

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 and tornados yield longer run increases in income, while floods do not. The longer run increase in income—which has on average become smaller over time—tends to rise with recent disaster experience and is absent for counties with no recent experience. Finally, state-level analyses and estimates of spatial spillovers across counties suggest 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 disasters 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, as has government aid spending on recovery.^{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 impact that natural disasters have on affected local economies is critically important. Economic policymakers need to estimate and forecast the 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 Furthermore, natural disaster 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. In addition to having devastating effects on mortality and well-being—important impacts that are outside the scope of

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, the upward trend in damages is driven by hurricanes and floods, which together account for 75% of county disaster observations. 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).

this paper—natural disasters can cause destruction to local wealth and capital stocks.⁶ That destruction could lead to business closures and the relocation of firms and businesses to other places, resulting in long-run declines in local income. Alternatively, the inflow of aid and insurance payouts to an affected area has the potential to finance reconstruction and other investments that could boost local income in the longer run. Given the potential for either of these scenarios to play out, 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. More generally, in reviewing studies examining responses of GDP to disasters in a variety of contexts one can find estimates consistent with each of the four paths depicted in the schematic (see von Peter, von Dahlen and Saxena (2012), Cavallo, Galiani, Noy, and Pantano (2013), Lackner (2019), and Sawada and Sachs (2019).) Hence, the true dynamic response is very much an open question and likely varies by context.

In this paper, we use U.S. county data to study the dynamic response of local economies following disasters. We focus on personal income, which is very highly correlated with GDP and, unlike GDP, is available at the county level back to 1980.⁷ To better understand the mechanisms by which disasters affect local income, we consider a broad range of other economic outcomes using a common methodology and data sample. We then examine heterogeneity, adaptation, and spatial spillover effects.

We start by asking what is the average response of local income to natural disasters? In contrast to the Hsiang and Jina (2014) cross-country findings discussed above of long-lasting

⁶ See Bakkensen and Barrage (2020) for an analysis of the welfare effects of cyclones.

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.

declines in national income per capita following disasters, we find robust evidence of long-lasting *increases* in local 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 0.6% above the baseline trend eight years after the disaster.

We then ask what drives the longer-run increase in income per capita? We find that the recovery in personal income is initially explained 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.

Next, we consider the extent to which the average post-disaster response of local income applies across different contexts. We uncover considerable heterogeneity in this response along several key dimensions. First, given projections that some disasters will become more severe with climate change and concerns that our average results may not apply to the most severe disasters, we examine heterogeneity by disaster severity. We find that the longer-run rise in income per capita actually increases with disaster severity as measured by per capita damages. Second, we examine whether our average findings apply across disaster types, an important question as many research papers focus only on one type of disaster like floods, cyclones, or fires. We find that while hurricanes and tornados result in longer-run increases in income per capita, the effects of floods, severe storms, extreme winter weather, and fires are small or statistically insignificant. Third, given the findings of heterogeneity by income in the cross-country literature as well as anecdotal reports that lower income households have less access to aid, we segment counties by initial income. We find that while the income boost in the first few years after a disaster appears to be concentrated in the richest quartile of counties, by the end of eight years, per capita income generally is higher regardless of initial income.

We next turn to the issue of adaptation. Economic agents – households, firms, and policymakers – may make adaptive investments and behavior changes if they anticipate an increase in disaster frequency going forward. Agents' beliefs regarding future disaster risk in their local area are likely driven, at least in part, by the recent frequency of disasters in their local area. That is, agents in places with many recent disasters may be more likely to anticipate future disasters than are agents in places with few or no recent disasters. However, the occurrence of multiple recent disasters can also overwhelm disaster response and recovery capacity, making it more difficult to rebuild quickly and effectively. We take two approaches to examine the extent of adaptation. First, consistent with local adaptation, we find that counties with more historical experience with disasters see larger increases in personal income over the longer run. Second, we test whether the average dynamic response of income per capita to disasters has changed over time. While the short-run response appears stable over time, we find the longer-run increase has fallen roughly in half over the course of our sample period.

Finally, we use two methods to 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. First, 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. 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. In our second analysis of spatial propagation, we examine state level outcomes using a continuous treatment measure that aggregates county disaster indicators. While the dynamic pattern is qualitatively similar to our baseline per capita income result at the county level, the state level impacts are small and statistically insignificant. These results 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, adaptation, and 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.⁸ 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.⁹ 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

⁸ See Botzen, Deschenes, and Sanders (2019) for a recent literature review.

⁹ 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.

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.” In another cross-country analysis, Cavallo, Galiani, Noy, and Pantano (2013) find that when they include controls for political revolutions that occurred after natural disasters, even the most severe disasters appear to have no significant effect on economic growth. Another recent cross-country study, Sawada and Sachs (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 (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, Kutzbach, and Polivka (2020) 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. (2020). Using county-by-decade panel data from 1940 to 2010, they estimate the contemporaneous (i.e., within same decade) effects of severe disasters on several economic outcomes. They find that counties affected by the most severe disasters experience higher net out-migration, higher poverty rates, and lower house prices. In this paper, we similarly find significant medium- to longer-run (up to 8 years out) increases in net out-migration and 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.¹⁰ 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.

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, Kawano, and Levitt (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

¹⁰ 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.

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 productivity and 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 out-migration 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 insurance payouts as well as 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 the Individual and Household Program (IHP) is a component of. The Small Business Administration (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 2006-2016.¹¹ FEMA's Public Assistance (PA) program, which issues grants to state and local governments to repair or rebuild public infrastructure,¹² averaged over \$3.3 billion a year in grants over the same period,¹³ while NFIP payouts averaged \$2.2 billion a year.¹⁴

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.

¹¹ 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.

¹² Though much smaller (in dollars), the Federal Highway Administration also provides funds for repair of federal-aid roads through its Emergency Relief Program.

¹³ See <https://www.fema.gov/data-visualization-summary-disaster-declarations-and-grants>.

¹⁴ See <https://www.fema.gov/loss-dollars-paid-calendar-year>.

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, Feiveson, Liscow, and Woolston (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.

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.¹⁵ 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.

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.^{16,17} 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

¹⁵ 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.

¹⁶ 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.

¹⁷ Given our focus on natural disasters, we exclude declarations due to terrorism or toxic substances.

physically affected.¹⁸ 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.¹⁹ 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 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.

¹⁸ 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.

¹⁹ Source: author conversations with FEMA staff.

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.²⁰ It should be noted that the distribution of per capita damages varies significantly across disaster types (see Appendix Figure A3). 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 We use disaster declaration and pecuniary damage data for our treatment measure for several key reasons. First, data on physical characteristics is not readily available at the U.S. county level for a broad set of disaster types. Second, even when this data is available, it is not easily comparable across disaster types. Finally, we are inherently interested in natural hazards that result in disastrous outcomes, which are a function of the built environment that those hazards occur in. The monetary damages caused by a disaster – i.e., the magnitude of the “treatment” represented by the disaster shock – of a given physical strength can vary greatly from place to place depending on the quantity and market value of local property as well as construction quality, 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). In our baseline analyses, we consider both the mean level of damages (for our baseline results) as well as different percentiles of the damages distribution.

²⁰ The geographic exposure to disasters varies significantly by disaster type (see Appendix Figure A2).

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.

Although our preferred treatment measure is based on disaster declarations and monetary damages, as a robustness check we use hurricane wind speed data to examine whether such a measure would change our baseline results (for hurricanes). In particular, we use county level wind speed data for hurricanes made available via Anderson et al (2020a) and Anderson et al (2020b) using the U.S. National Hurricane Center’s Best Track Atlantic hurricane database (HURDAT2.)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. We also examine local poverty rates from the Census Bureau’s Small Area Income and Poverty Estimates (SAIPE) program, as described in Appendix B1.

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, when estimating IRFs for the construction employment, we drop counties with more than 5 months of missing or zero construction employment. Our data on total nonfarm employment and wages covers the period January 1980 to December 2016, while the construction employment data start in January 1990.²³

²² See the Appendix B3 for more details.

²³ Our employment and wages data cover “nonfarm” employment and so exclude any employment in agriculture, ranching, fishing, and hunting.

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.

To examine the potential role of compositional shifts, we supplement the AWW data with an industry mix-implied wage measure. We construct this measure using CEPR yearly extracts of the CPS Outgoing Rotation Group micro-data and Eckert, Fort, Schott, and Yang (2021)’s version of the Census Bureau’s County Business Patterns (CBP) data, as described in Appendix B2.

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 use 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

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 $h \geq 0$:

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

$y_{c,t}$ 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. \mathbf{X}_{ct} is a vector of control variables with parameters $\boldsymbol{\gamma}^h$. Specifically, $\mathbf{X}'_{ct} \boldsymbol{\gamma}^h$ is defined as

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

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 $\alpha_{r(c),t}^h$ 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

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 $D_{c,t}^0$ 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).

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.

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:

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

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

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

The estimated coefficients, $\hat{\beta}_p^h$ for $p = 0, \dots, 3$, 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:

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

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

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

We also investigate heterogeneity in treatment effects in terms initial income. To do so, 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:

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

where $M_{c,t-1}^q$ is one of four income quartile indicators indexed by q and $\mathbf{X}'_{ct}\boldsymbol{\gamma}^h$ 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.

C. Adaptation

We apply to methods to examine adaptation. First, we estimate equation (7), where $M_{c,t-1}^q$ is one of 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.

Second, we interact our disaster indicator with a continuous time variable in order to estimate how the impulse response function has evolved over time as shown below:

$$y_{c,t+h} - y_{c,t-1} = \theta^h \cdot t \cdot D_{c,t} + \beta^h D_{c,t} + \mathbf{X}'_{ct} \boldsymbol{\gamma}^h + \alpha^h_{r(c),t} + \alpha^h_{c,m(t)} + \epsilon_{c,t+h}. \quad (8)$$

Here θ^h estimates how the response has evolved over time, where a positive value would reflect that personal income has increased more (or decreased less) over time.

D. Spatial Spillovers and Wider Geographies

We use two approaches to examine how natural disaster impacts propagate to neighboring regions. First, 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 :

$$y_{c,t+h} - y_{c,t-1} = \sum_{b \in B} \pi^{h,b} D_{c,t}^b + \beta^h D_{c,t} + \mathbf{X}'_{ct} \boldsymbol{\gamma}^h + \alpha^h_{r(c),t} + \alpha^h_{c,m(t)} + \epsilon_{c,t+h} \quad (9)$$

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 :

$$D_{ct}^b \equiv \sum_{i \neq c} 1[b \leq d_{ci} < b'] \omega_{ci} D_{it}, \quad (10)$$

where

$$\omega_{ci} \equiv \frac{pop_i}{\sum_i 1[b \leq d_{ci} < b'] pop_i}, \quad (11)$$

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.

In our second approach to understanding wider geographic impacts, we estimate the baseline specification in equation (1) at an aggregated state level. Specifically, we replace the $D_{c,t}$ indicator with a continuous measure of the share of the state's population living in a county hit by a disaster in a given year. For this analysis, we cluster the standard errors at the state and time-by-Census division levels.

