers

Although the average dynamic response of local economic activity to natural disasters presented above is informative, the response to any given disaster is likely heterogeneous, varying along several important dimensions that we explore in this section. In particular, we consider heterogeneity in terms of disaster severity, disaster type (i.e., floods, hurricanes, etc.), county historical experience with disasters, and county income prior to the disaster.

A. Heterogeneity in disaster severity

As described in section V.B., we allow the impulse response of a given outcome to a disaster to vary as a function of the monetary damages caused by the disaster. Examining the same six economic outcomes as in **Figure 3**, **Figure 5** displays the estimated IRFs for different levels of damages corresponding to various percentiles of the distribution of (non-zero) damages p.c. in our sample.[38] In particular, in each panel the solid thick blue line depicts the IRF corresponding to a disaster with per capita damages equal to the 50th percentile of all disasters (with positive damages), while the thick solid orange line depicts the IRF for a disaster with per capita damages equal to the 99th percentile. The thin solid, dashed, and dash-dotted lines show the IRFs for other percentile damages.

[36] This interpretation is also supported by IRF estimates for the wage and salary component of personal income, which is provided in **Appendix Figure A6**. The IRF for wage and salary income p.c. is similar to that for personal income p.c.

[37] Note that if the increase in the house price index reflects an increase in the *quality-adjusted* cost of housing services, then it implies an increase in local consumer prices (cost of living), which could offset the benefits of higher income for local residents.

[38] For completeness, we also provide results by severity for the government transfer income and disaster relief in **Appendix Figure A7**.

Panel (a) shows the results for personal income p.c. The IRF for a median-damages disaster is quite similar to the IRF for the mean disaster shown in **Figure 3**, panel (a), with a modest initial drop followed by a modest positive response over the medium run and a larger positive response over the longer run. In particular, personal income p.c. following a median-damages disaster is estimated to be around 0.6% higher after eight years. Note also that the 25th percentile IRF is visually indistinguishable from the 50th. In fact, notable differences in either the level or shape of the IRF do not really emerge until damages rise above the 95th percentile. For the most severe disasters – those with damages above the 95th percentile – personal income p.c. increases substantially both in the short-run and over the longer-run. For instance, we estimate that a disaster in the top 1% of damages causes personal income p.c. to increase by over 1% in the initial year and by over 1.5% after eight years.

Looking at the analogous results for the other outcomes in panels (b)-(f) allows us to unpack this result. First, we find that the most severe disasters cause large and persistent increases in both total employment (panel b) and average weekly wages (panel d), with employment and AWW up about 0.75% after eight years.[39] Within overall employment, construction employment increases by nearly 6% by 1-2 years after the disaster but then comes down to a level similar to that after a more typical disaster. In other words, the short- to medium-run increase in construction activity after a disaster is much higher for very severe disasters, but the longer-run increase is roughly independent of the disaster's severity.

We uncover an interesting pattern for house prices, in that the medium-run (1-3 years out) response to very severe disasters is strongly positive – peaking at nearly 3% for 99th percentile disasters – while the longer-run response is strongly negative – falling more than 4% for 99th percentile disasters as of 5-6 years out. House prices appear to recover somewhat after that trough, but by eight years out they are still down over 2% (for 99th percentile damages disasters).

This longer-run decline in house prices after very severe disasters may be partially explained by the population responses shown in panel (f). While population responds very little to disasters with damages up to the 90th percentile, population falls substantially after the most severe disasters. This longer-run drop in population should reduce demand for housing, putting downward pressure on home prices.

[39] The large increase in average weekly wages over the longer run is consistent with the worker-level evidence of higher long term wages following the major 2005 hurricanes, Katrina and Rita, provided by Groen, et al. (2019)

In addition, the longer-run population response helps understand the magnitude of the longer-run increase in personal income p.c. In particular, we find that a disaster with damages p.c. equal to the 99th percentile causes population to decline by roughly 0.75% after eight years. This result in turn suggests that the roughly 1.5% longer-run increase in personal income p.c. after very severe disasters (panel (a)) is about half due to higher total county personal income and half due to reduced population.

Why do more severe disasters cause larger increases in county income? One possibility is that very severe disasters trigger investment in new, modern public and private infrastructure, funded perhaps by government aid as well as private insurance, which spurs local economic development, consistent with the "build back better" scenario from **Figure 2**. This is not unlike the theory and evidence on war destruction of capital, and subsequent investment-led growth, discussed in Section III. Another possibility, consistent with the large decline in population, is that the composition of households in affected counties is changed by the most severe natural disasters, with lower-income households more likely to move out of the county.[40] This possibility is consistent with Sheldon and Zhan (2019), who find that post-disaster out-migration increases with the severity of the disaster and more so the lower the income of the population.[41]

B. Heterogeneity by type of disaster

In **Figure 6**, we show that there is significant heterogeneity in how personal income p.c. responds to different types of natural disasters. We see substantial medium- to longer-run increases in personal income p.c. for hurricanes, tornados, and fires. However, fires are quite rare in our sample, accounting for just 2 percent of the disasters, and thus their IRFs are imprecisely estimated. Non-hurricane floods, on the other hand, account for 60% of the disasters in our sample. For floods, we estimate a statistically significant negative effect in

[40] Indeed, as shown in **Appendix Figure A5**, we find that after the most severe damages both in-migration and out-migration increase over the medium term, with out-migration apparently dominating such that population falls.

[41] It is worth noting that our finding of a significant longer-run increase in income p.c. after very severe disasters is consistent with the observed pattern of income p.c. following the most severe disaster in our sample, Hurricane Katrina in 2005. Appendix **Figure A8** plots actual income p.c. for Orleans Parish, Louisiana, from 1980 to 2017. Relative to the approximately linear trend up to 2005, income p.c. spikes in the first 2-3 years after the disaster before gradually returning to the pre-disaster growth trend but at a permanently higher level.

the year of the disaster, followed by a modest positive effect in the medium term, and no significant effect in the longer run.

Interestingly, our results on hurricanes here contrast somewhat with prior findings by Strobl (2011). Strobl estimates the effect of hurricanes on income p.c. *growth* for coastal counties in the U.S. and finds that it falls significantly in the initial year then returns to the pre-hurricane growth rate in the following year. This dynamic growth pattern translates into an initial year decline in the *level* of income p.c. that is not made up thereafter (which would require above-trend growth in the following year), which contrasts with our positive impact even in the first year. Strobl's estimates do not speak to whether income rises or falls beyond one year out.

We show results for heterogeneity by disaster type for other outcomes in **Appendix Figure A9**. These results show that there is heterogeneity in what drives the personal income patterns for different disaster types. For example, the solid growth in personal income p.c. following hurricanes appears to be driven both by persistent increases in employment and average weekly wages which on net outpace more modest increases in population. In contrast, the climb in personal income p.c. after tornados appears to be driven by rising wages, as employment is relatively flat. Similar to our baseline results, a persistent rise in average weekly wages alone can explain the modest increase in income p.c. after non-hurricane floods.

C. Heterogeneity by county pre-disaster income

Figure 7 shows the results of estimating equation (7), which allows for separate IRFs by quartile of pre-disaster county income. We find that our baseline results of a longer-run (as of eight years out) increase in income p.c. after a disaster holds for all four quartiles, though the timing of the increase differs. Specifically, for counties with below-median pre-disaster income p.c., there is no increase in income p.c. (relative to the no-disaster counterfactual) until around 6 years after the disaster. By contrast, above-median counties see a positive response as early as 1 year after the disaster. It is possible that higher income counties have more private insurance and are thus able to recover and rebuild more quickly.[42]

[42] Looking at the other outcomes (shown in **Appendix Figure A10**), we find that the growth in personal income for the top quartile appears to be more driven by employment while for the bottom quartile it is driven more by an increase in wages. In fact, employment falls over the longer run for the bottom quartile. We also find that post-disaster house price increases come primarily from the upper three quartiles, again suggesting that higher income

D. Heterogeneity by historical disaster experience

Finally, we investigate whether disaster IRFs vary with a county's historical experience with disasters. As in the prior subsection, we estimate equation (7) but now $M^{q}_{c,t-1}$ represents one of four categories of county disaster experience, measured using a 10-year trailing count of prior periods (months, quarters, or years) with disasters in that county.[43] The categories are: (a) no periods, (b) 1 period, (c) 2-3 periods, or (d) 4 or more periods with disasters in the previous 10 years, where periods are monthly, quarterly, or annual, based on the outcome of interest.

The results are shown in **Figure 8**. In contrast to the notion that disaster-prone areas adapt and become more resilient to disasters, we find that the immediate decline in income p.c. after a disaster is absent for counties that had not experienced a disaster in the prior ten years. Counties with more recent disaster experience do exhibit an initial decline in income p.c., (though it is not statistically significant for the 4+ group). This may reflect that counties recently hit by disasters may be less able to quickly absorb the effects of subsequent disasters. In the medium- to longer-run, increased personal income p.c. occurs in all cases except for counties that have experienced zero disasters in the prior ten years. This could reflect higher climate change adaptation investment by counties most prone to disasters.[44]

E. The Impact of Disasters in Other Counties

We next turn to our results on spatial spillovers to see how the effects of a disaster in one county propagate to other counties of varying distances away. In **Figure 9**, we show the results of estimating equation (8) for bands of counties that are up to 199, 200-399, and 400-599 miles away from a county affected by a disaster.[45] The thin blue curves show the IRFs for the directly-

counties may be better insured and thus better able to rebuild and improve the housing stock. Construction employment increases across all income quartiles, though the longer-run increase is much larger for the bottom quartile.

[43] The count applies to the number of time periods with disasters. For annual outcomes like personal income, this will show the number of years with any disasters with positive damages, which for monthly outcomes like total non-farm employment, the count will show the number of months with any disasters with positive damages.

[44] When examining other outcomes, shown in **Appendix Figure A11**, the larger longer-run increases in income p.c. for counties with more prior disasters appear to stem from larger increases in average weekly wages (panel d) given that overall employment is, if anything, reduced in disaster-prone areas (panel b). We also find the increase in home prices is stronger in areas with more disaster experience (panel e), where population also appears to increase more (panel f).

[45] See **Appendix Figure A12** for a visual illustration of the spatial lags for a single year of disasters.

hit counties, while the orange curves show the spatial lag IRFs.[46] These results show that nearby counties (within 199 miles) experience a medium-run boost to personal income, consistent with residents of nearby counties participating in recovery efforts and experiencing positive spillovers (panel (a)). However, these counties do not appear to share in any longer run boost to income per capita. Counties that are 200-399 miles away see a persistent decline in personal income, as shown in panel (b). This could be explained by regional resources being redirected to the counties directly affected by disasters. Counties in the furthest band, 400-599 miles away, experience some modest intermediate gains in income per capita followed by a longer run decline (panel (c)).

In panel (d) we show an estimate for the net effect on personal income per capita within 600 miles of disasters. Here we estimate the sum of the four curves shown in panels (a) – (d), where each IRF is rescaled by multiplying each of the β^h and $\pi^{h,b}$ terms by the unconditional mean of the corresponding variable. With the estimated $\hat{\beta}^h$ and $\hat{\pi}^{h,b}$ coefficients representing the average effect for a county within each category at each horizon, intuitively, we are taking an average of the contribution of these responses to estimate a net effect. This post-estimation rescaling of the IRF coefficients is equivalent to a pre-estimation mean-normalization. These results suggest that while the longer run *local* impact of a disaster on income per capita in the area directly hit by a disaster is positive, the longer run impact for the broader region appears to be negative. This could result from resources being diverted from other counties in a region to those hit by disasters.

[46] In panels (a)-(c), the spatial lag coefficients have been normalized such that $D_{c,t}^b$ has been divided it by its mean, conditional on $D_{c,t}^b > 0$. Given this normalization, a one-unit change in each spatial lag variable represents the average population share in that distance band of disaster-hit counties in the event of at least one disaster. These conditional means vary slightly across horizons because the regression samples are horizon-specific. For the 50-199 mile band, the conditional mean varies from 0.27 to 0.28. For the 200-399 band, it rounds to 0.24 across all horizons; and for the 400-599 band, it varies from 0.23 to 0.24. The coefficients $\pi^{h,b}$ can then be interpreted as the impact in county *c* from the average disaster event hitting at least one county *b* to *b'* miles away.

VIII. Conclusion

We have shown that the average response of local economic activity to natural disasters is quite dynamic over the short- to medium- to longer-run. In particular, personal income per capita in a county hit by the average disaster declines significantly in the year of the disaster, but then recovers and rises over subsequent years to a level above where it would have been otherwise. While a rise in employment contributes to the initial boost, we find the longer-run increase in income per capita is driven largely by an increase in average weekly earnings rather than an increase in employment or a decrease in population. This could be explained by disasters causing a persistent labor demand shock combined with inelastic labor supply.

We have also found that there is significant heterogeneity in disaster effects. The post-disaster response of personal income per capita depends on the severity of the disaster, the type of disaster, the pre-disaster income level of the county, and the frequency by which the county has experienced disasters in the past. We find that the positive medium- to longer-run effect of disasters on personal income per capita is amplified for more severe disasters. For the most severe disasters, part of the effect is due to a drop in population, though most of it comes from an increase in the aggregate county income. Across disaster types, we find that the longer-run increase in income per capita is true for all types except extreme winter weather and severe storms; the increase is largest for tornadoes, fires, and hurricanes. We find that the longer-run increase holds for both rich and poor counties, as measured by their pre-disaster levels of income per capita. Lastly, we find that the longer-run increase in income per capita is strongest for counties that have experienced past disasters (over the previous ten years); counties without that recent disaster experience see no significant effect on income per capita after around four years.

Last but not least, while the main focus of this paper has been on the *local* impact of natural disasters, our spatial lag analysis suggests that the long run increase in personal income locally may come at the cost of, and be more than offset by, a long run decline in personal income in surrounding counties. This could potentially be explained by a diversion of resources to areas affected by disasters.

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Table 1: Dependent Variable Descriptions

Variable	Frequency	Form	Winsorized	Per capita	Source
Personal income	annual	log	no	yes	BEA
Total nonfarm employment	monthly	log	0.5, 99.5	no	QCEW
Construction employment	monthly	log	0.5, 99.5	no	QCEW
Average weekly wages	quarterly	log	0.5, 99.5	no	QCEW
House price index	quarterly	log	0.5, 99.5	no	CoreLogic
Population	annual	log	0.5, 99.5	no	Census
Government transfers	annual	log	no	yes	BEA
Income maintenance transfers	annual	log	no	yes	BEA
UI transfers	annual	log	no	yes	BEA
FEMA IHP aid	annual	$\log(1+\cdot)$	0.5, 99.5	yes	FEMA
SBA disaster loans	annual	$\log(1+\cdot)$	0.5, 99.5	yes	SBA
NFIP payouts	annual	$\log(1+\cdot)$	0.5, 99.5	yes	FEMA
Wage & salary income	annual	log	no	yes	BEA

Note: Although the IHP Aid and NFIP Payment data are available at higher frequency in terms of the disasters which they cover, we use them entirely in annual terms as they are combined with annual SBA Loan data to examine the effect of aid on annual outcomes. Furthermore, we do not observe when the IHP aid and NFIP claims are paid out, but only when the damages they apply to occur. Note that the annual SBA Loan data are based on the fiscal year closing at the end of September each year. We examine $\log(1+\cdot)$ form for the aid variables to address the very high share of observations with 0 aid.