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.

Although these results establish that the longer run *average* income increases in counties directly affected by natural disasters, they do not tell us whether income increases across the income distribution or whether these average effects are instead driven, for example, by the top end of the distribution which would imply a rise in inequality. Before turning to the mechanisms driving the average effects on personal income, we briefly report results on the response of the poverty rate to natural disasters. Shown in Appendix Figure A6, our findings suggest a positive but statistically insignificant longer-run effect of average disasters on the poverty rate. However, if the personal income increase were experienced equally by all parts of the income distribution, we would expect the poverty rate to decline as some see their income rise above the poverty threshold. Thus, these results suggest that despite an increase in average personal income per capita, local inequality may rise after natural disasters.

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.

To assess how much of the increase in AWW derives from this second channel – changes in industry mix of disaster-hit counties – we estimate the disaster IRF for the measure of industry mix described in Section IV. The results are provided in Appendix Figure A7. Consistent with this channel, we find that a gradual shift in the industry mix of disaster-hit counties toward higher-wage industries can explain roughly half of the longer run increase in AWW, though the response is not statistically significant at all horizons.

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 In Appendix Figure A8, we drill down into the population response by estimating the IRFs separately for in-migration and out-migration, each measured as the number of migrants divided by pre-disaster ($t - 1$) population. We find that the near-zero population response is not due to a lack of migration responses. Rather, there are modest negative responses over the longer-run of both in-migration and out-migration that roughly cancel each other out.

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 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

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.

potentially affect personal income over the medium to longer run.³³ 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) – (c) show the post-disaster increases for IHP aid, SBA loans and NFIP payouts, in log per capita terms.³⁴ As one would expect, each of these aid outcomes increases substantially after a natural disaster.³⁵ 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 (d) 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 (e). UI transfers, on the other hand, are elevated for the first few years but are essentially unchanged over the longer run (see panel (f)). 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 (d)).

C. 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 longer-run increase in labor earnings (average weekly wages) rather than

³³ 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).

³⁴ Because these disaster-specific aid variables yield many observations with zeros, we use the log of the observed per capita aid amount plus 1.

³⁵ In results not shown, we find that aid increases with disaster severity.

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, Adaptation, and Spatial Spillovers

We now explore three sets of extensions relating to heterogeneity of disaster responses along several key dimensions, adaptation to disasters over time and based on county-specific experience, and spatial spillover effects.

A. Heterogeneity

Although the average dynamic response of local economic activity to natural disasters presented above is informative, this average response may well mask heterogeneity 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.), and county income prior to the disaster.

1. Heterogeneity by disaster severity

In our first heterogeneity analysis, we examine the role of disaster severity, which is important in light of projections that some disasters will become more severe with climate change. Furthermore, we need to understand whether our average results apply to the most severe disasters. 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

³⁶ This interpretation is also supported by IRF estimates for the wage and salary component of personal income, which is provided in Appendix Figure A9. 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.

levels of damages corresponding to various percentiles of the distribution of (non-zero) damages p.c. in our sample. 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.

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 over 1% after eight years.³⁸ 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 while the longer-run response is strongly negative. This longer-run decline in house prices after very severe disasters may be

³⁸ 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, Kutzbach, and Polivka (2020).

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.³⁹ This longer-run drop in population should reduce demand for housing, putting downward pressure on home prices.

In addition, the longer-run population response helps explain 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.

In addition to our preferred specification, we examine two alternative versions of the severity analysis. First, we use the original SHELDUS data rather than our adjusted version that spreads duplicate damage observations evenly across counties on a per capita basis. As Figure A10 shows, all of the severity results are qualitatively unchanged except for the population result, which shows that the population increase by the end of 8 years is unaffected by severity. In our view the original SHELDUS data incorrectly assign larger damages on a per capita basis to counties with smaller populations, which are going to be disproportionately represented among the top percentile damages in the original SHELDUS data. Panel (f) in this figure shows that those counties eventually experience the same larger growth as the median counties, and thus the original SHELDUS data hide the negative population effects of the most severe disasters that we find in our baseline outcome.

Results for the second set of alternative severity analyses, which use hurricane wind speed rather than monetary damages to measure severity, are shown in Figure A11. For this analysis, we replace the $s_{c,t}$ term in equation (4) with hurricane wind speed. The results for our primary outcome, personal income per capita, are qualitatively the same when using this alternative measure of severity. The wage results are also similar. However, there are some interesting differences to the remaining outcomes. Notably, by the end of eight years, the counties with the

³⁹ Appendix A6 provides results separately for annual in-migration and out-migration flows as a share of pre-disaster population. While both increase substantially in the first 3-4 years after the most severe disasters, the out-migration effect is much larger. Over the longer-run (up to 8 years out), both the in- and out-migration responses to severe disasters become somewhat negative, though out-migration continues to be higher (less negative). The higher out-migration response is consistent with the estimated decline in population over the medium and longer runs for the most severe disasters. These results points to considerable population “churn” after a disaster.

highest wind speeds see even higher home prices, similar population increases and construction increases as the median hurricane wind speed disaster. There are some nonlinearities for our employment outcomes, such that the 90th percentile events see higher employment for both total nonfarm employment and construction employment by the end of 8 years, but the 99th percentile among wind speeds see close to median outcomes.

We consistently find that increases in personal income are larger for more severe disasters. What can explain this phenomenon? 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

2. Heterogeneity by type of disaster

We next explore how economic responses to natural disasters vary by disaster type. 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 A8, 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 A12 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.

This finding could reflect differences in destruction. To the extent that hurricanes and tornados tend to more fully destroy structures such that they must be completely rebuilt, this could yield more productivity-enhancing improvements in the capital stock. Another potential explanation is that while floods may increase the perceived risk of future flooding in the same exact location, hurricanes and tornados may be perceived to be unlikely to strike the same exact spot again soon, increasing relative willingness to make rebuilding and recovery investments.

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 A13. 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.

The heterogeneity in responses based on disaster type is reflected in results on heterogeneity by Census Division. As can be seen in Appendix Figure A14, only the South has the response in personal income reflected in our average response. These Census division results are consistent with the disaster type responses and the distribution of disaster types shown in Appendix Figure A2. In particular, the South has a high concentration of hurricanes and tornados, which tend to have the impulse response functions most consistent with our baseline finding in Figure 3.

3. *Heterogeneity by county pre-disaster income*

In our third heterogeneity analysis, we examine the role of pre-disaster income in the disaster response. This analysis is prompted by the findings in the literature that lower income countries see worse outcomes in GDP after natural disasters. Furthermore, households in higher income countries may have more private insurance. This, combined with reports that lower income households tend to receive less aid, would lead to higher income counties having more resources with which to fund their recovery and rebuilding activities. In Figure 7 we show the results of estimating equation (7), which estimates separate IRFs by quartile of pre-disaster county income. We find that the point estimates for all four quartiles are consistent with our baseline results of a longer-run (as of eight years out) increase in income p.c., although they are not all statistically significant. Furthermore, the timing of the increase differs, as only counties in the top quartile of pre-disaster income p.c., experience a statistically significant increase in income in the first four years after the disaster (relative to the no-disaster counterfactual.) Thus, if we looked only a couple of years post-disaster, our findings would be consistent with those showing increases in income or GDP only for higher income countries.⁴²

B. Adaptation

An increase in disaster frequency can spur adaptation, as greater experience with disasters leads to learning and expectations of more future disasters spur investments in resilience. However, intensification can also overwhelm disaster response and recovery capacity, making it more difficult to rebuild quickly and effectively. We take two approaches to examine the extent of adaptation.

We next examine the extent to which local areas adapt to the occurrence of disasters. We address this question in two ways. First, we investigate whether disaster IRFs vary with a county's historical experience with disasters. For instance, have counties that are historically more disaster-prone better adapted to absorbing disaster shocks and hence see more positive economic responses after new disasters? Applying the methodology described in section

⁴² Looking at the other outcomes (shown in Appendix Figure A15), 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 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.

V.C., the results in Figure 8, panel (a) show limited evidence for adaptation. In contrast to the notion that disaster-prone areas adapt and become more resilient to disasters, we find that only counties *with* disaster experience show an immediate negative hit to income p.c. (statistically significant at the 90% level for the two intermediate categories). A possible explanation is that counties hit by other disasters within the previous 10 years may not have had time to fully recover and rebuild private and public capital, leaving them vulnerable to the impact of new 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.

A closely related adaptation question is how the average disaster response across *all* counties—regardless of their individual disaster experiences—has evolved over time. Given the increased aggregate frequency of disasters that we documented in Figure 1, communities throughout the United States may be anticipating a higher likelihood of disasters going forward, which could in turn lead to adaptations to mitigate the initial negative impacts on income, not to mention the negative impacts to wealth, property, and health. We estimate equation (8) and then calculate the implied IRF for the earliest (1983) and latest (2009) years in the sample, excluding the years in the earliest pre-trend interval (3 years) and the latest longer-run interval (8 years) using our estimate of $\hat{\theta}^h$. The results for income p.c. are shown in Figure 8, panel (b). The initial impact coefficient has become less negative, shifting toward zero over time, consistent with adaptation; however, the shift is not statistically significant. The magnitude of the longer-run post-disaster increase in income has also decreased over time. In particular, in addition to dipping in the medium run, the longer-run increase as of the latest year in our analysis (2009) is about 0.4%, which is less than half the increase as of the earliest year of the analysis (1983). This result suggests that going forward, as disasters become more frequent and severe, counties that are affected may not see such significant boosts in personal income afterward.

C. Spatial Spillovers and Wider Geographies

Our focus thus far has been on estimating the economic impacts of natural disasters at the local level, proxied by counties. The impacts at higher levels of aggregation could be different as important spatial spillovers could propagate the effects of a disaster in one county to other counties of varying distances away. We investigate this issue in two complementary ways. First, we construct geographic circular bands (“donuts”) of counties of given distance ranges surrounding each focal county hit by a disaster and then jointly estimate the impact of disasters

on both the focal county and on the geographic areas defined by each surrounding band. Second, we aggregate to the state level our treatment and outcome variables and repeat our baseline IRF specifications at the state, rather than county, level.

In Figure 9, we show the results of estimating equation (9) for personal income for bands of counties that are up to 199, 200-399, and 400-599 miles away from a county affected by a disaster.⁴³ The thin blue curves show the IRFs for the directly-hit counties, while the orange curves show the spatial lag IRFs.^{44,45} 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) – (c), 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. As shown in Figure A18, it appears that this is driven by a long-run net decline in average weekly

⁴³ See Appendix Figure A17 for a visual illustration of the spatial lags for a single year of disasters.

⁴⁴ Note that the blue curve shown here differs from our baseline estimate shown in Figure 3 because many disasters affect multiple neighboring counties, in which case we would have to add to the blue curve the effect captured in the orange curve in panel (a).

⁴⁵ In panels (a)-(c), the spatial lag coefficients have been normalized such that $D_{c,t}^b$ has been divided 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.

wages in the region of the disaster. This could result from resources being diverted from other counties in a region to those hit by disasters.

Figure 10 shows results of estimating equation (1) on state-aggregated data where the treatment (“disaster”) variable is now defined as the share of the state’s population living in a county hit by a disaster in a given year.⁴⁶ The dynamic pattern is qualitatively similar to our baseline per capita income result at the county level (Figure 3, panel (a)). However, the state-level disaster impacts are small and statistically insignificant, consistent with the results above showing a statistically insignificant net effect of disasters on income per capita for broad geographic areas.⁴⁷

VIII. Conclusion

We have found that, on average, counties hit by natural disasters initially see a decline in income per capita but then experience a medium to longer run boost, lasting at least eight years. 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, and, to a lesser extent, the pre-disaster income level of the county. 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

⁴⁶ Using a simple indicator variable for whether there was a disaster in any county in a given state-year results in very few no-treatment observations and also lumps together disasters of widely varying geographic breadth.

⁴⁷ We also investigated whether the state-level impact varied with the scale/breadth of the disaster by interacting the disaster treatment variable with four dummy variables indicating whether the percentage of the state population in a county hit by a disaster was below 10%, 10-50%, 50-90%, or above 90%. Shown in panel (b) of Appendix Figure A19, the longer-run positive impacts are found to increase with the scale/breadth of the disaster, though the results were not statistically significant.

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.

We have found mixed evidence when it comes to adaptation. On the one hand, consistent with adaptation, counties with more historical experience with disasters see larger post-disaster increases in personal income over the longer run. However, we find that the longer-run increase in personal income per capita has fallen roughly in half over the course of our sample period—a period in which disasters nationwide have become more frequent and severe—suggesting that the ability to recover and rebuild from disasters in a way that yields lasting economic benefits has declined over time, the opposite of what one might expect from adaptation.

Lastly, while the main focus of this paper has been on the *local* impact of natural disasters, our spatial analyses 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.

Taken together, our results suggest that despite the immense toll that disasters take, local economies have generally recovered successfully in terms of income. Indeed, not only does local income recover fully after a few years, it ends up somewhat higher in the longer run than what it would have been without the disaster. However, this average finding masks significant heterogeneity across contexts and a potential rise in inequality after disasters, given the lack of any decline in the poverty rate.

Our results contrast with some prior international evidence, especially that focused on developing countries, which has found long-lasting negative national income responses to certain disasters. An important difference in the U.S. setting is the wide availability of private and public insurance, the latter coming in the form of government aid. Going forward, climate change may lead to more, and more damaging, disasters, which could put increasing strains on insurance markets and government budgets.

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Tables and Figures

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 |

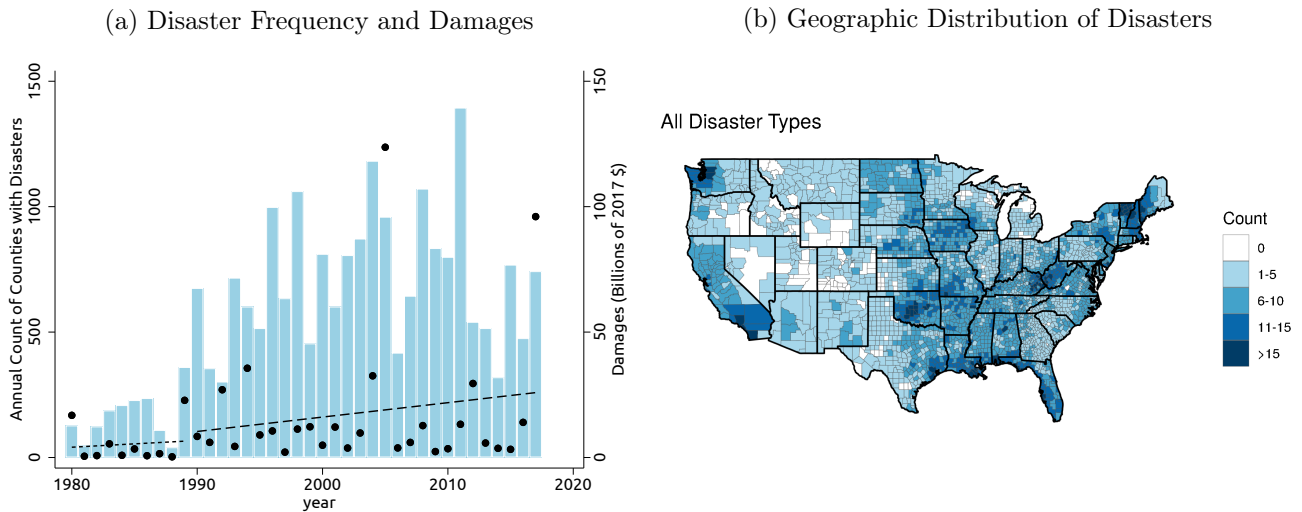
Note: Although the IHP Aid and NFIP Payment data are available at higher frequency in terms of the disasters which they cover, we use them entirely in annual terms as they are combined with annual SBA Loan data to examine the effect of aid on annual outcomes. Furthermore, we do not observe when the IHP 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.

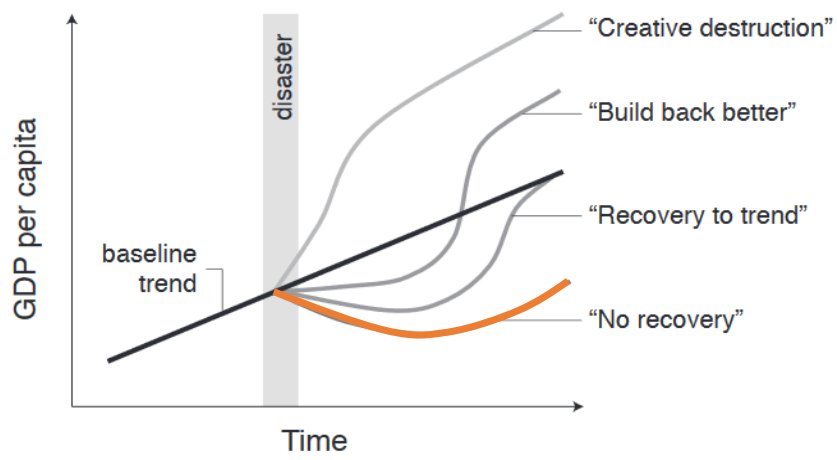
Figure 1: Natural Disaster Trends and Distribution, 1980 - 2017



Source: FEMA and SHELUDS.

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)

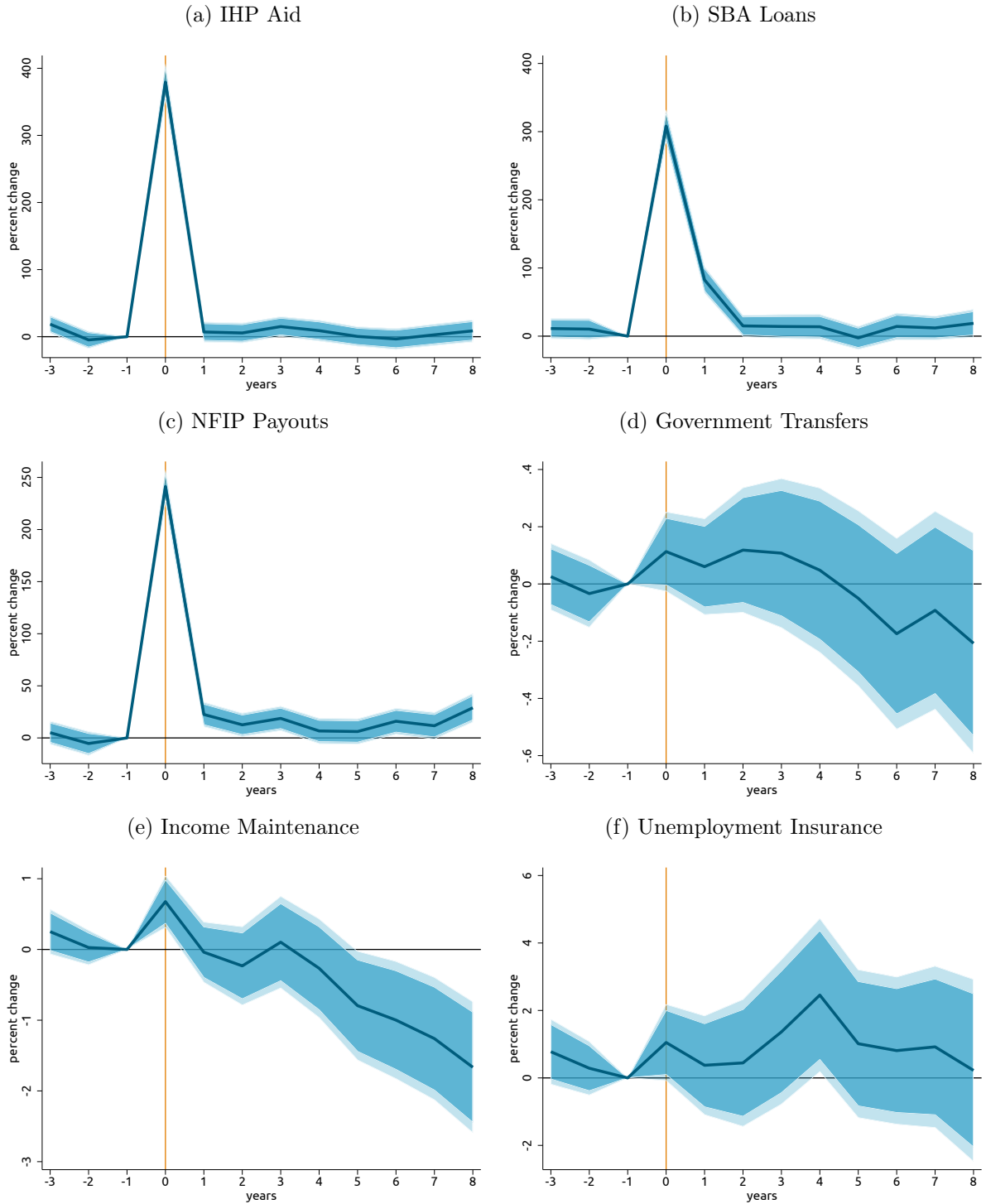
Figure 3: Baseline Effects - All Disasters



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 ($t = -1$).