Table 2: Summary Statistics

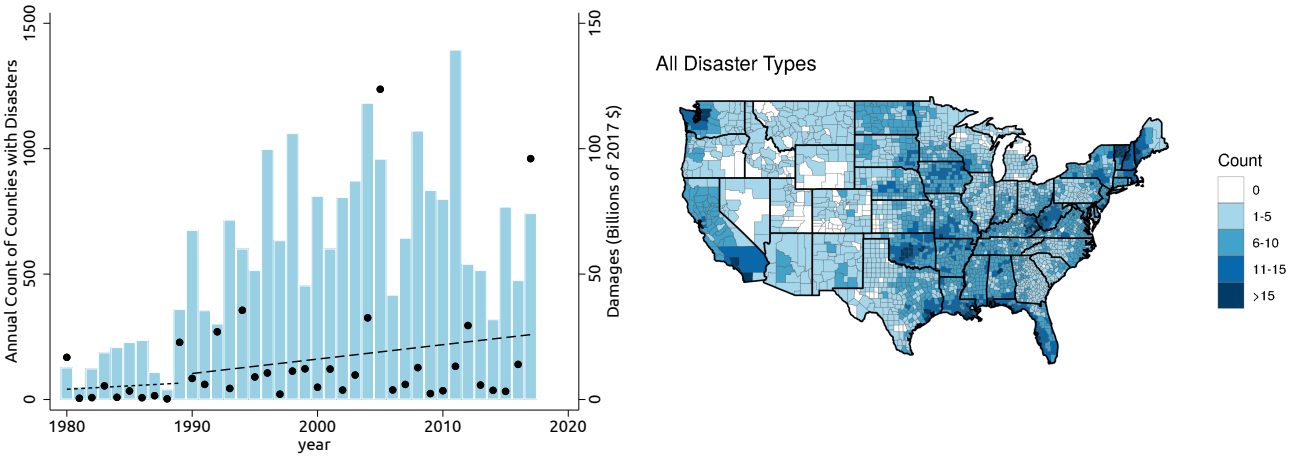
	Mean	Std Dev	Min	Max	N
Personal income p.c.	23,201	11,991	2583	204,67	111,516
Total nonfarm employment	30,501	117,547	0	3,875,009	1,317,168
Construction employment	2,566	7,609	0	181,710	662,688
Average weekly wages	460	190	0	8,456	441,523
House price index	102	44	19	369	186,560
Population	89,195	290,606	55	10,163,510	116,581
Government transfers p.c.	4,512	2,751	218	18,223	111,516
Income maintenance transfers p.c.	434	328	8	2,995	111,516
UI transfers p.c.	113	104	8	2,995	111,516
FEMA IHP aid p.c.	3	47	0	6,548	116,581
SBA disaster loans p.c.	5	100	0	14,282	92,037
NFIP payouts p.c.	5	151	0	34,950	116,581
Wage & salary income p.c.	9,385	7,449	710	272,927	111,516

Source: QCEW, Census, CoreLogic, BEA, FEMA, and SBA.

Figure 1: Natural Disaster Trends and Distribution, 1980 - 2017

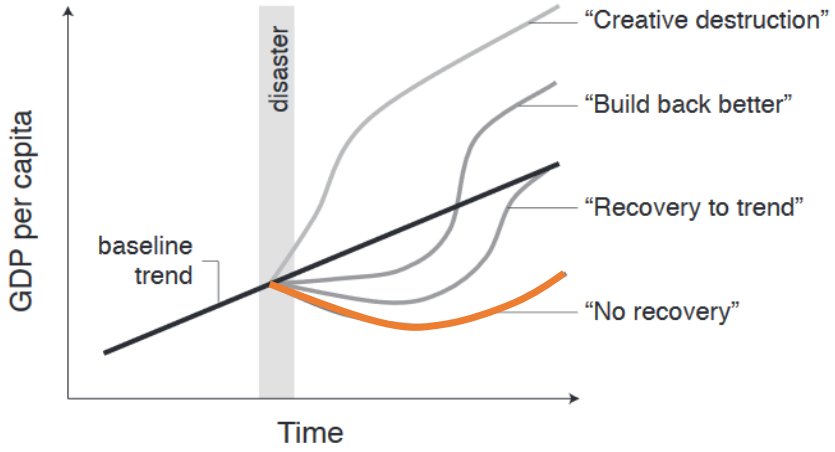
(a) Disaster Frequency and Damages

(b) Geographic Distribution of Disasters



Source: FEMA and SHELDUS.
Note: The count in panel (a) shows the number of counties each year with at least one disaster declaration. The count in panel (b) shows the number of years with disaster declarations for each county over the period 1980-2017.

Figure 2: Theoretical paths for disaster recovery

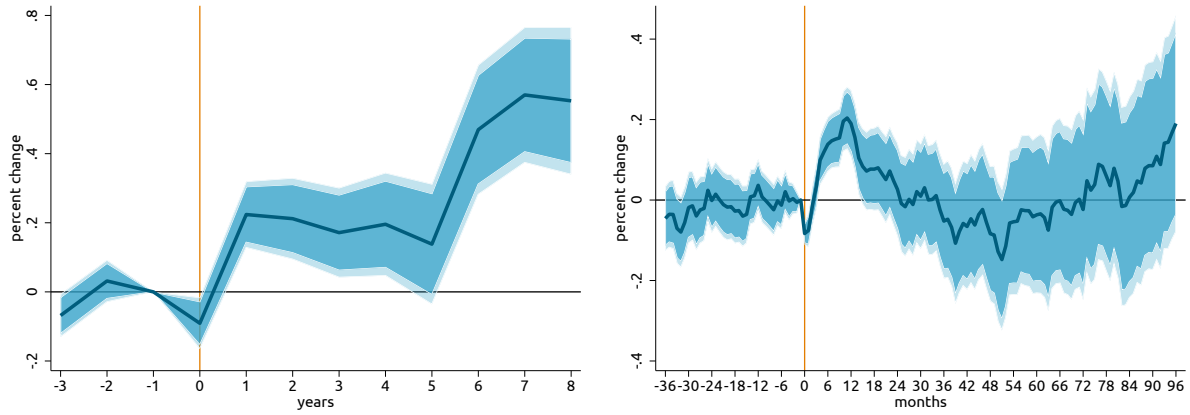


Source: Hsiang and Jina (2014)

Figure 3: Baseline Effects - All Disasters

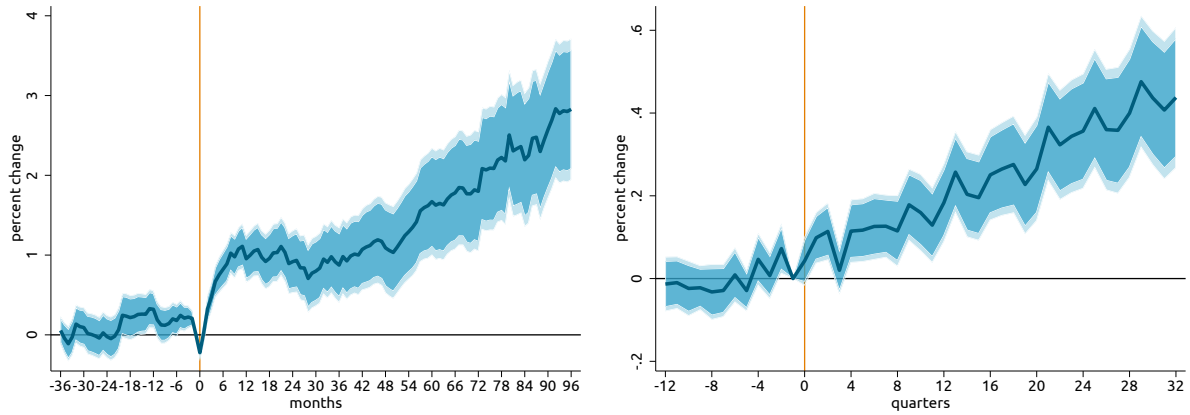
(a) Personal Income (per capita)

(b) Total Nonfarm Employment



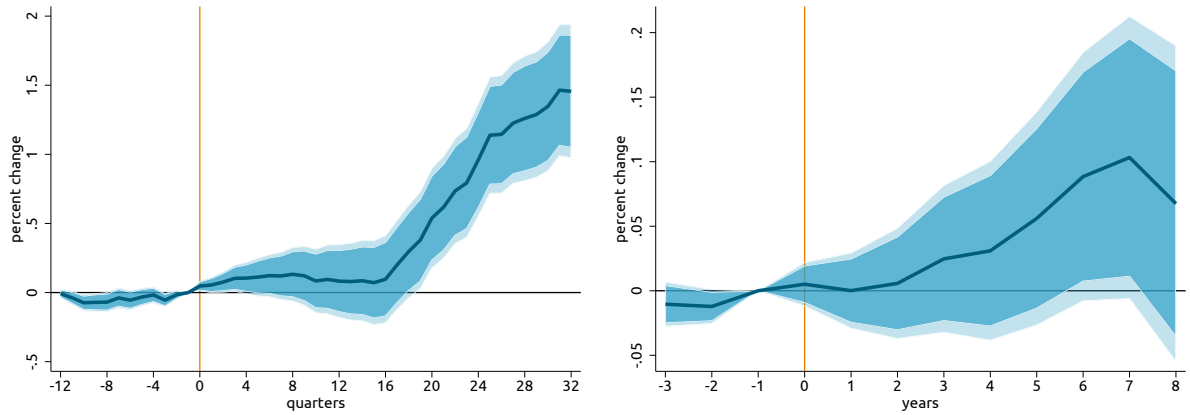
(c) Construction Employment

(d) Average Weekly Wages



(e) Home Prices

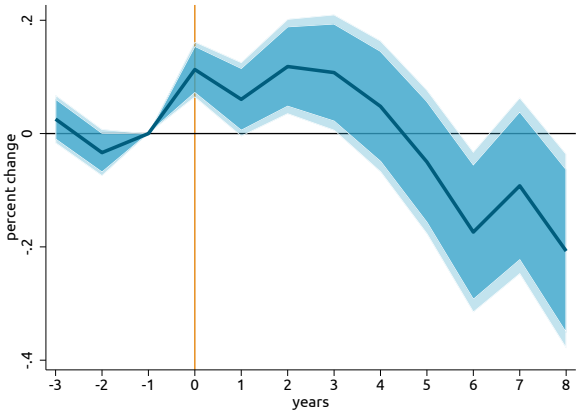
(f) Population



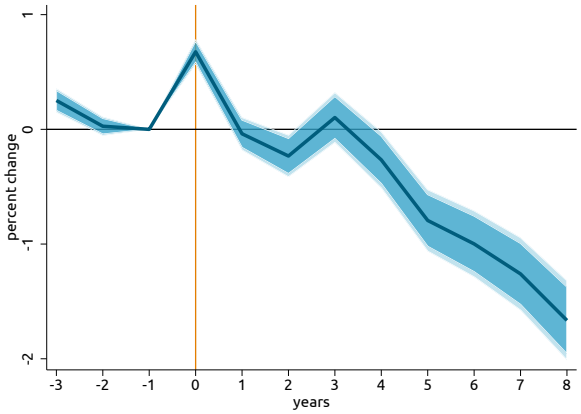
Source: FEMA, SHELDUS, BLS, Census, BEA, and CoreLogic.
Note: These plots show the IRFs from estimating equation (1), where the inner shaded regions indicate the 90 percent confidence intervals, and the lighter outer shaded regions indicate the 95 percent confidence intervals. All variables are observed at the county level and modeled as cumulative differences in logs between the horizon pictured and the period before the disaster ($t = -1$).

Figure 4: Effects on Government Transfers (per capita)