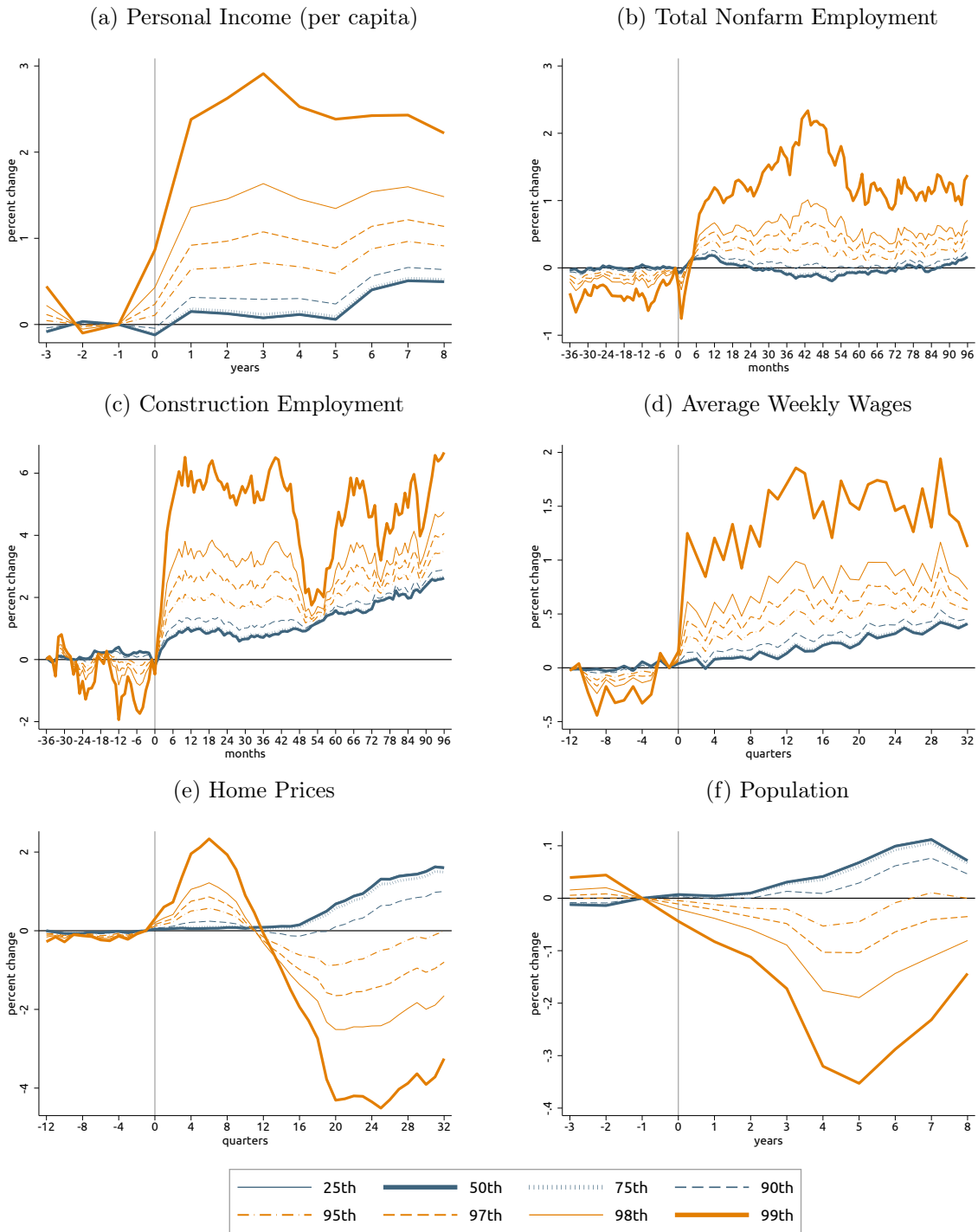
Figure 4: Effects on Government Transfers (per capita)



Source: FEMA, SHELDUS, SBA, FIMA NFIP Redacted Claims data, 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 ($t = -1$).

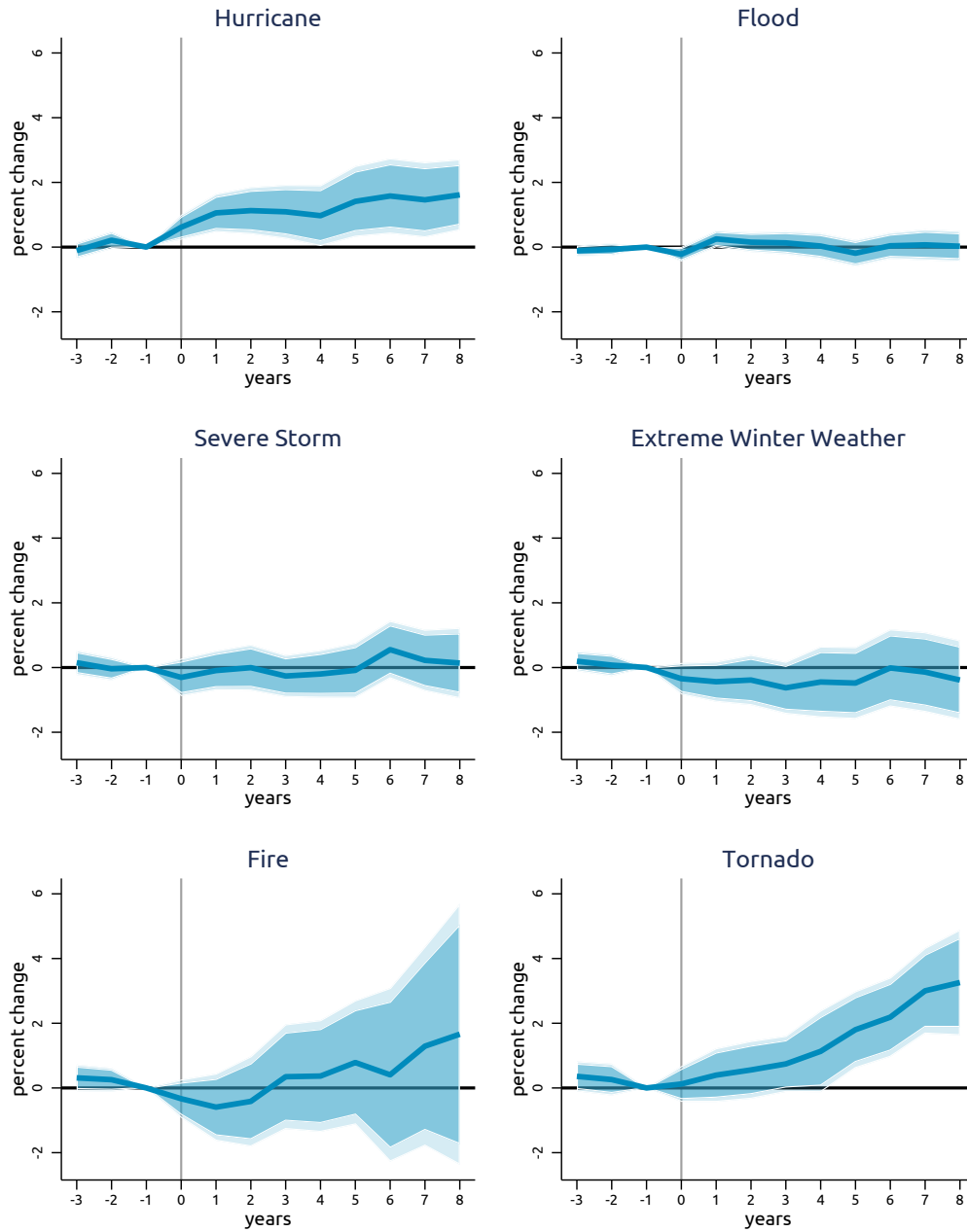
Figure 5: Effects by Damages Percentile



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 ($t = -1$).

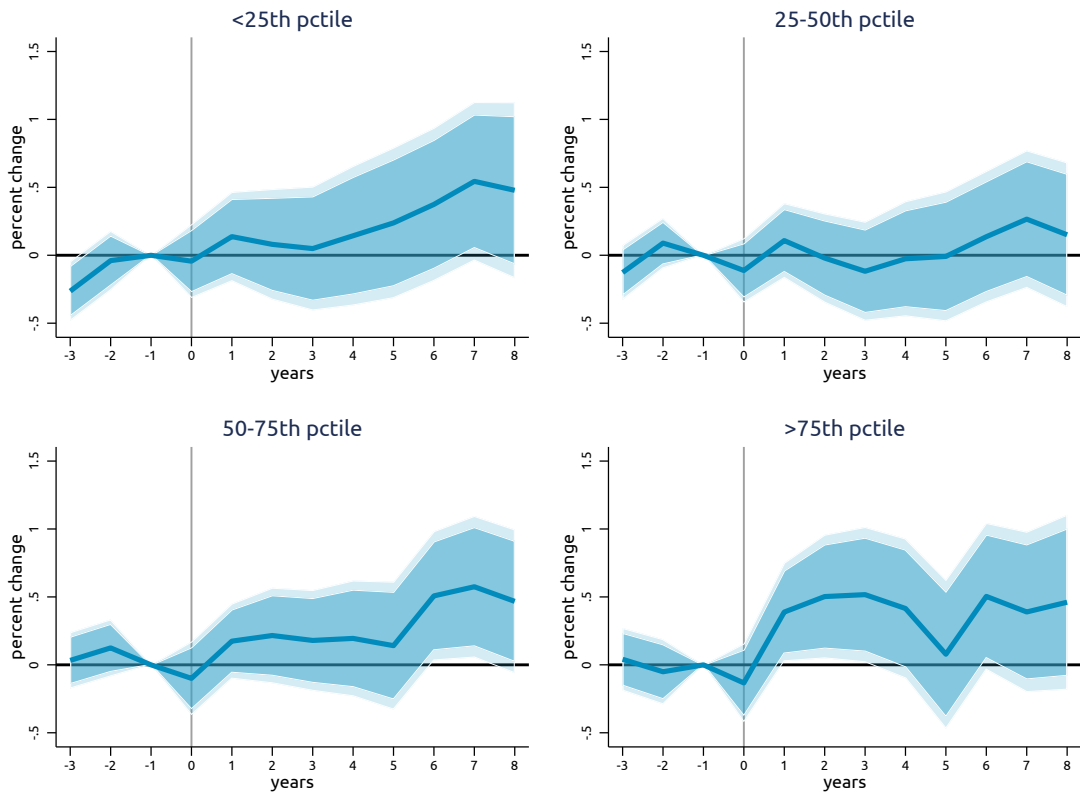
Figure 6: Personal Income (per capita) Effects By Disaster Type



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

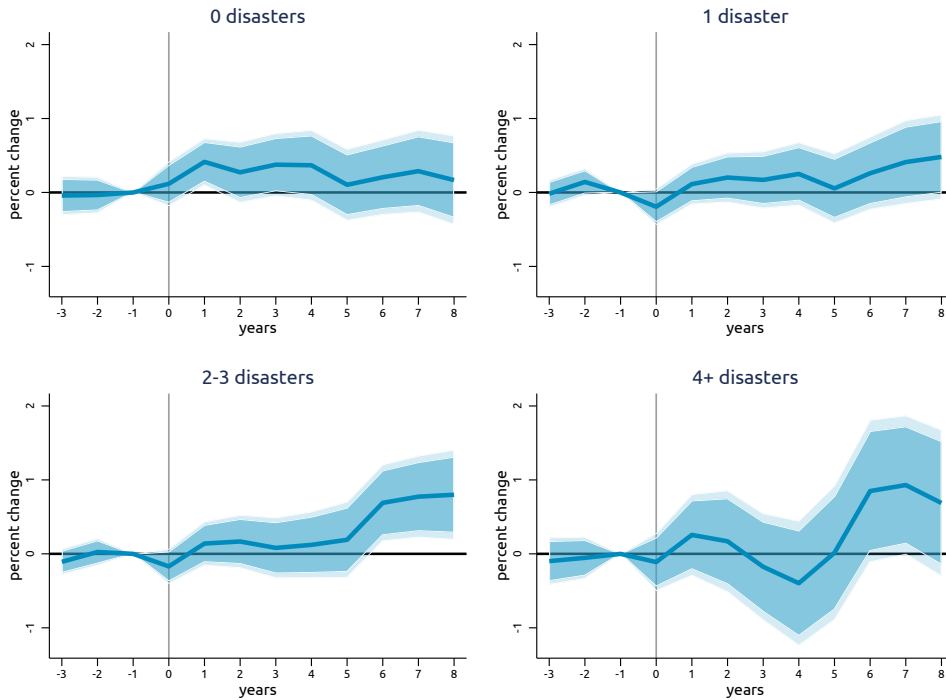


Source: FEMA, SHELDUS, BEA, and Census.

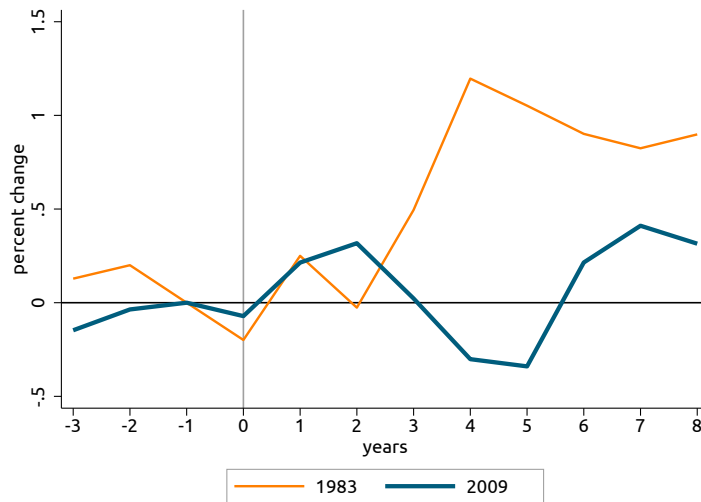
Note: These plots show the IRFs from estimating equation (7), where the shaded regions show the 90 and 95 percent confidence intervals. The quartiles of initial personal income per capita are based on the personal income in year -1 relative to the national distribution in that year. Personal income per 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: Adaptation and Personal Income Per Capita

(a) Heterogeneous Effects By Local Historical Disaster Exposure



(b) IRFs for Earliest and Latest Years Based on Time Trend Interaction

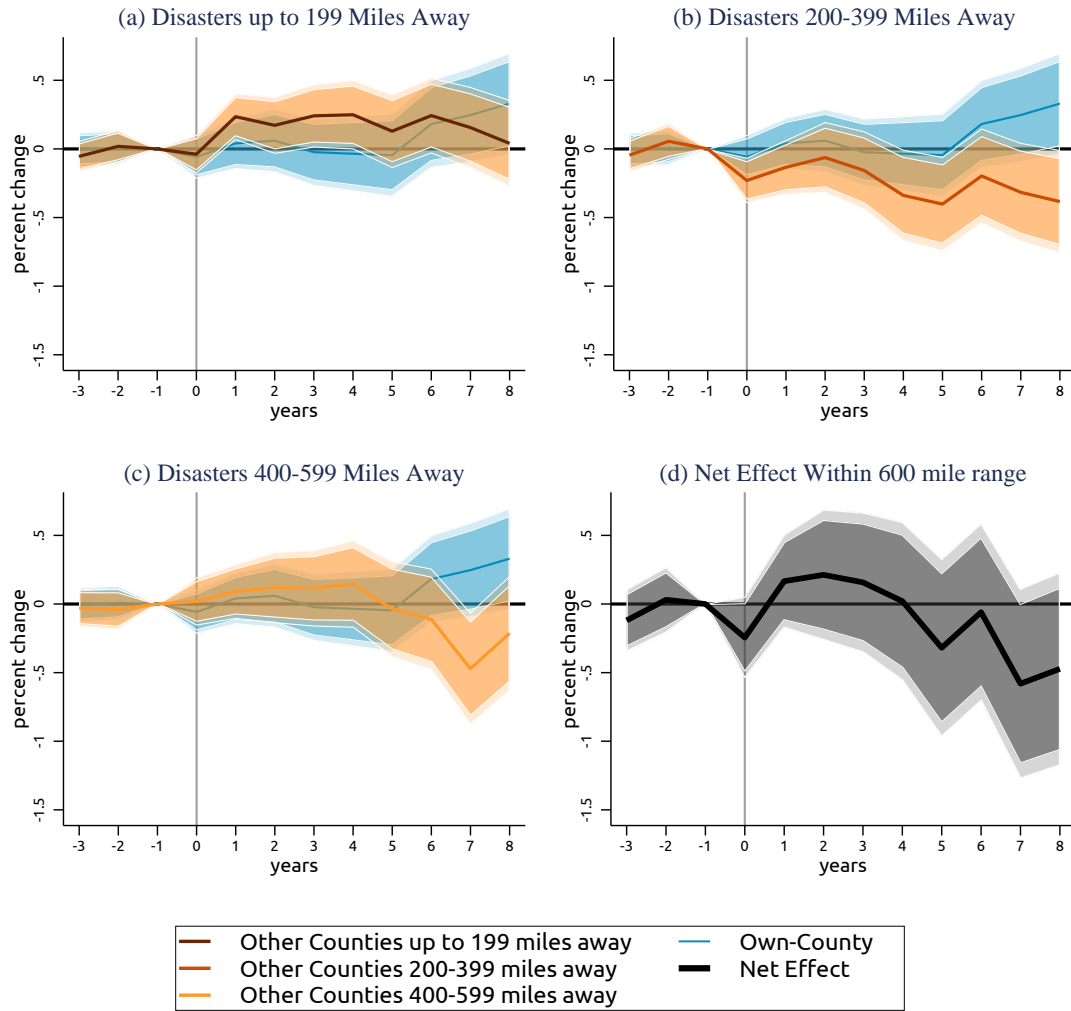


Source: FEMA, SHELDUS, BEA, and Census.

Note: Panel (a) shows 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. Panel (b) shows the implied IRFs from estimating equation (8) and then calculating the implied IRF for the earliest (1983) and latest year (2009) possible given our sample period and leads and lags. 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.)

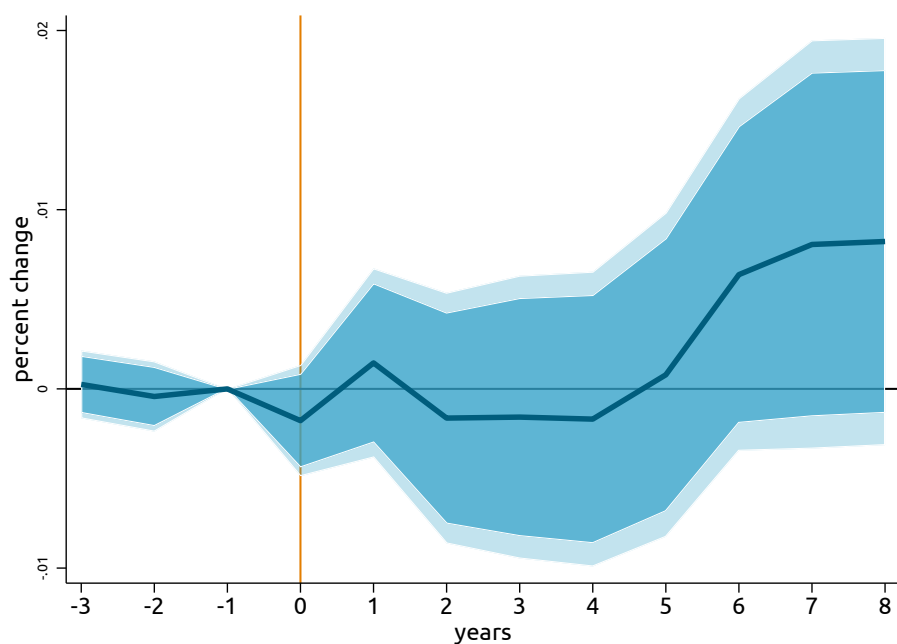
Results for spatial lags of varying distance bands



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 ($t = -1$).

Figure 10: State-Level Impacts of Disasters on Personal Income (p.c.)