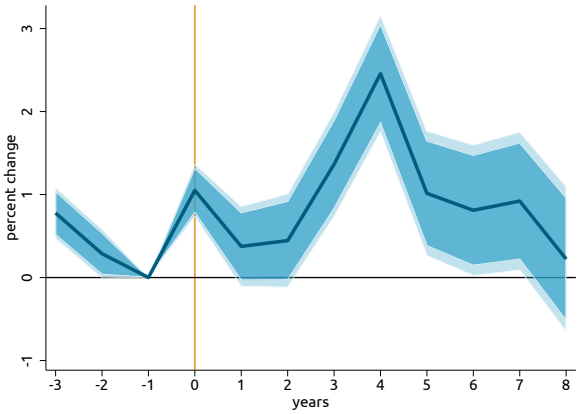
(a) Government Transfers



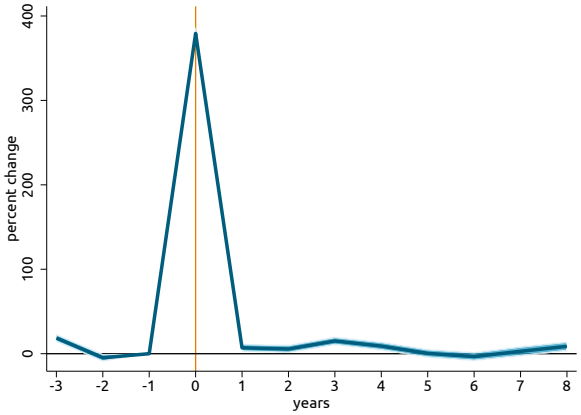
(b) Income Maintenance



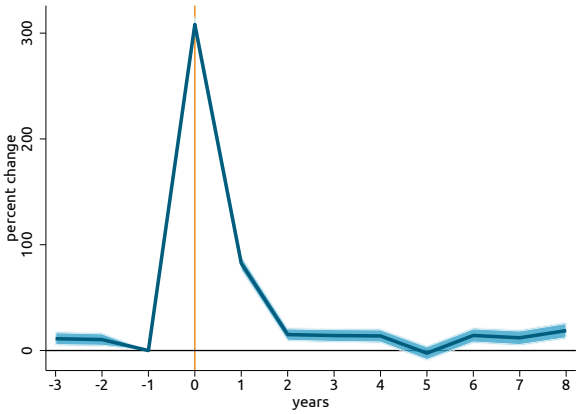
(c) Unemployment Insurance



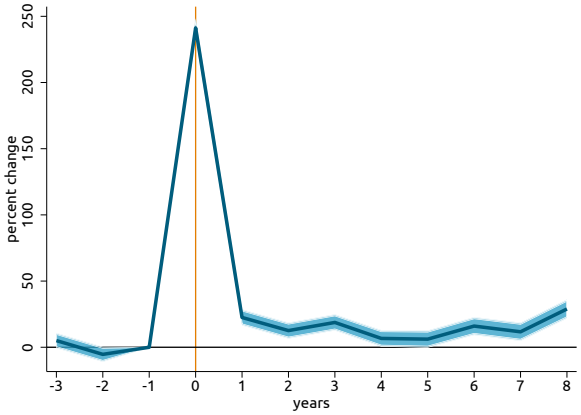
(d) IHP Aid



(e) SBA Loans

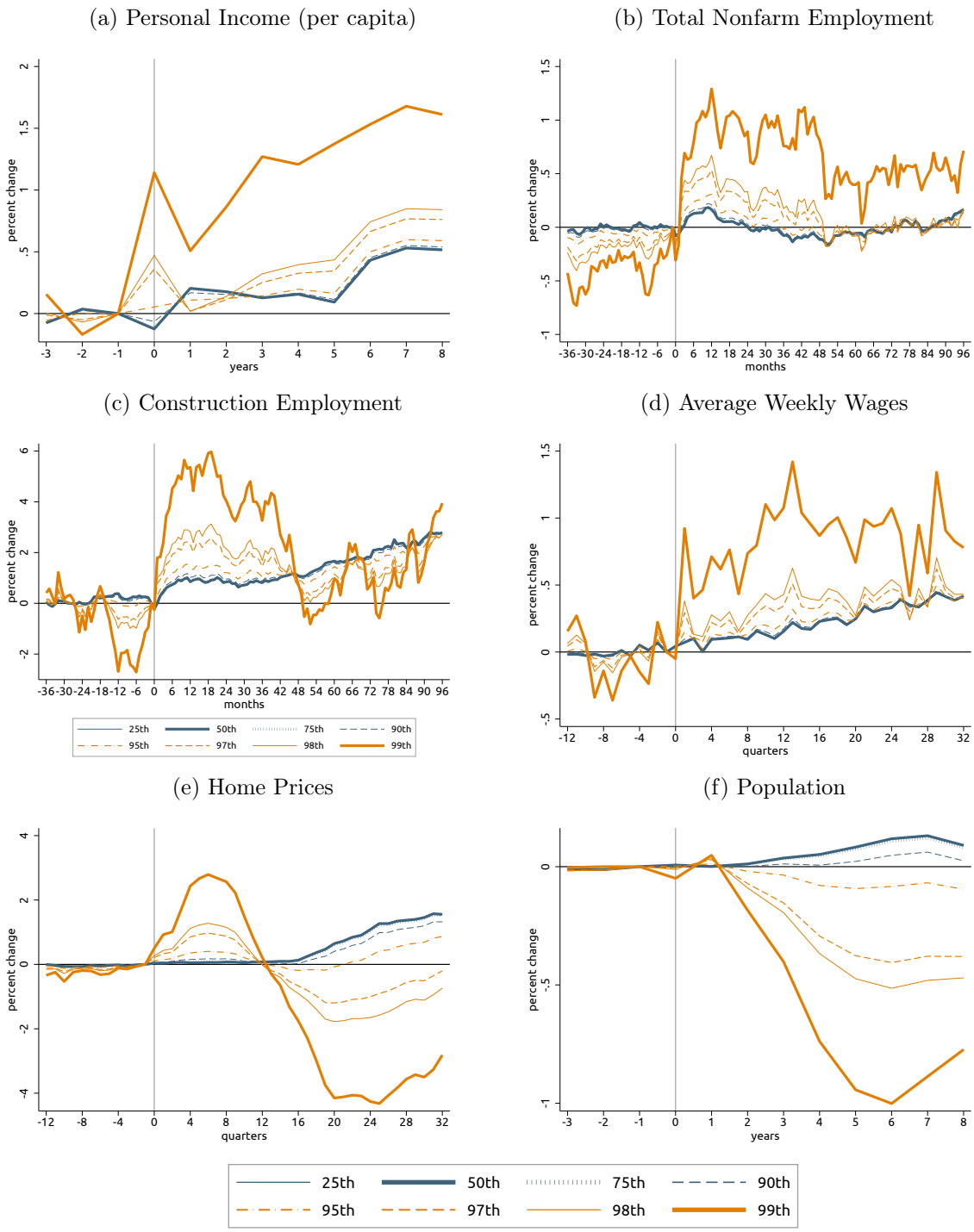


(f) NFIP Payouts



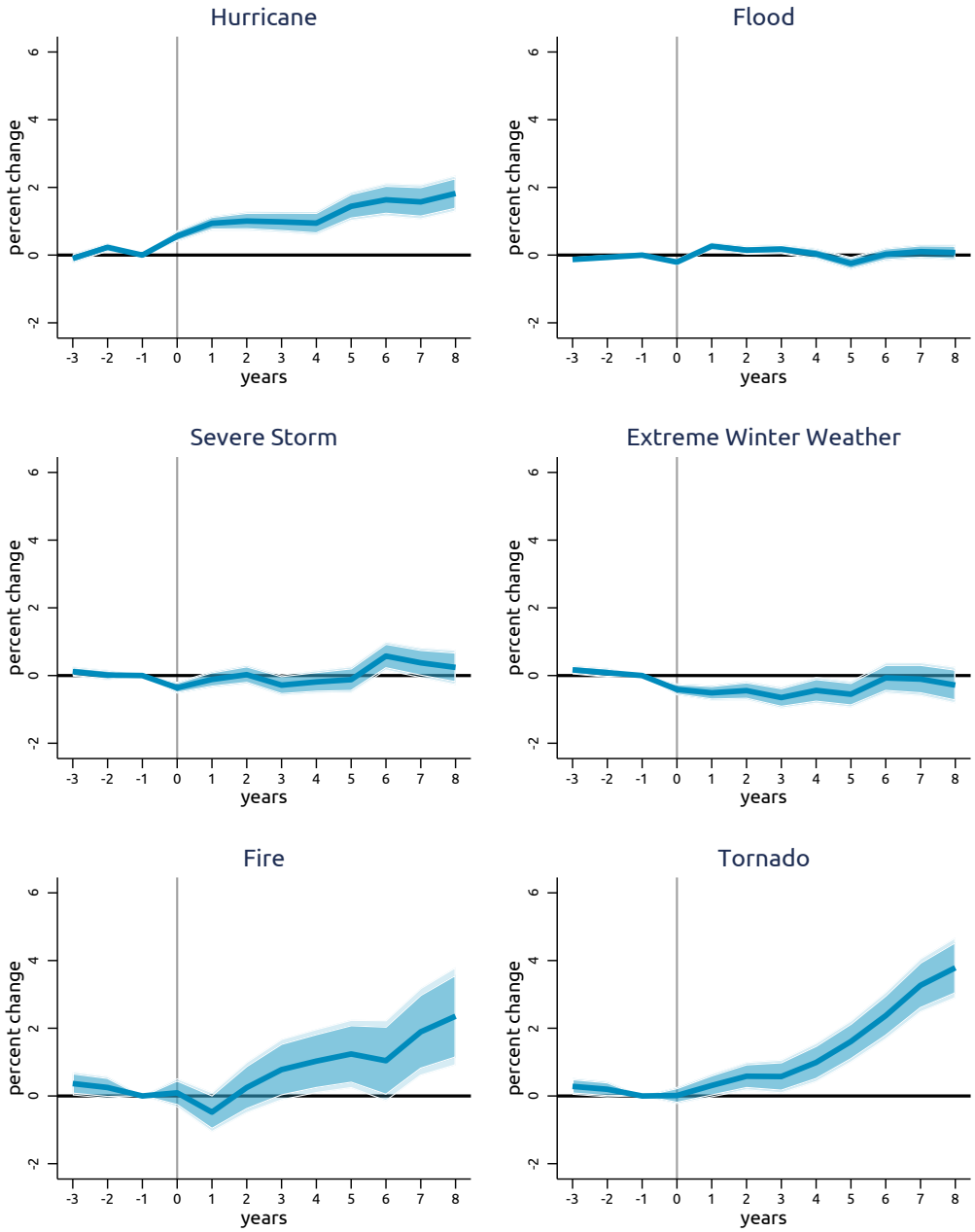
Source: FEMA, SHELDUS, Census, and BEA.
Note: These plots show the IRFs from estimating equation (1), where the shaded regions indicate the 90 and 95 percent confidence intervals. All variables are observed at the county level and modeled as cumulative differences in logs between the horizon pictured and the period before the disaster ($t = -1$).

Figure 5: Effects by Damages Percentile



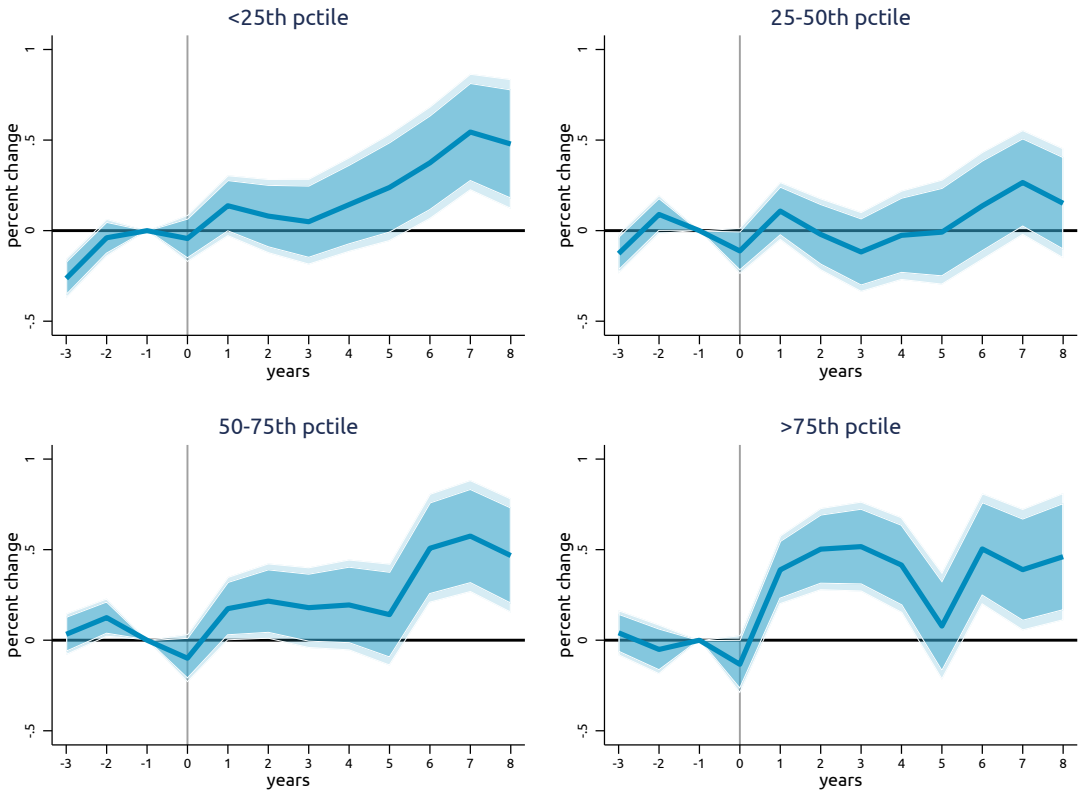
Source: FEMA, SHELDUS, BLS, Census, BEA, and CoreLogic.
Note: These plots show the IRFs from estimating equation (4), where the percentile lines reflect the model predictions given the per capita damage distributions for all county-month observations with FEMA disaster declarations. All variables are observed at the county level and modeled as cumulative differences in logs between the horizon pictured and the period before the disaster ($t = -1$).

Figure 6: Personal Income (per capita) Effects By Disaster Type



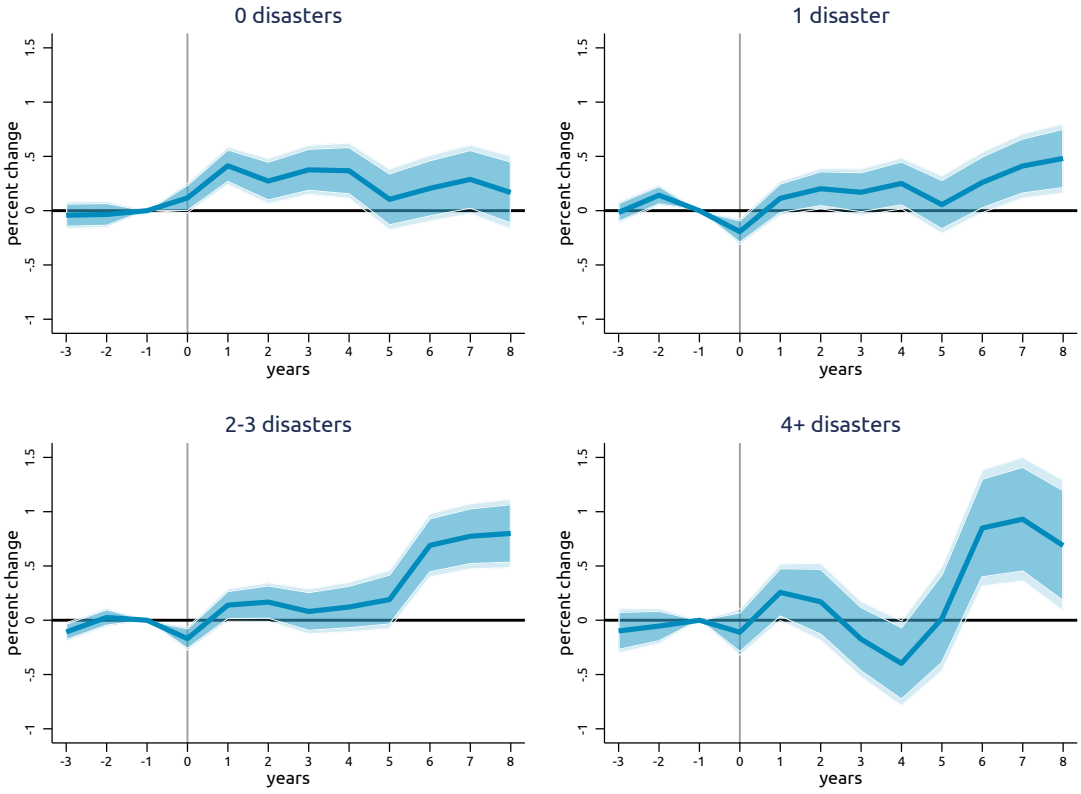
Source: FEMA, SHELDUS, BEA, and Census.
Note: These plots show the IRFs from estimating equation (5), where the shaded regions show the 90 and 95 percent confidence intervals. The disaster type categories are based on FEMA declaration types and titles, with the flood category excluding floods associated with hurricanes. One disaster cannot have two categories, however, within a year a county can experience multiple disaster types. Personal income per capita is observed at the county level and modeled as cumulative differences in logs between the horizon pictured and the period before the disaster ($t = -1$).

Figure 7: Personal Income (per capita) Effects By Initial Personal Income Per Capita



Source: FEMA, SHELDUS, BEA, and Census.
Note: These plots show the IRFs from estimating equation (7), where the shaded regions show the 90 and 95 percent confidence intervals. The quartiles of initial personal income per capita are based on the personal income in year -1 relative to the national distribution in that year. Personal income per capita is observed at the county level and modeled as cumulative differences in logs between the horizon pictured and the period before the disaster ($t = -1$).

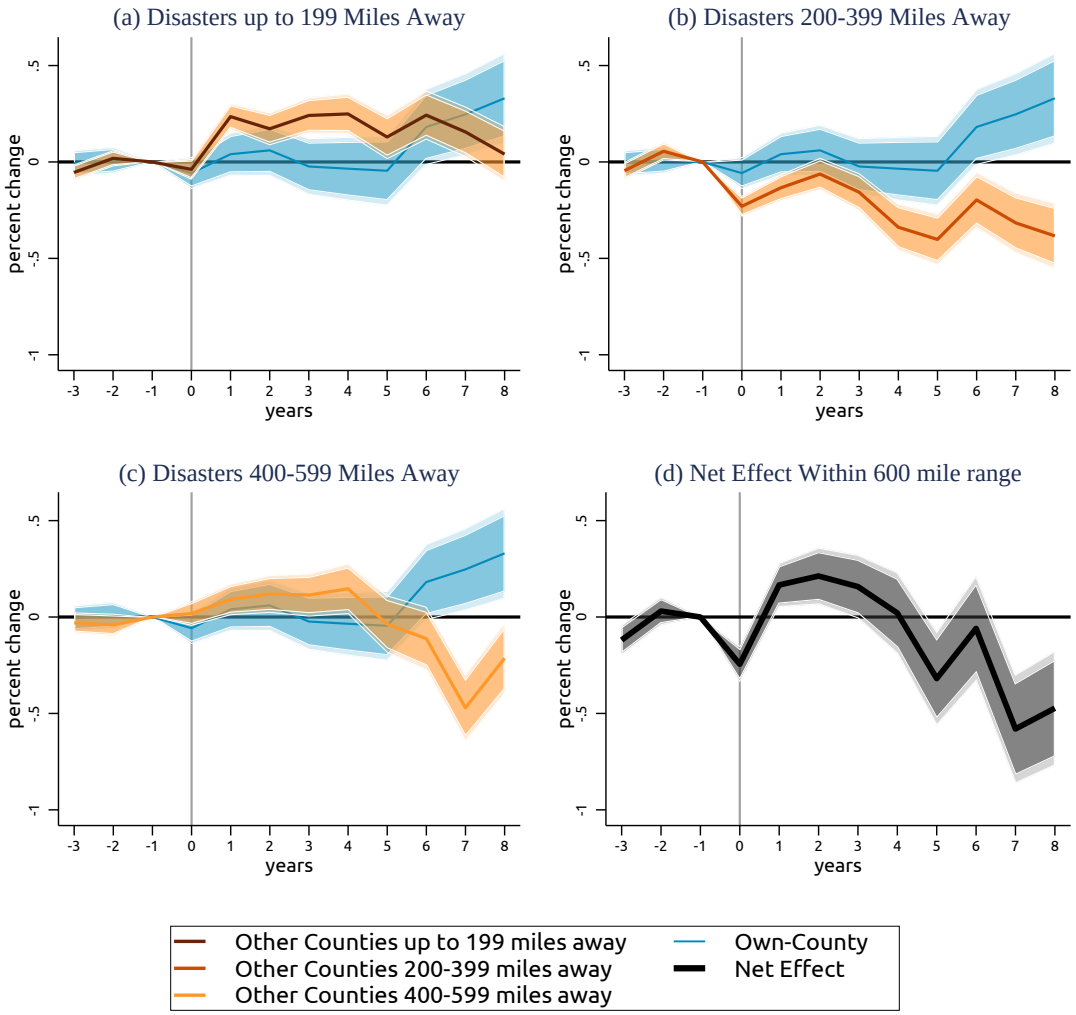
Figure 8: Personal Income (per capita) Effects By Local Historical Disaster Exposure



Source: FEMA, SHELDUS, BEA, and Census.
Note: These plots show the IRFs from estimating equation (7), where the shaded regions show the 90 and 95 percent confidence intervals. The four categories of historical disaster experience (0, 1, 2-3, and 4+) represent the number of years within years -10 to -1 in which a county experienced a major disaster with positive damages. Personal income per capita is observed at the county level and modeled as cumulative differences in logs between the horizon pictured and the period before the disaster ($t = -1$).

Figure 9: Impacts of Own-county Disasters vs. Spatially-Lagged Disasters on Personal Income (p.c.)

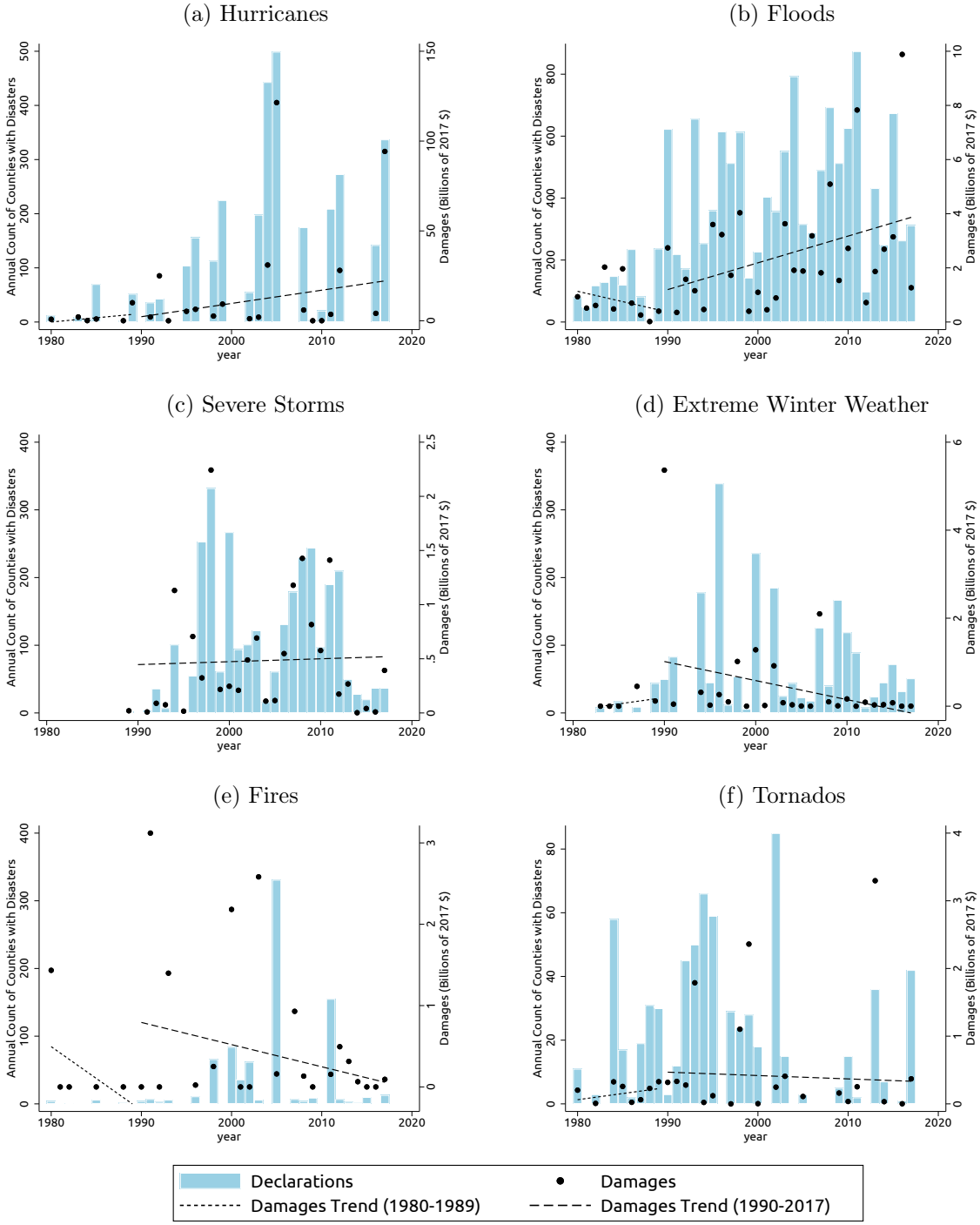
Results for spatial lags of varying distance bands



Source: FEMA, SHELDUS, Census, and BEA.
Note: Panels (a)-(c) show the IRFs from estimating equation (8), where the shaded regions show the 90 and 95 percent confidence intervals. The thin blue curve (repeated in each panel) reflects the IRF estimated for counties directly experiencing a disaster. The orange curves depict the IRFs for the counties within the indicated mile ranges of counties experiencing disasters. The intensity of treatment for the orange curves is the share of population within each band that has experienced a disaster in period 0. Each of the orange curves has been rescaled by the mean population share for positive observations within the band. Thus the curves represent the average effect on counties having at least one county within the given range experience a disaster in period 0. Panel (d) shows the net effect on personal income within these bands, where each coefficient has been rescaled by the variable's unconditional mean. Personal income per capita is observed at the county level and modeled as cumulative differences in logs between the horizon pictured and the period before the disaster ($t = -1$).

Appendix A

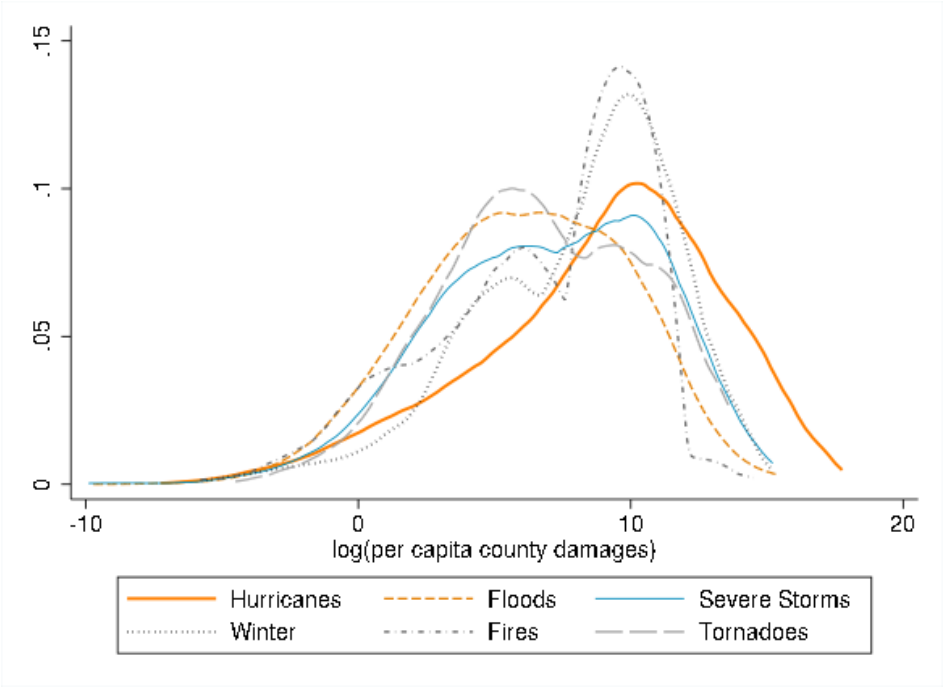
Figure A1: The Frequency and Costs of Disasters 1980 - 2017



Source: FEMA and SHELDUS.

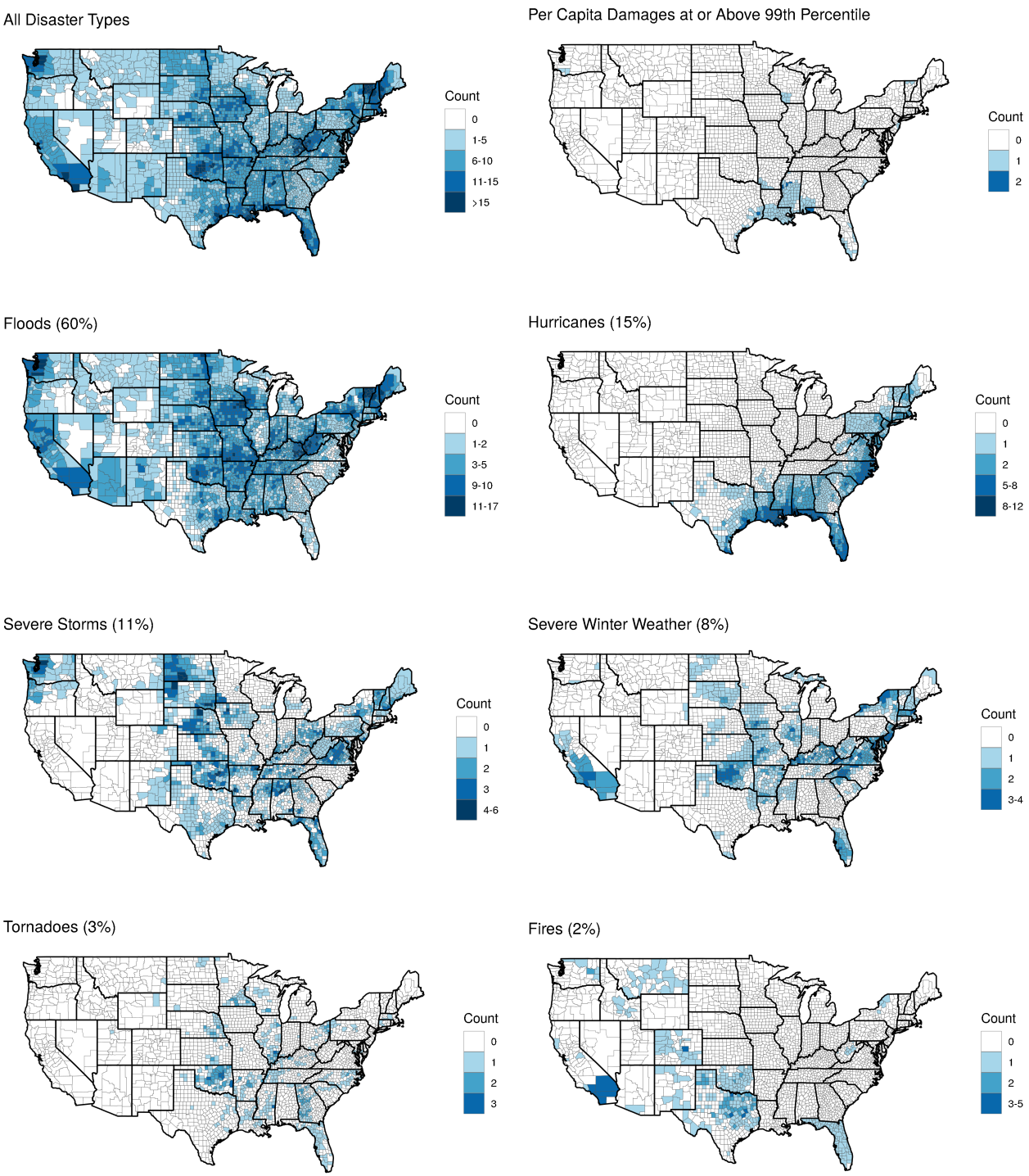
Note: The blue bars show the number of counties each year with at least one disaster declaration in the listed categories. The black dots indicate total damages in USD 2017. If a county experienced flooding due to a hurricane, that will show up only on the hurricane plot. If a county receives two separate disaster declarations in a month, one for a hurricane and one for a flood not caused by the hurricane, this will also only show up on the hurricane plot. Similarly, severe storms exclude disaster declarations with the string "flood" in the title.