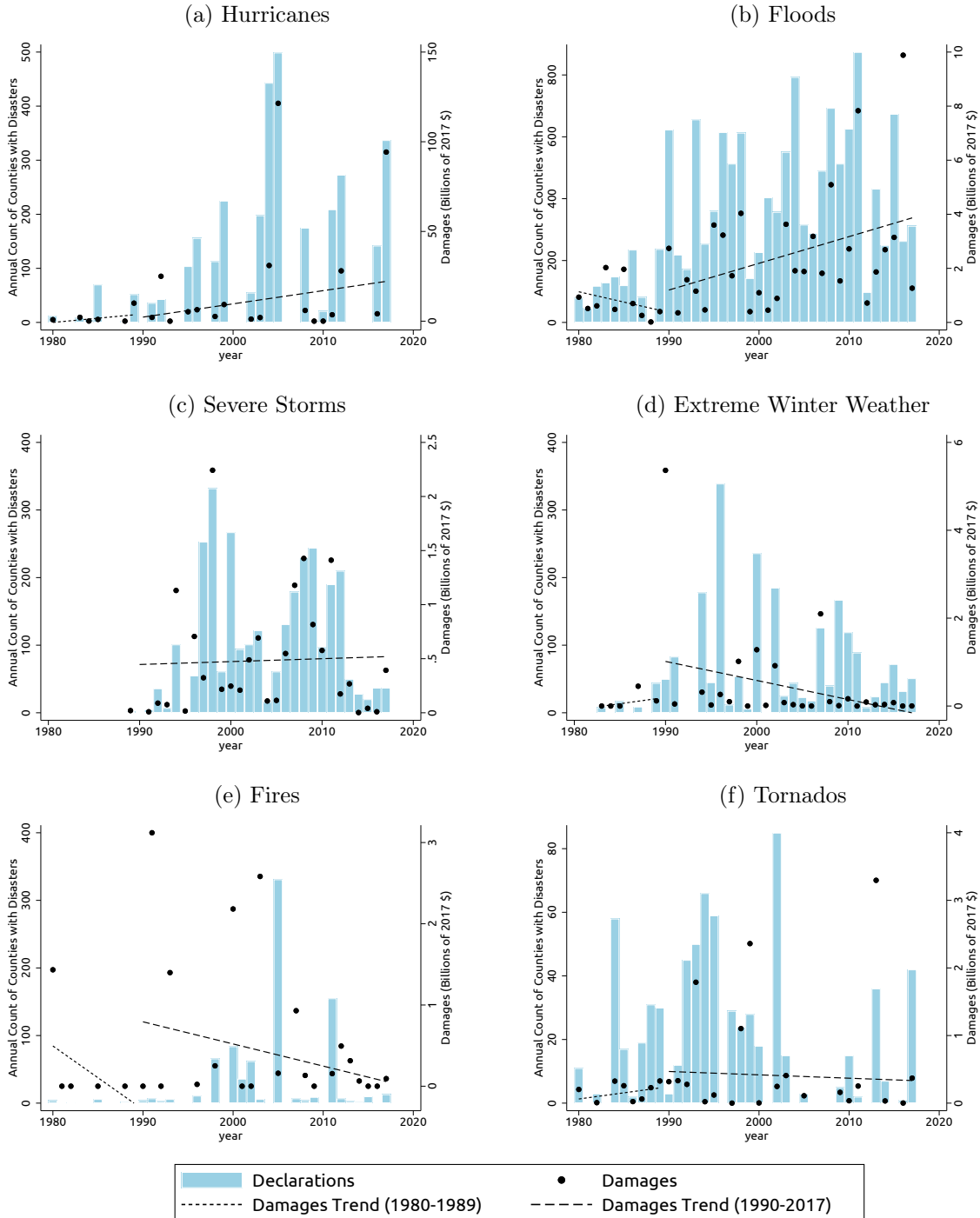


Source: FEMA, SHELDUS, BLS, Census, BEA, and CoreLogic.

Note: This figure shows the IRF from estimating equation (1) on state-aggregated data, where the treatment is the share of the state's population living in a county hit by a disaster. The inner shaded region indicates the 90 percent confidence intervals, and the lighter outer shaded region indicates the 95 percent confidence intervals. Personal income is aggregated at the state level and modeled as cumulative differences in logs between the horizon pictured and the period before the disaster ($t = -1$). Standard errors are clustered at the state and at the time-by-division levels.

Appendix A

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

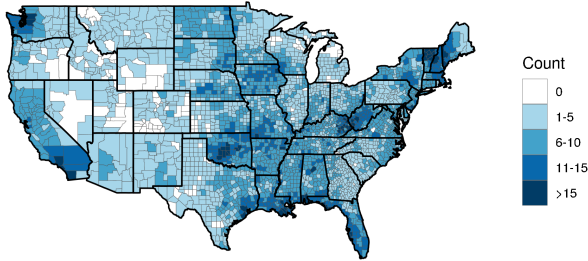


Source: FEMA and SHELDUS.

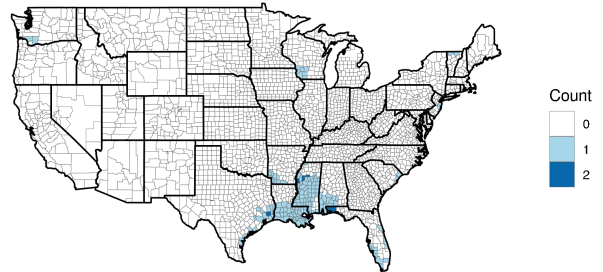
Note: The blue bars show the number of counties each year with at least one disaster declaration in the listed categories. The black dots indicate total damages in USD 2017. If a county experienced flooding due to a hurricane, that will show up only on the hurricane plot. If a county receives two separate 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 Disaster Declarations

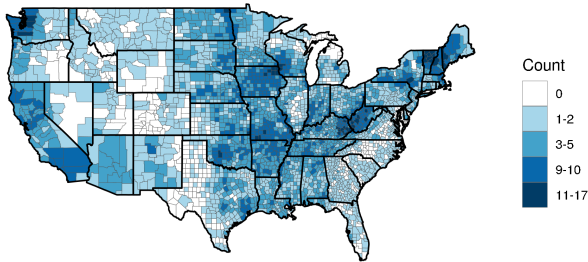
All Disaster Types



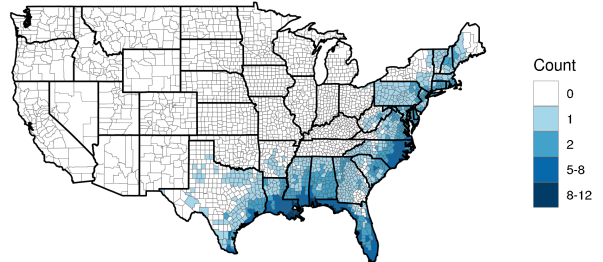
Per Capita Damages at or Above 99th Percentile



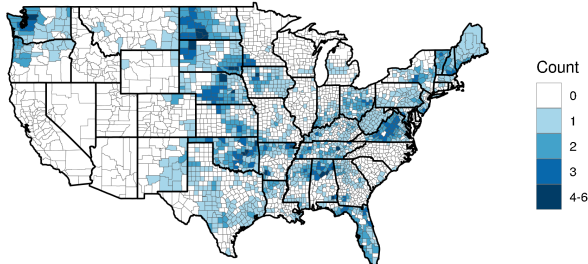
Floods (60%)



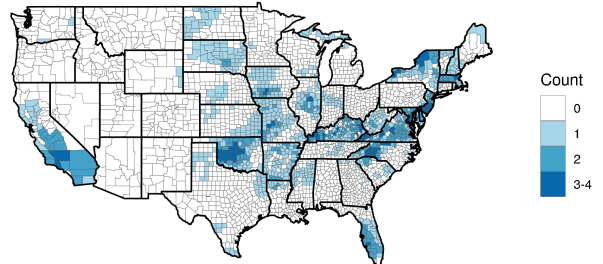
Hurricanes (15%)



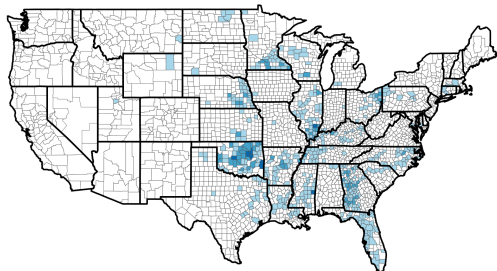
Severe Storms (11%)



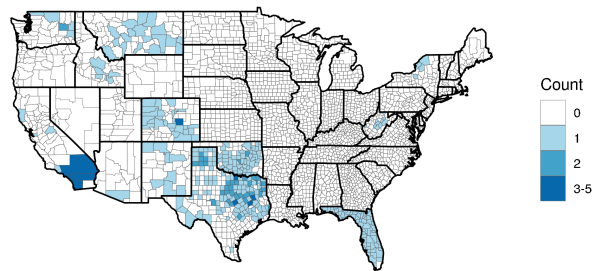
Severe Winter Weather (8%)



Tornadoes (3%)



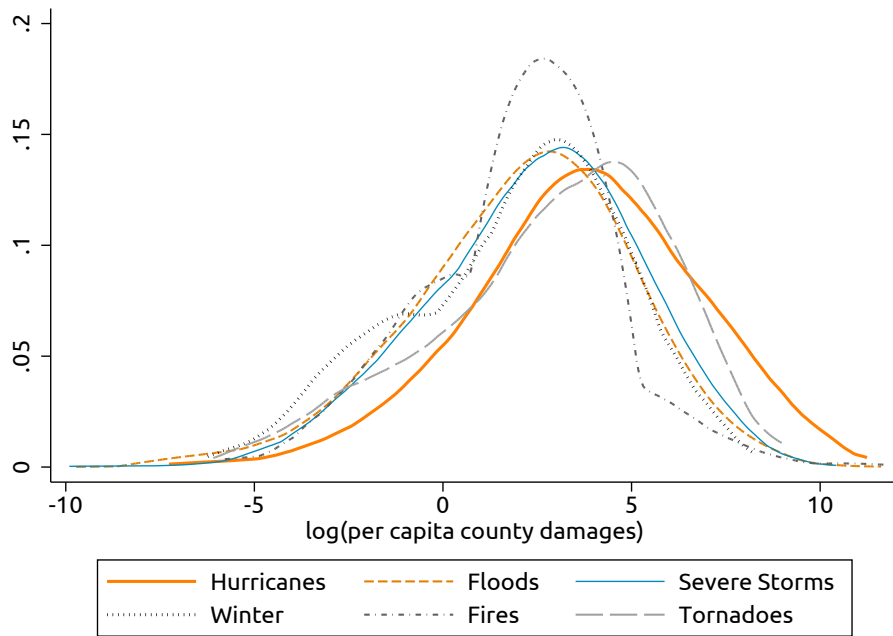
Fires (2%)



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 A3: Distribution of Per Capita County Damages by Disaster Type