Figure A2: Distribution of Per Capita County Damages by Disaster Type



Source: FEMA, SHELDUS.
Note: The y-axis shows density and not frequency.

Figure A3: Distribution of Disaster Declarations

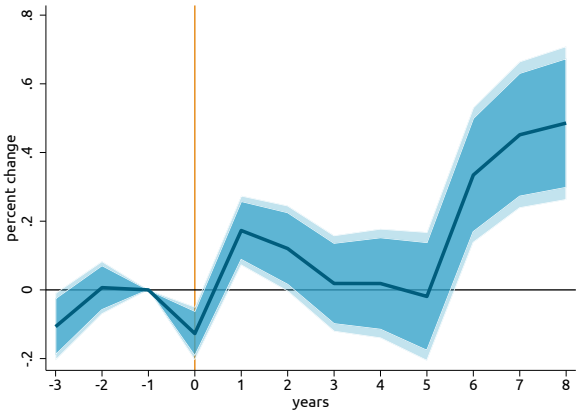


Source: FEMA, SHELDUS.
Note: The All Disaster Types map shows counts of months with at least one disaster with damages reported in SHELDUS. The Per Capita Damages at or Above 99th Percentile map shows the number of months a county's disasters had per capita damages in the 99th percentile of those with FEMA disaster declarations from 1980 to 2017. The remaining maps show the counts of months in which the disaster type was declared in a given county with some hierarchical ordering. If a county experienced flooding due to a hurricane, that will show up only on the hurricane map. If a county receives two separate disaster declarations in a month, one for a hurricane and one for a flood not caused by the hurricane, this will also only show up on the hurricane map.

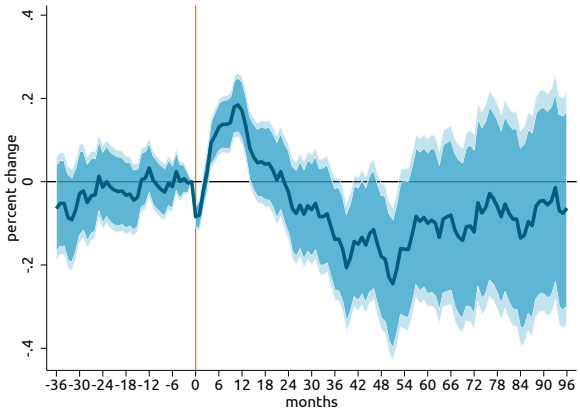
Figure A4: Alternative Specification - County-Specific Linear Time Trend

Impacts - All Disasters

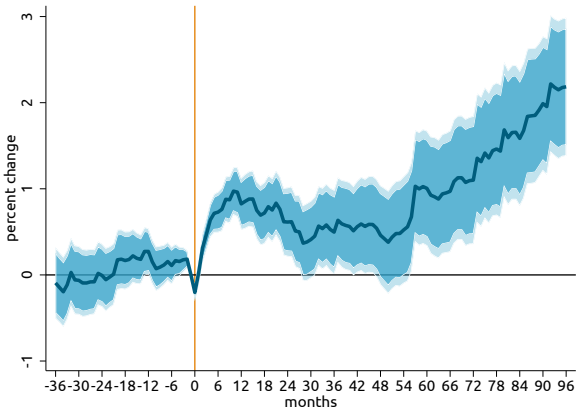
(a) Personal Income (per capita)



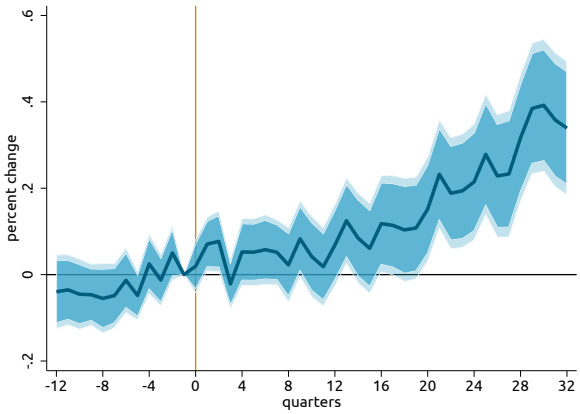
(b) Total Nonfarm Employment



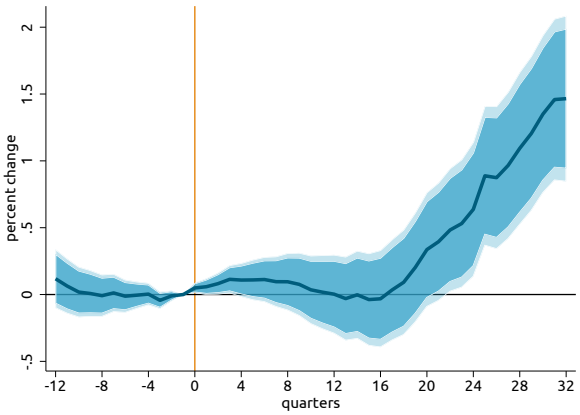
(c) Construction Employment



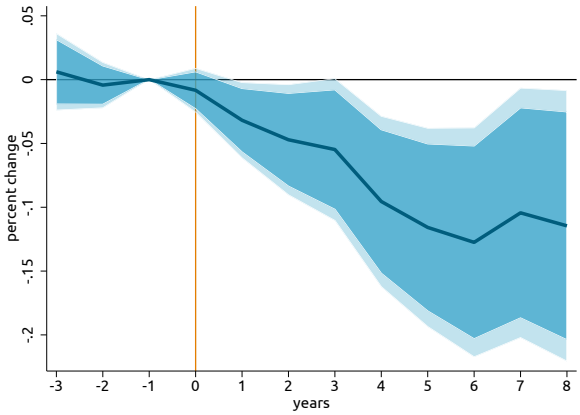
(d) Average Weekly Wages



(e) Home Prices



(f) Population

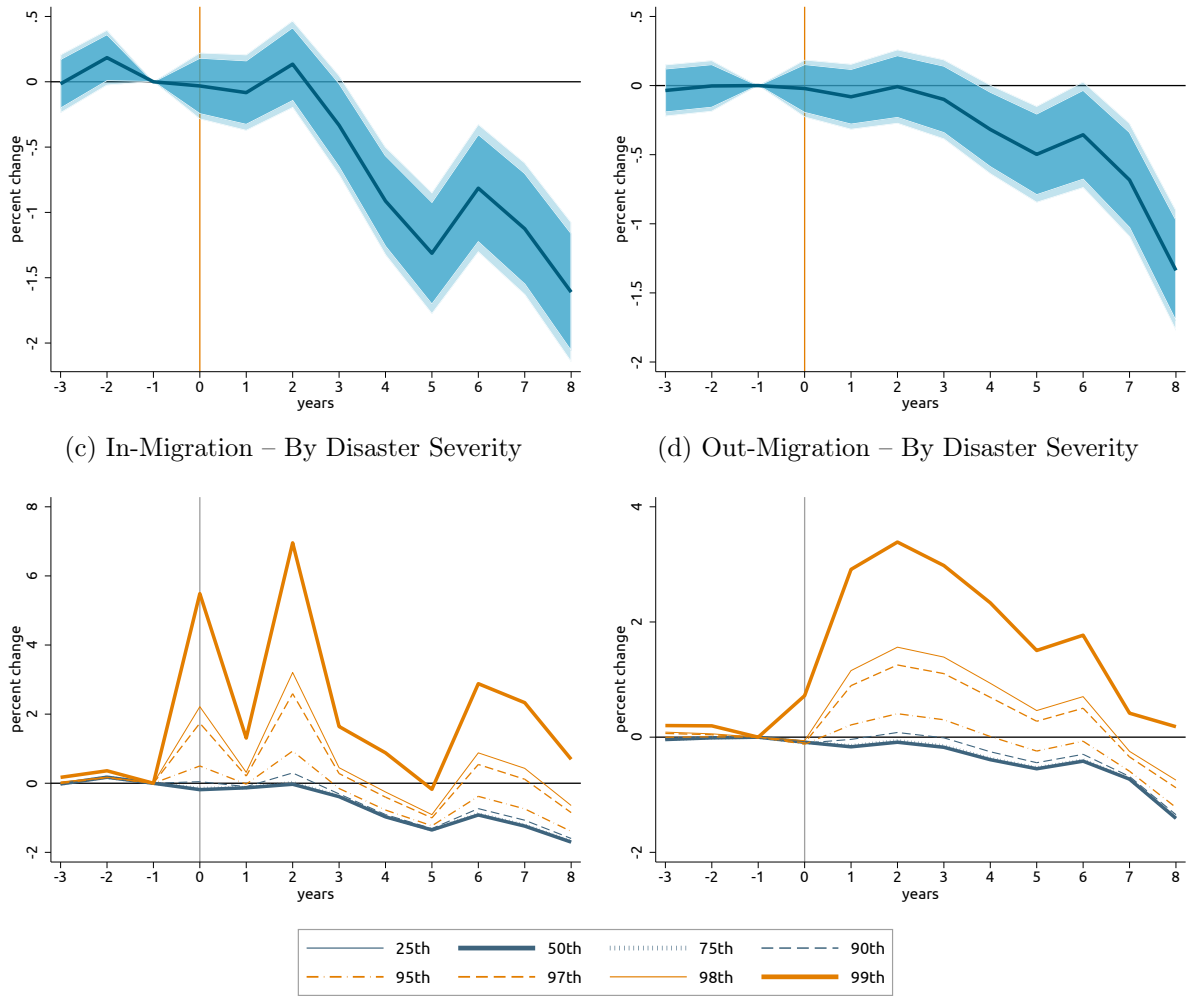


Source: FEMA, SHELDUS, BLS, Census, BEA, and CoreLogic.
Note: These plots show the IRFs from estimating an alternative to equation (1), the equation (2) pre-trend term has been replaced with a county-specific time trend. The inner shaded regions indicate the 90 percent confidence intervals, and the lighter outer shaded regions indicate the 95 percent confidence intervals. All variables are observed at the county level and modeled as cumulative differences in logs between the horizon pictured and the period before the disaster ($t = -1$).

Figure A5: Disaster Effects on Migration

(a) In-Migration – All Disasters

(b) Out-Migration – All Disasters

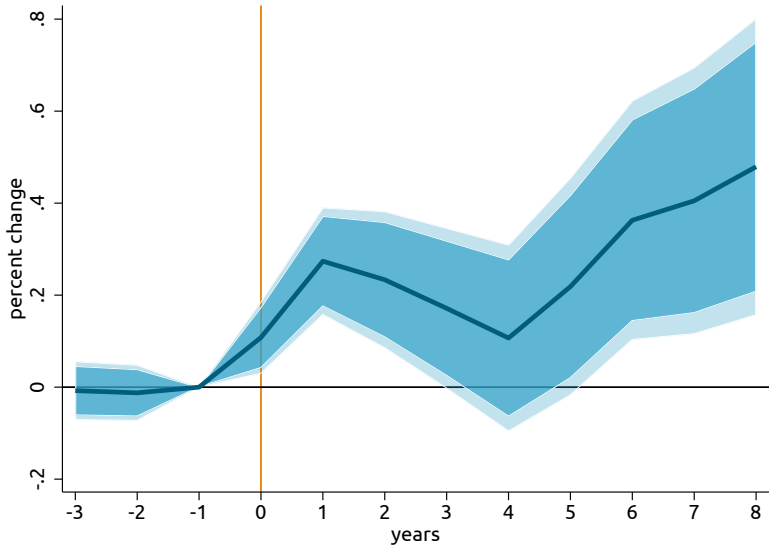


(c) In-Migration – By Disaster Severity

(d) Out-Migration – By Disaster Severity

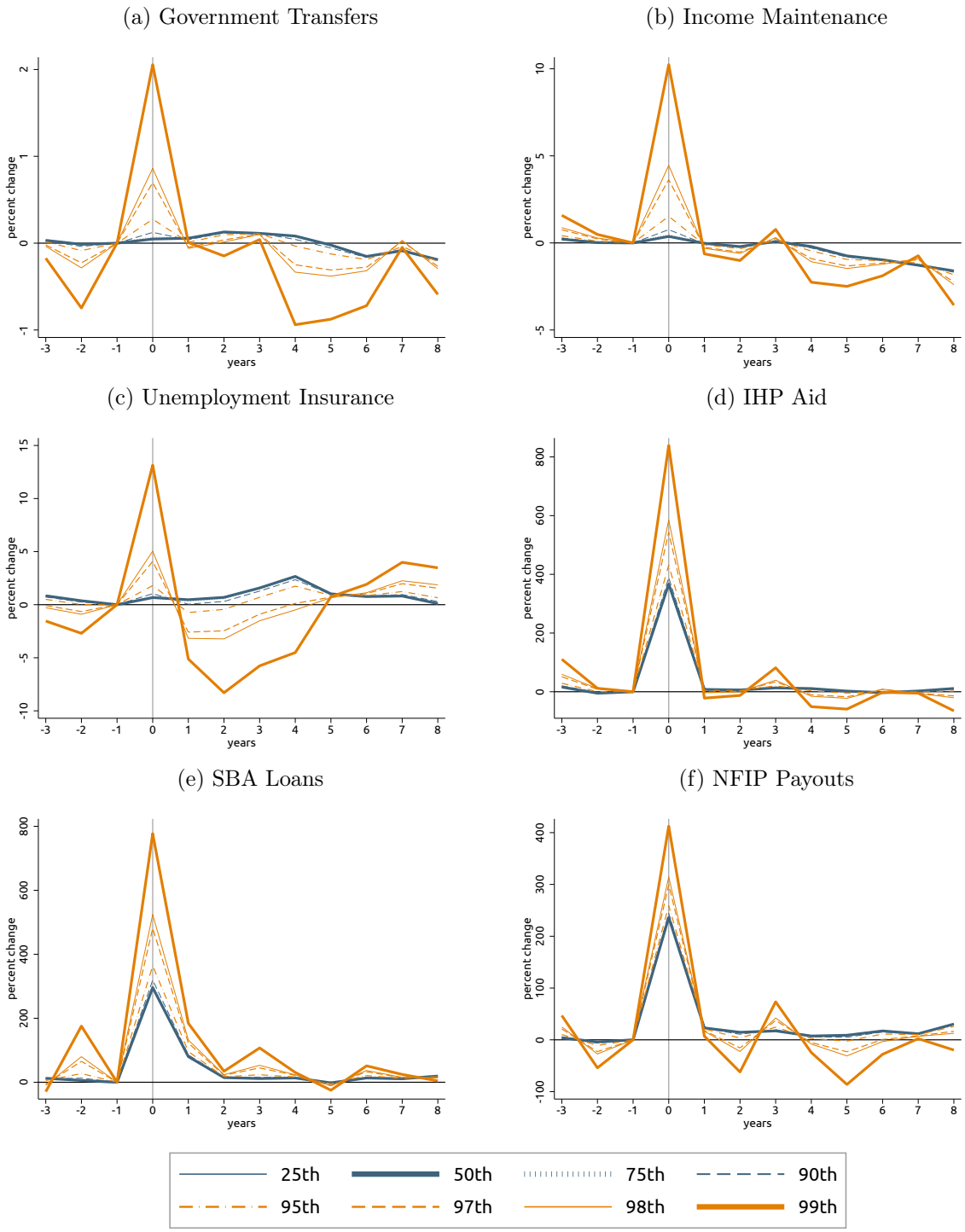
Source: FEMA, SHELDUS, BLS, Census, BEA, and CoreLogic.
Note: Plots (a) and (b) show the IRFs from estimating equation (1), where the shaded regions indicate the 90 and 95 percent confidence intervals. Plots (c) and (d) show the IRFs from estimating equation (4), where the percentile lines reflect the model predictions given the per capita damage distributions for all county-month observations with FEMA disaster declarations. All variables are observed at the county level and modeled as cumulative differences in logs between the horizon pictured and the period before the disaster ($t = -1$).

Figure A6: Wage & Salary Income (per capita)



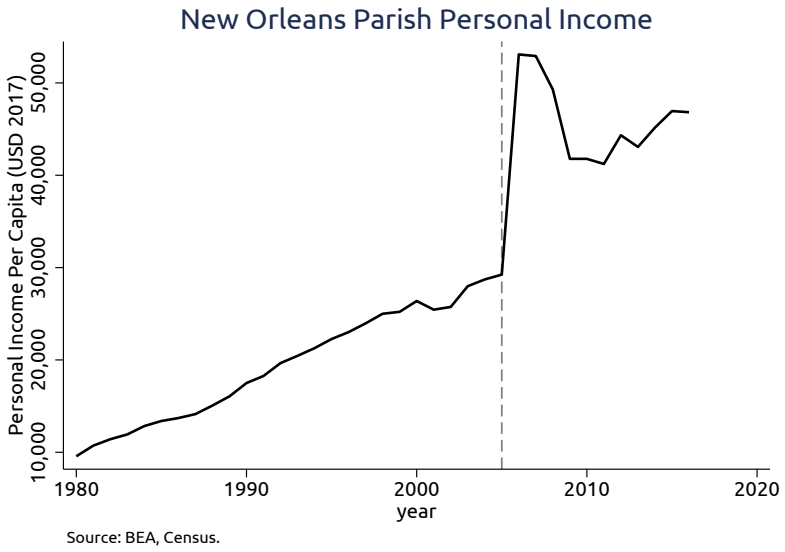
Source: FEMA, SHELDUS, Census, and BEA.
Note: This plots show the IRFs from estimating equation (1), where the inner shaded regions indicate the 90 percent confidence intervals and the lighter outer shaded regions indicate the 95 percent confidence intervals. Wage & salary income isobserved at the county level and modeled as cumulative differences in logs between the horizon pictured and the period before the disaster ($t = -1$).

Figure A7: Effects on Government Transfers (per capita) By Severity



Source: FEMA, SHELDUS, Census, and BEA.
Note: Plots show the IRFs from estimating equation (4), where the percentile lines reflect the model predictions given the per capita damage distributions for all county-month observations with FEMA disaster declarations. All variables are observed at the county level and modeled as cumulative differences in logs between the horizon pictured and the period before the disaster ($t = -1$).

Figure A8: Historical Per Capita Personal Income in New Orleans

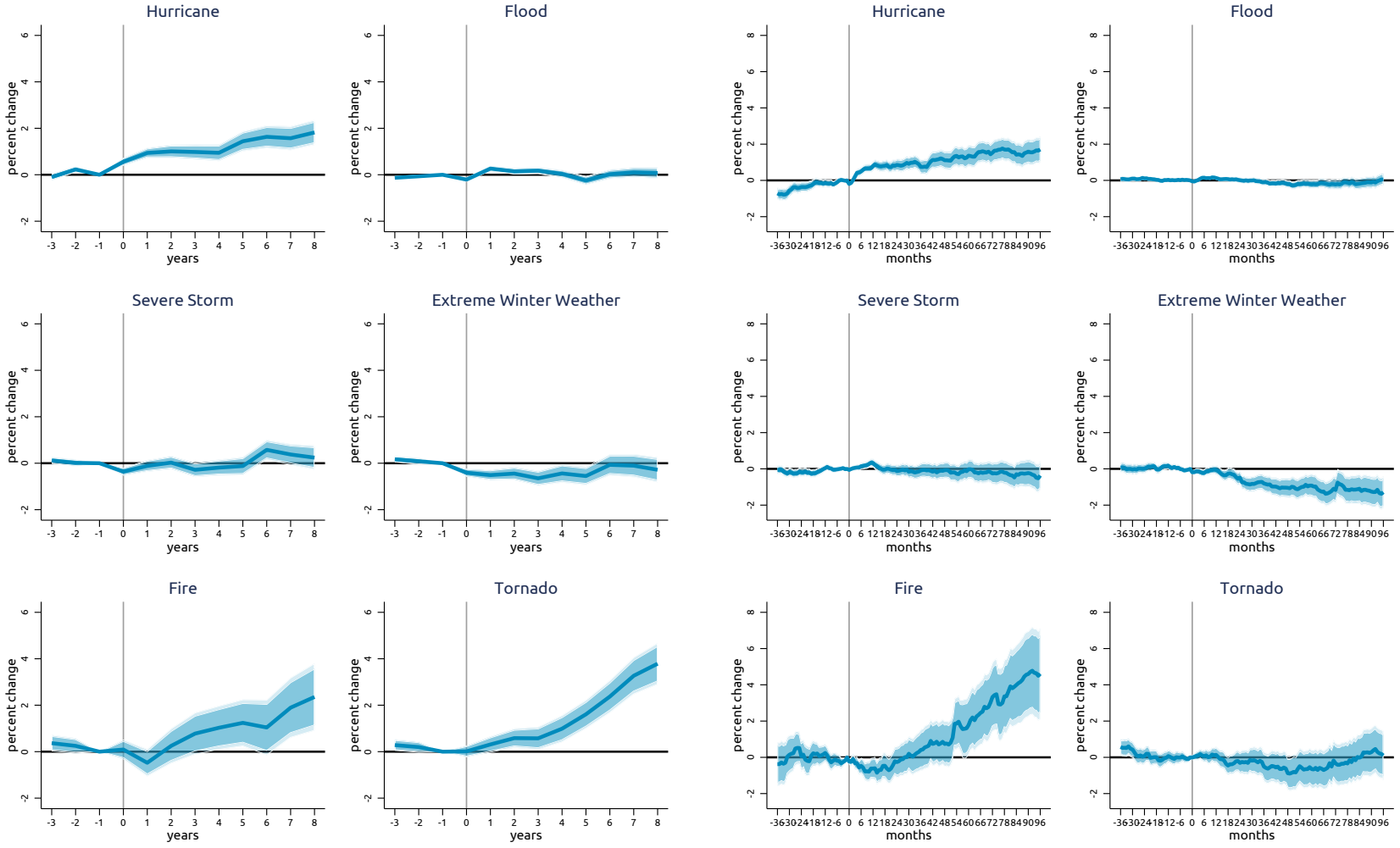


Source: BEA and Census.
Note: Vertical red line indicates 2005, the year of Hurricane Katrina.

Figure A9: Effects By Disaster Type

(a) Personal Income (per capita)

(b) Total Nonfarm Employment

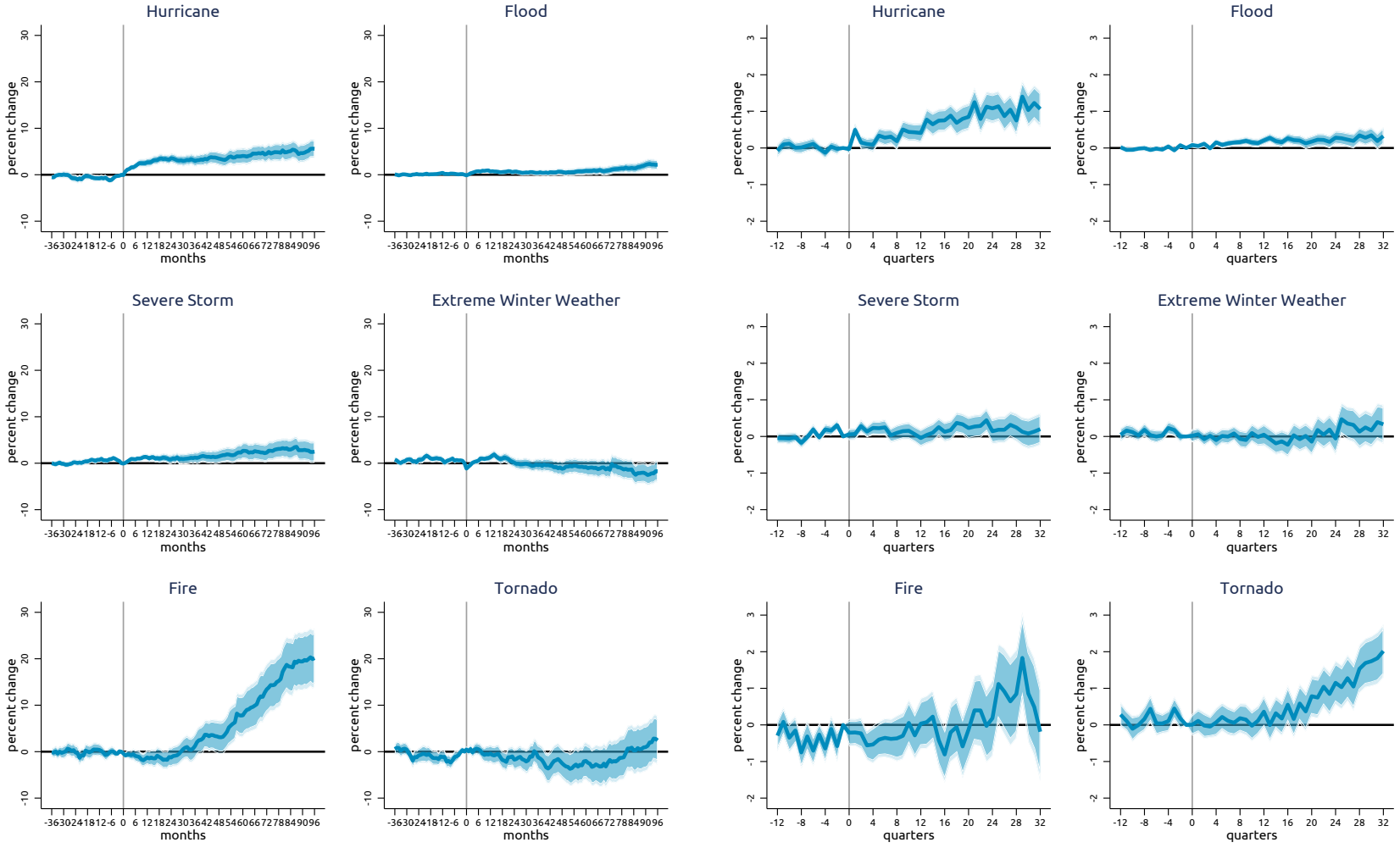


See notes at end of figure.

Figure A9: Effects By Disaster Type (continued)

(c) Construction Employment

(d) Average Weekly Wages

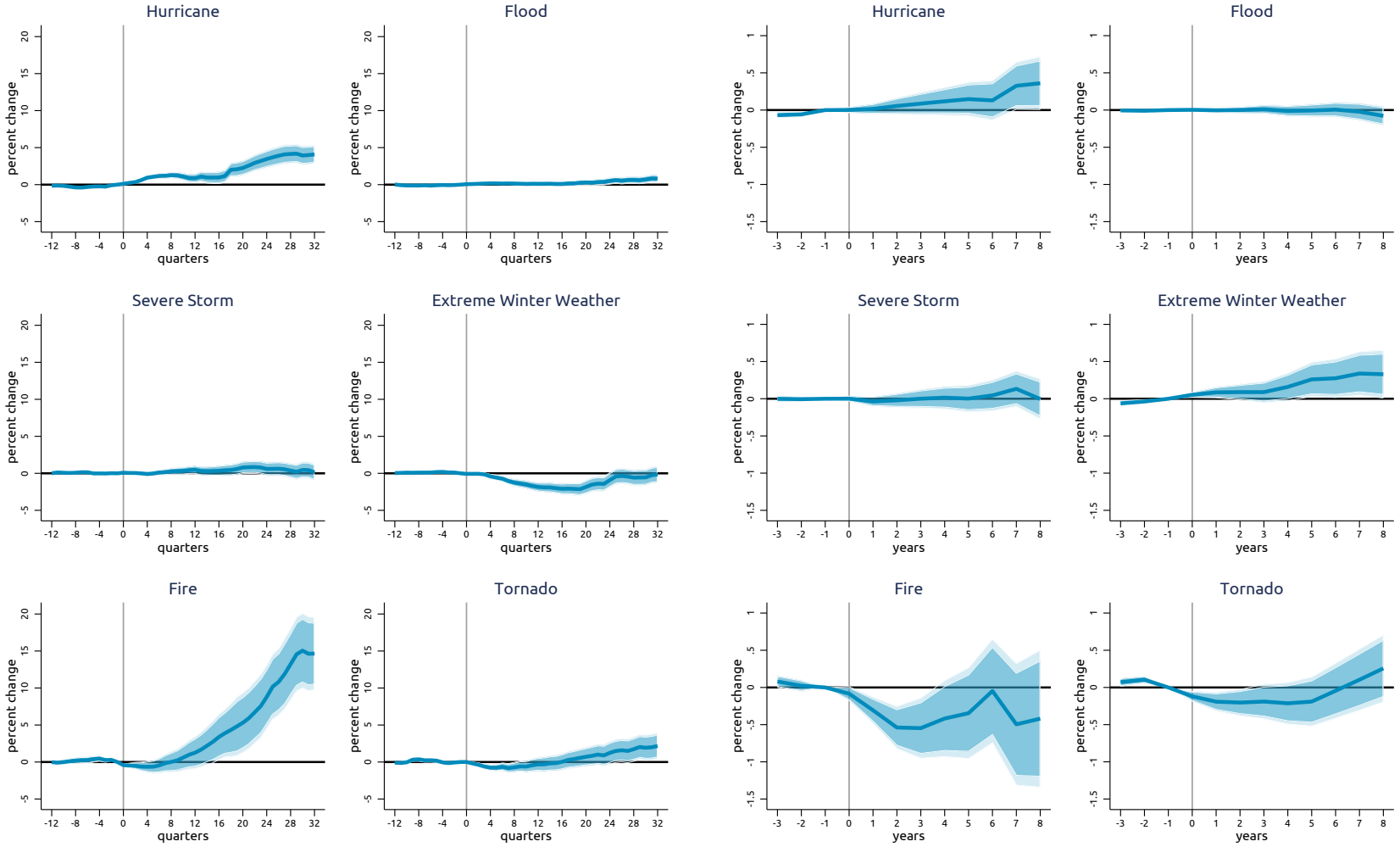


See notes at end of figure.