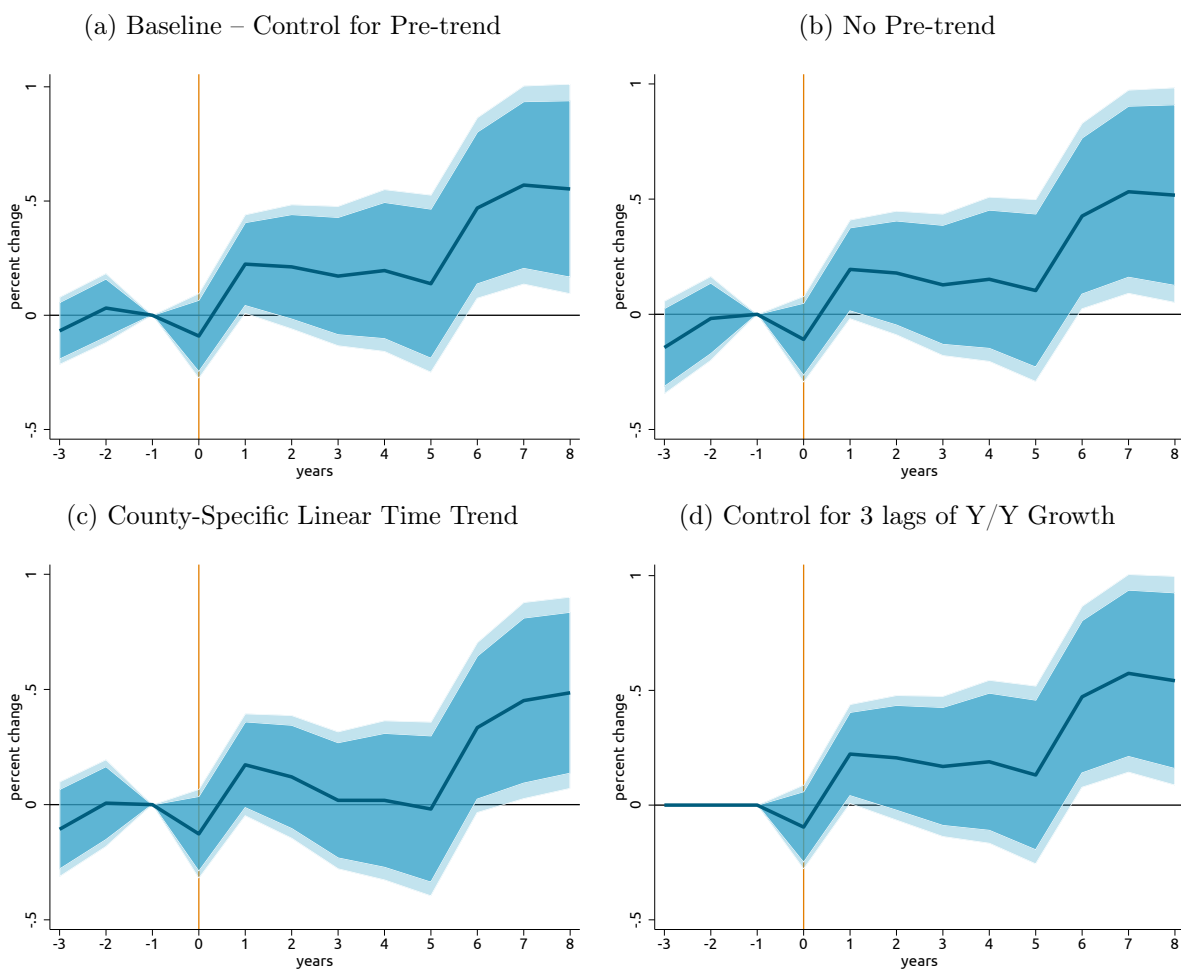


Source: FEMA, SHELDUS.

Note: The y-axis shows density and not frequency.

Figure A4: Alternative Specifications for Trends

Impacts on Personal Income Per Capita - All Disasters

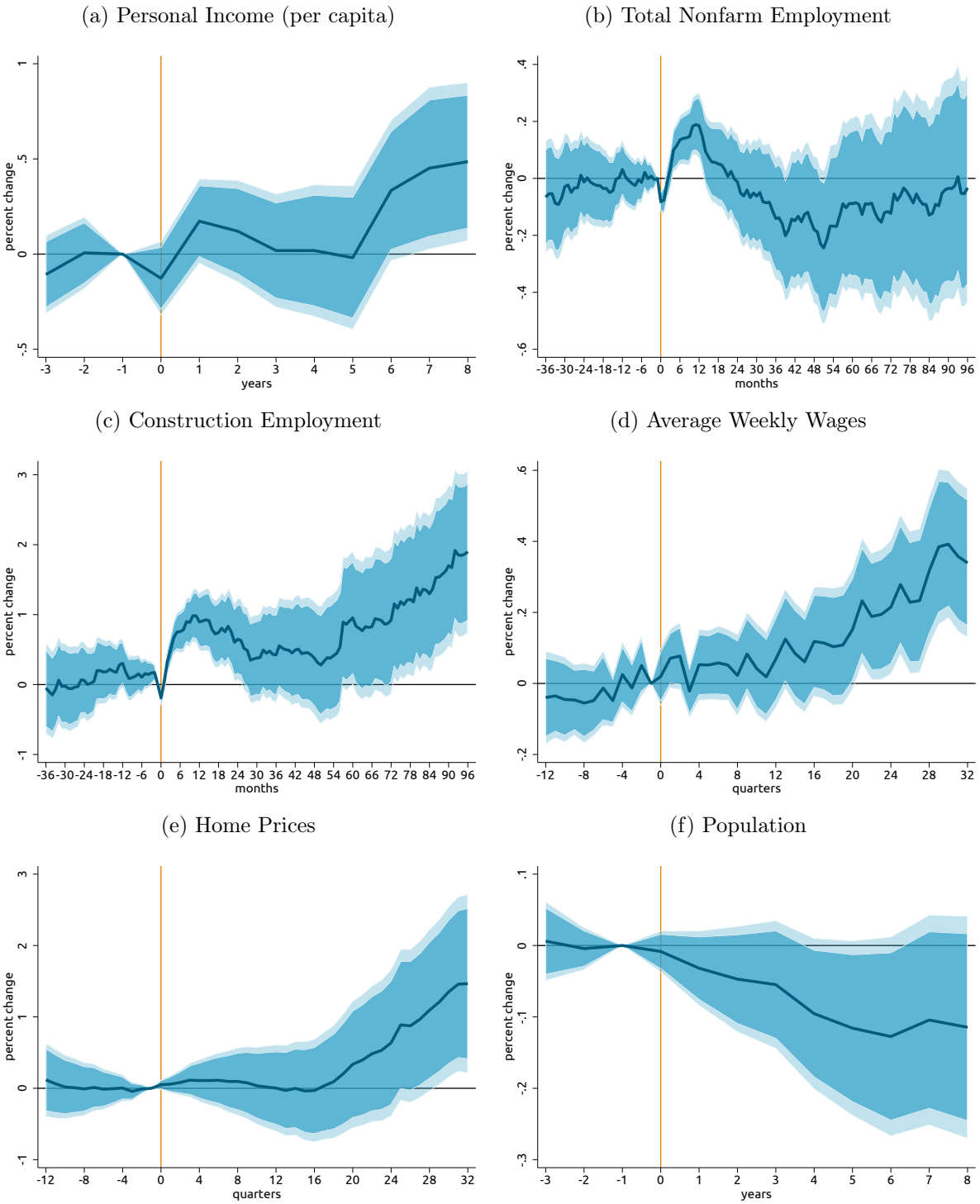


Source: FEMA, SHELDUS, BLS, Census, BEA, and CoreLogic.

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: Alternative Specification - County-Specific Linear Time Trend

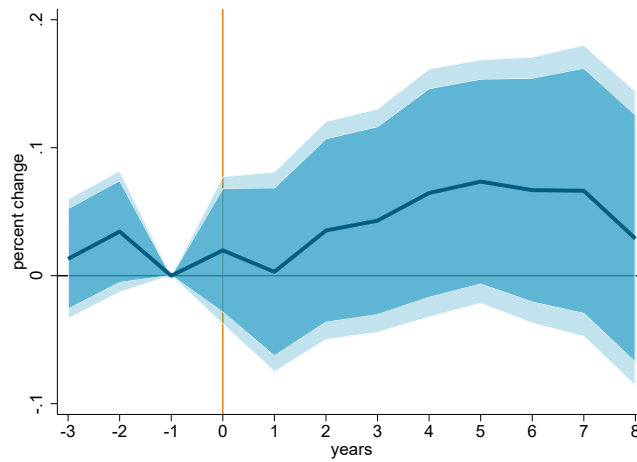
Impacts - All Disasters



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 ($t = -1$).

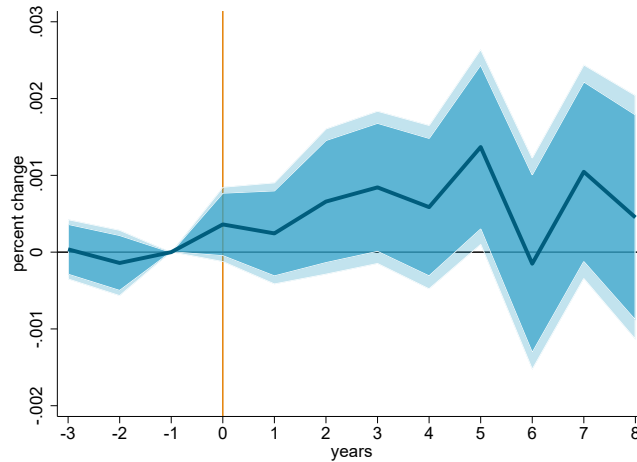
Figure A6: Impact of Disasters on Poverty Rate



Source: FEMA, SHELDUS, and the Census Bureau’s Small Area Income and Poverty Estimates (SAIPE) program.

Note: Figure shows the IRF from estimating equation (1) where the dependent variable is the poverty rate. The inner shaded regions indicate the 90 percent confidence intervals, and the lighter outer shaded regions indicate the 95 percent confidence intervals. Standard errors are clustered at the county and time-by-state level.

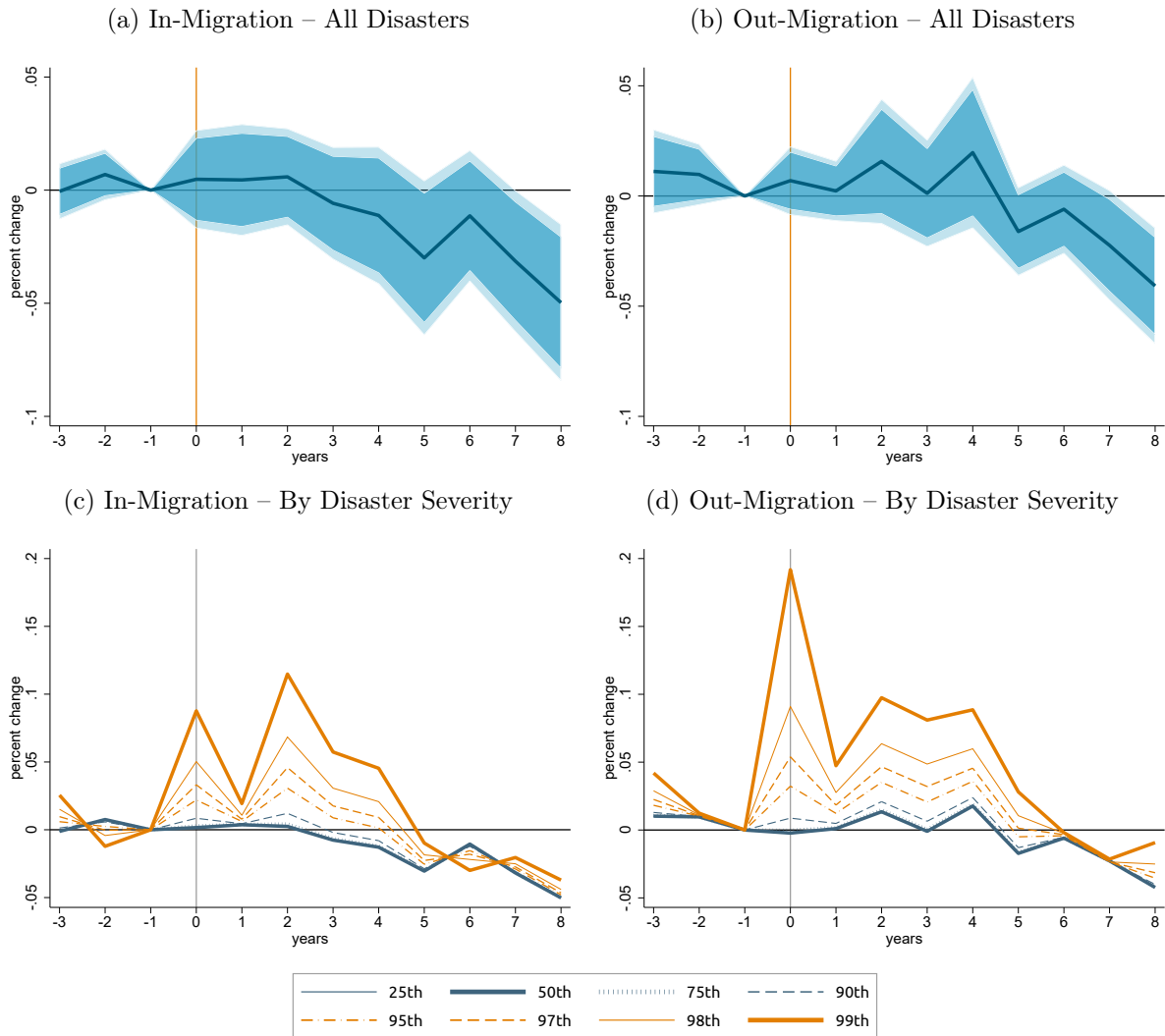
Figure A7: Impact of Disasters on Wages Implied by Local Industry Composition and National Wages



Source: FEMA, SHELDUS, CEPR yearly extracts of the CPS Outgoing Rotation Group micro-data, and the Census Bureau’s County Business Patterns.