Figure A9: Effects By Disaster Type (continued)

(e) Home Prices

(f) Population

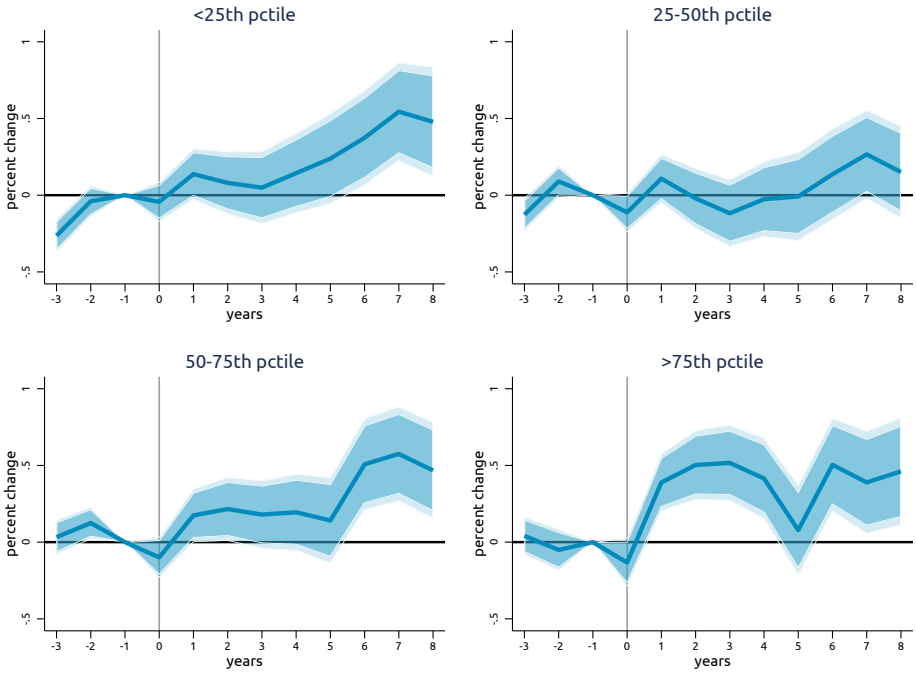


Source: FEMA, SHELDUS, BLS, and Census.

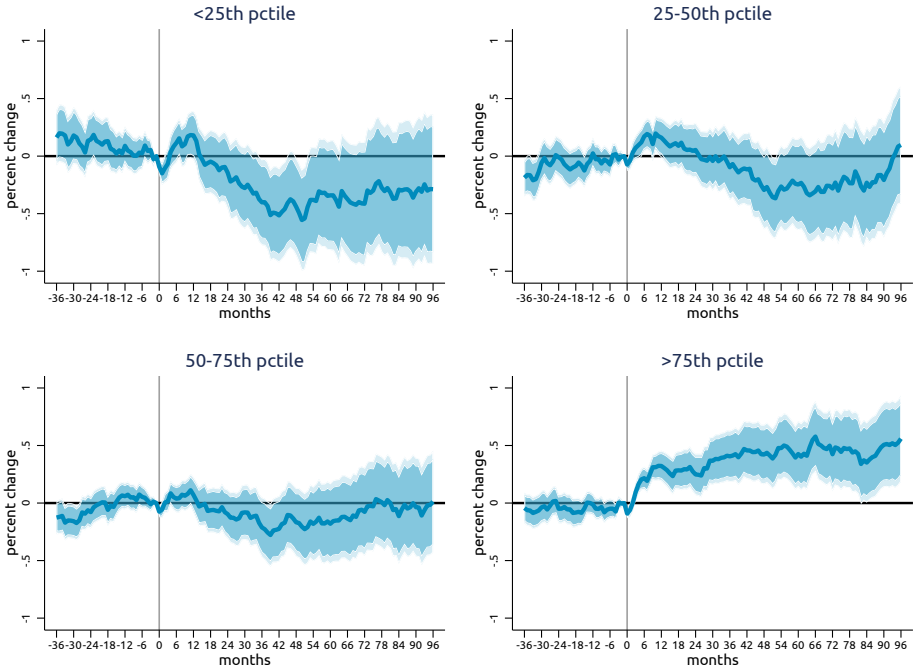
Note: These plots show the IRFs from estimating equation (5), where the shaded regions show the 90 and 95 percent confidence intervals. The disaster type categories are based on FEMA declaration types and titles, with the flood category excluding floods associated with hurricanes. All outcomes are observed at the county level and modeled as cumulative differences in logs between the horizon pictured and the period before the disaster ($t = -1$).

Figure A10: Effects By Initial Personal Income Per Capita

(a) Personal Income (per capita)



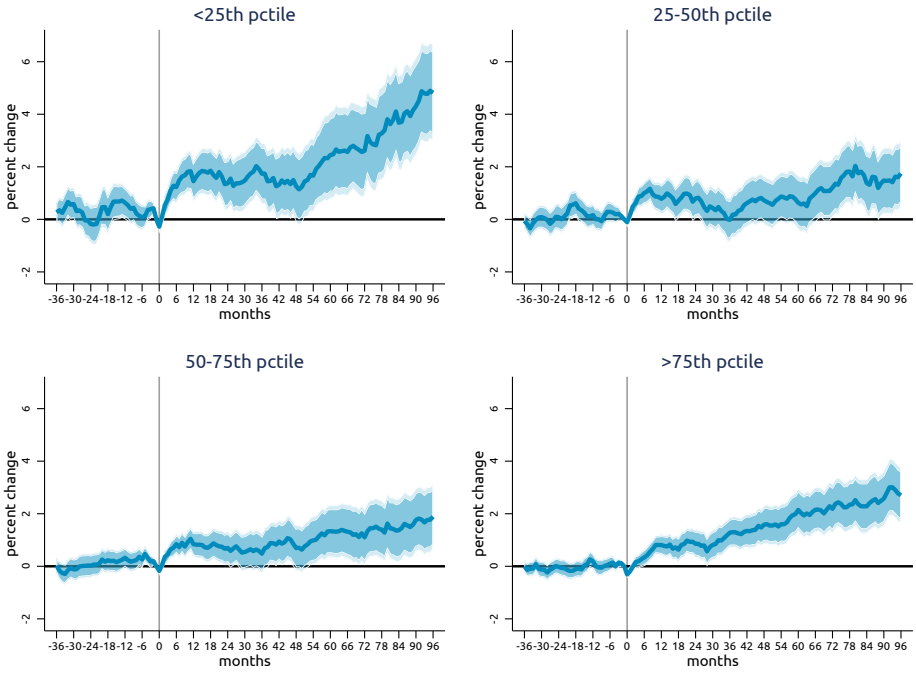
(b) Total Nonfarm Employment



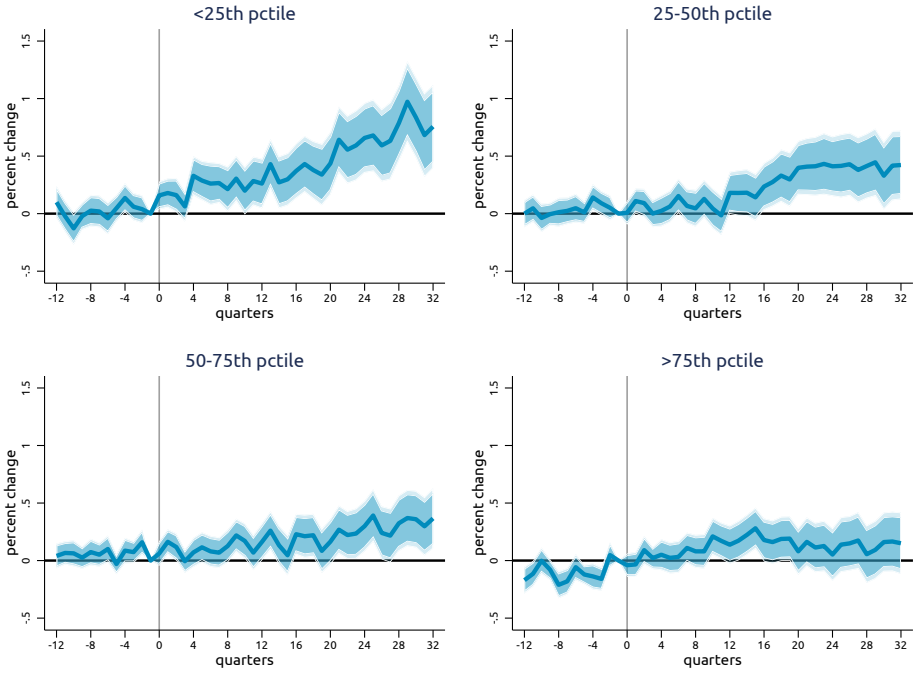
See notes at end of figure.

Figure A10: Effects By Initial Personal Income Per Capita (continued)

(c) Construction Employment



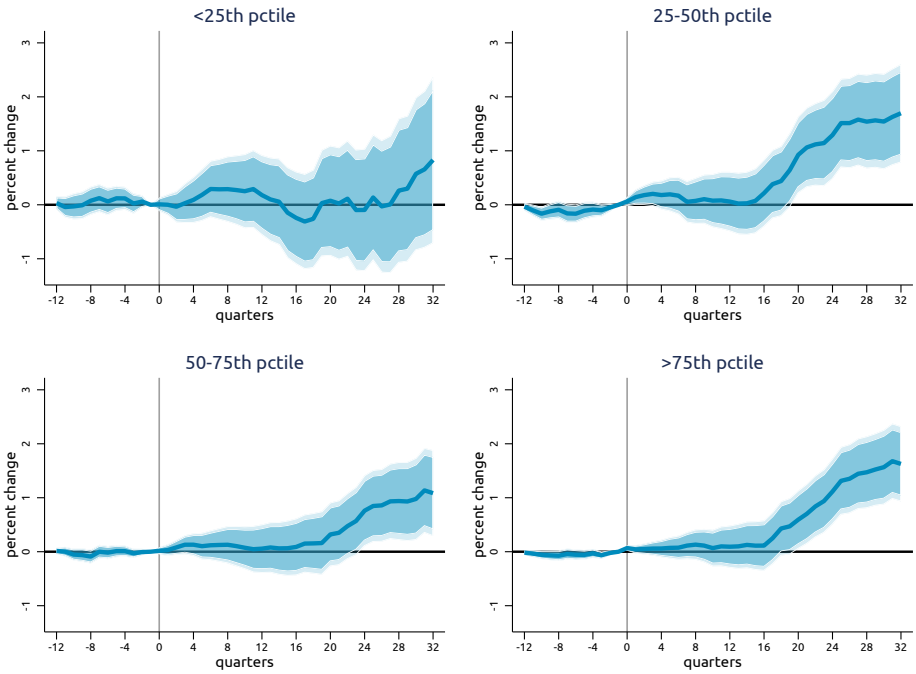
(d) Average Weekly Wages



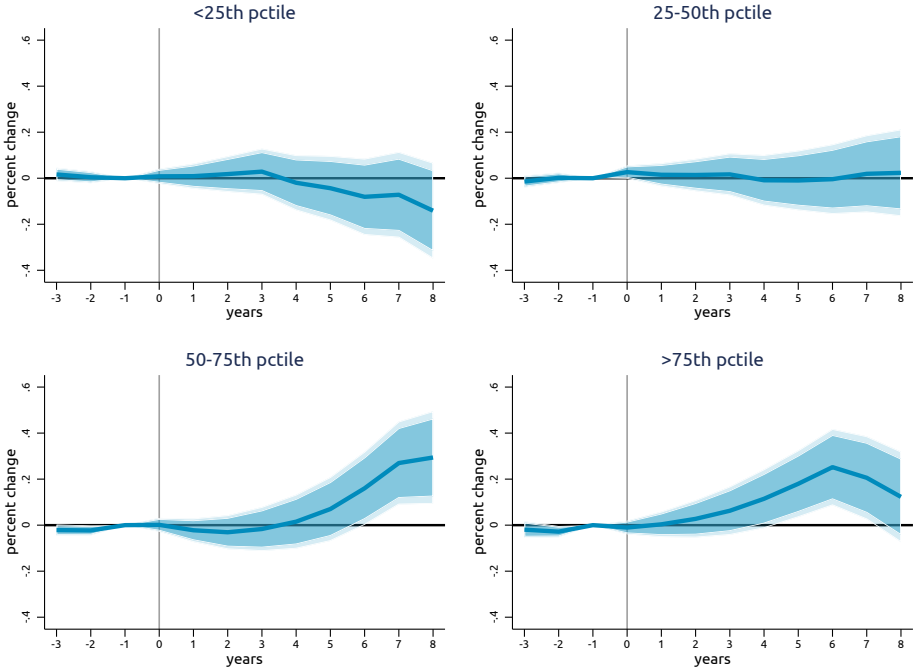
See notes at end of figure.

Figure A10: Effects By Initial Personal Income Per Capita (continued)

(e) Home Prices



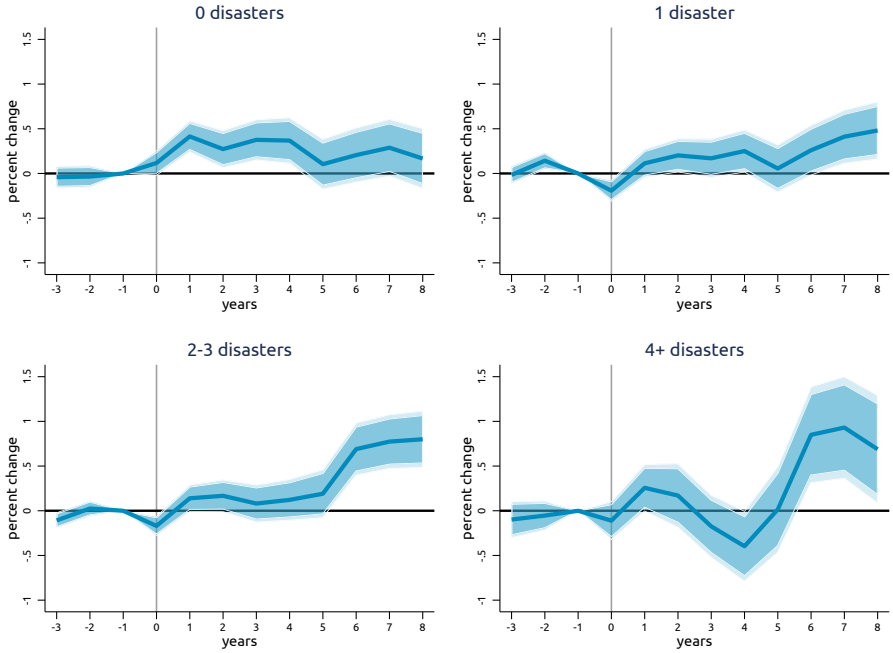
(f) Population



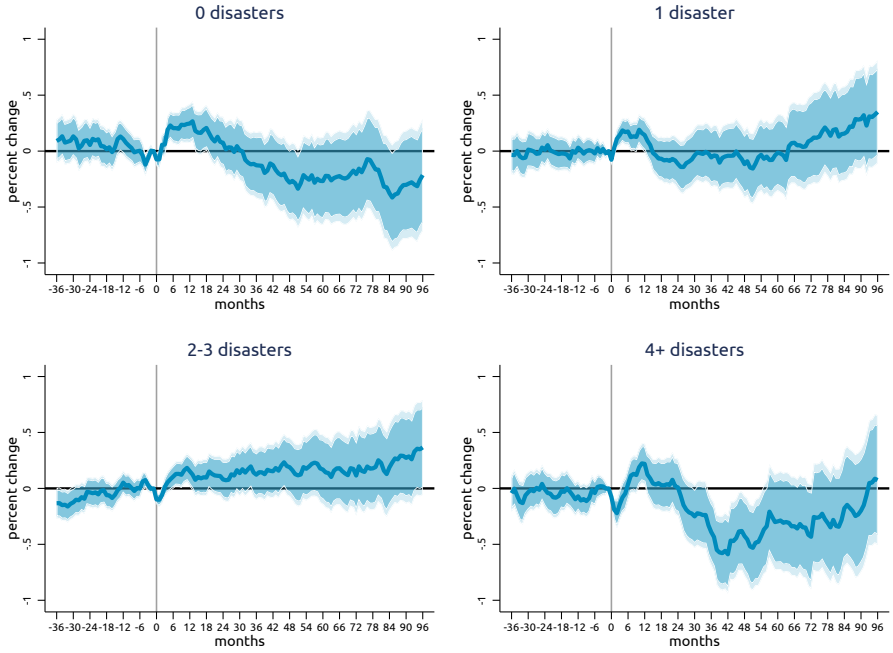
Source: FEMA, SHELDUS, BEA, and Census.
Note: These plots show the IRFs from estimating equation (7), where the shaded regions show the 90 and 95 percent confidence intervals. The quartiles of initial personal income per capita are based on the personal income in year -1 relative to the national distribution in that year. All outcomes are observed at the county level and modeled as cumulative differences in logs between the horizon pictured and the period before the disaster ($t = -1$).

Figure A11: Effects By Local Historical Disaster Exposure

(a) Personal Income (per capita)



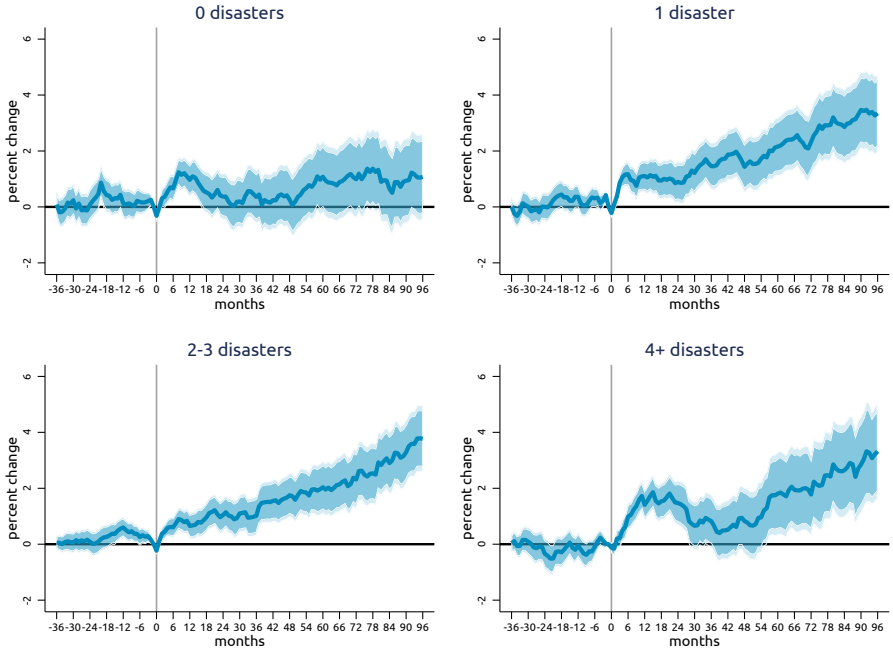
(b) Total Nonfarm Employment



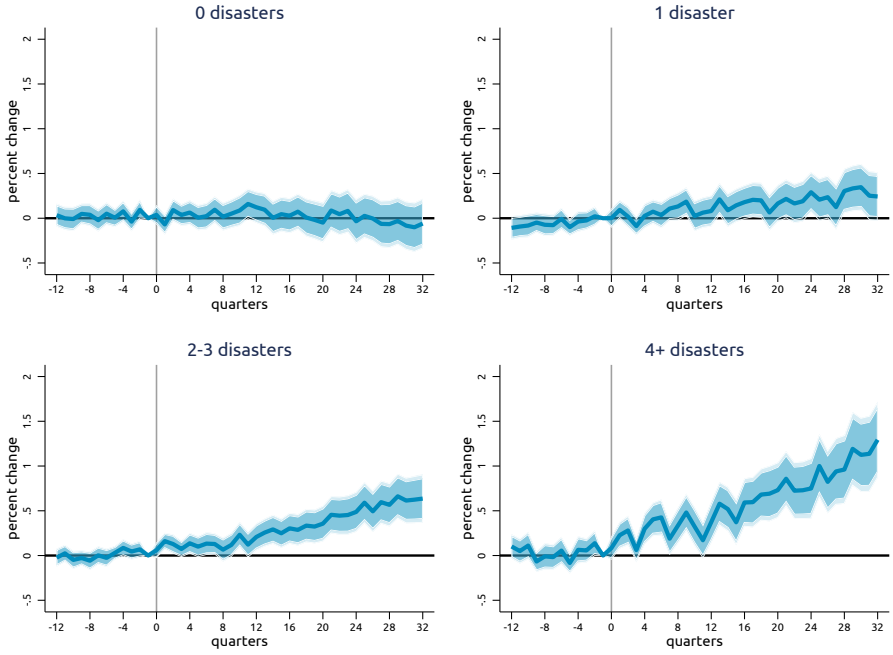
See notes at end of figure.

Figure A11: Effects By Local Historical Disaster Exposure (continued)

(c) Construction Employment



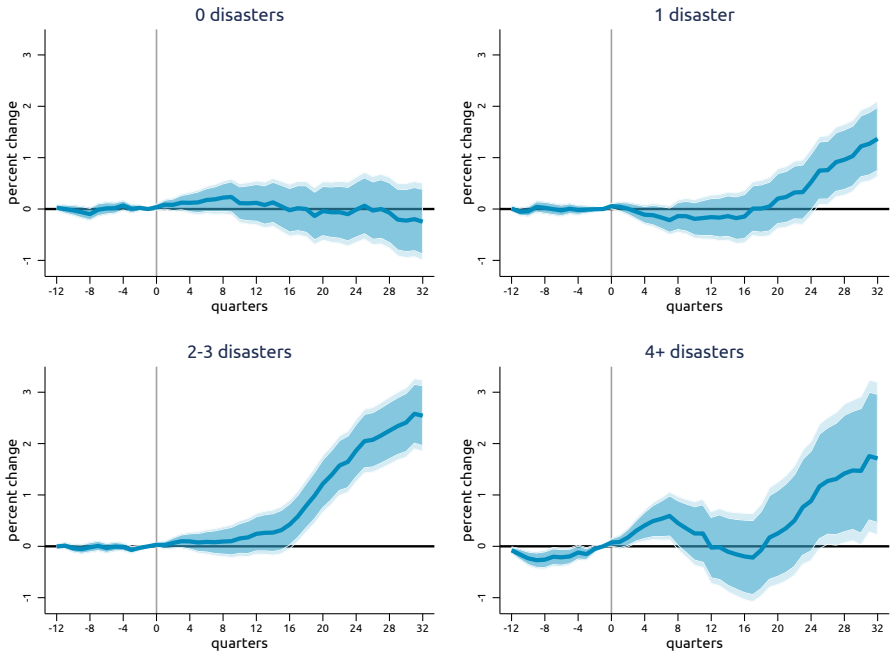
(d) Average Weekly Wages



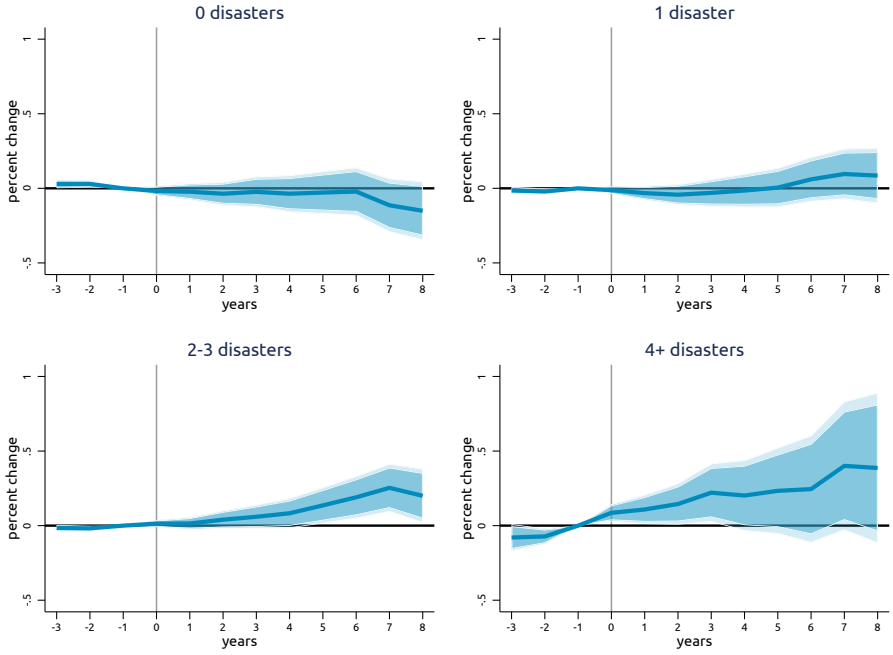
See notes at end of figure.

Figure A11: Effects By Local Historical Disaster Exposure (continued)

(e) Home Prices



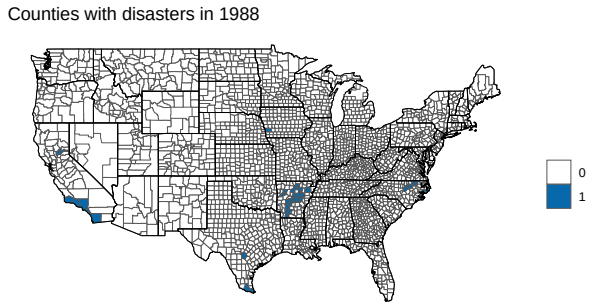
(f) Population



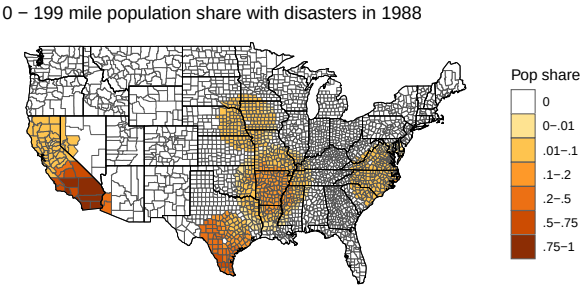
Source: FEMA, SHELDUS, BEA, BLS, Census, and CoreLogic.
Note: These plots show the IRFs from estimating equation (7), where the shaded regions show the 90 and 95 percent confidence intervals. The four categories of historical disaster experience (0, 1, 2-3, and 4+) represent the number of years within years -10 to -1 in which a county experienced a major disaster with positive damages. All outcomes are observed at the county level and modeled as cumulative differences in logs between the horizon pictured and the period before the disaster ($t = -1$).

Figure A12: Spatial Lags in 1988

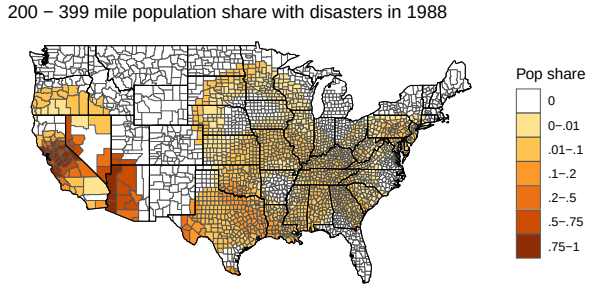
(a) Disasters with damages



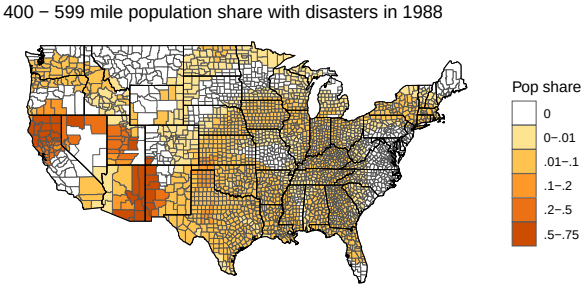
(b) < 199 miles



(c) 200-399 miles



(d) 400-599 miles



Source: FEMA, SHELDUS.

Note: Using 1988 as an example, panel (a) depicts the counties that received major disaster declarations from FEMA with positive damages in SHELDUS. Panels (b)-(c) depict the share of population within each band (50-199, 200-399, and 400-599 miles) of a given county that had disaster declarations with damages. Darker shading in panels (b)-(d) indicate a higher population share.