Note: Figure shows the IRF from estimating equation (1) where the dependent variable is an estimate of what the mean wage would be if the local wage composition is applied to the national wage rates. The inner shaded regions indicate the 90 percent confidence intervals, and the lighter outer shaded regions indicate the 95 percent confidence intervals. Standard errors are clustered at the county and time-by-state level.

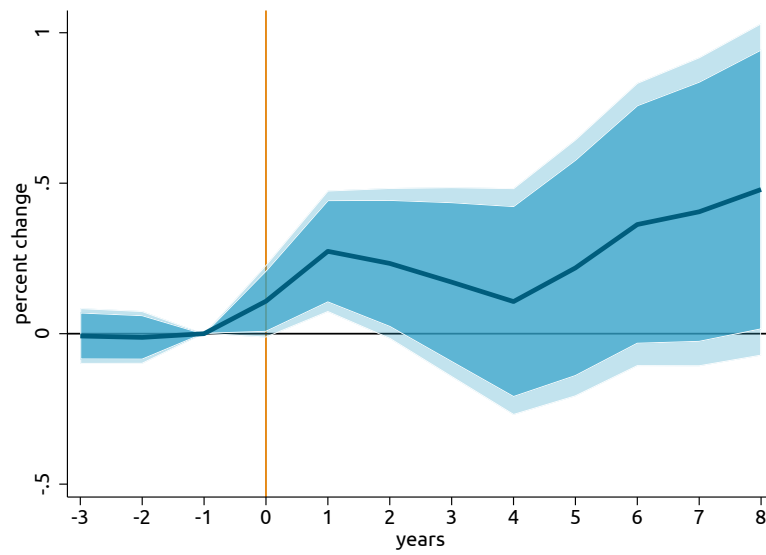
Figure A8: Disaster Effects on Migration



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 ($t = -1$).

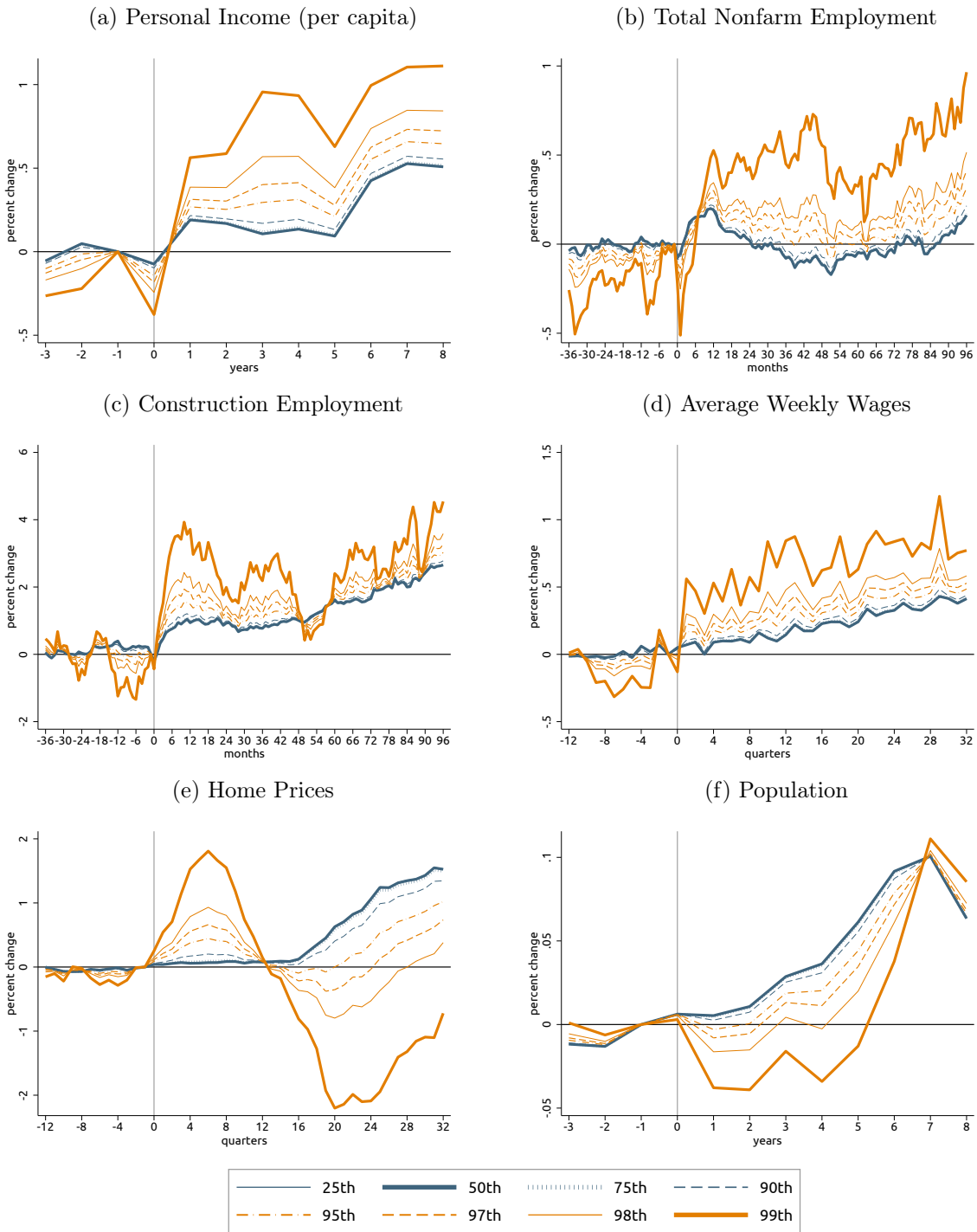
Figure A9: Wage & Salary Income (per capita)



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 is observed at the county level and modeled as cumulative differences in logs between the horizon pictured and the period before the disaster ($t = -1$).

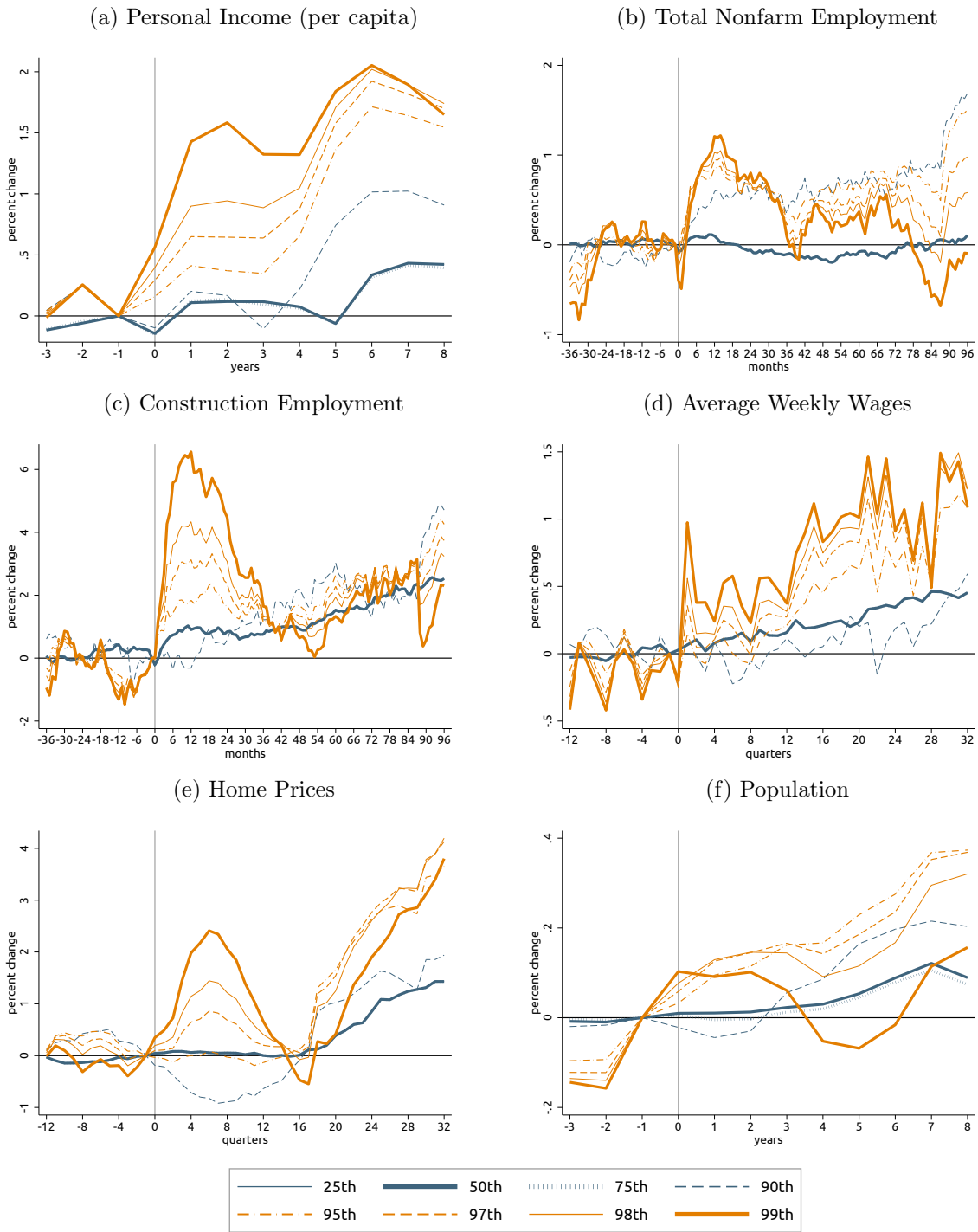
Figure A10: Effects by Damages Percentile – Using Original SHEL DUS per capita damages



Source: FEMA, SHEL DUS, BLS, Census, BEA, and CoreLogic.

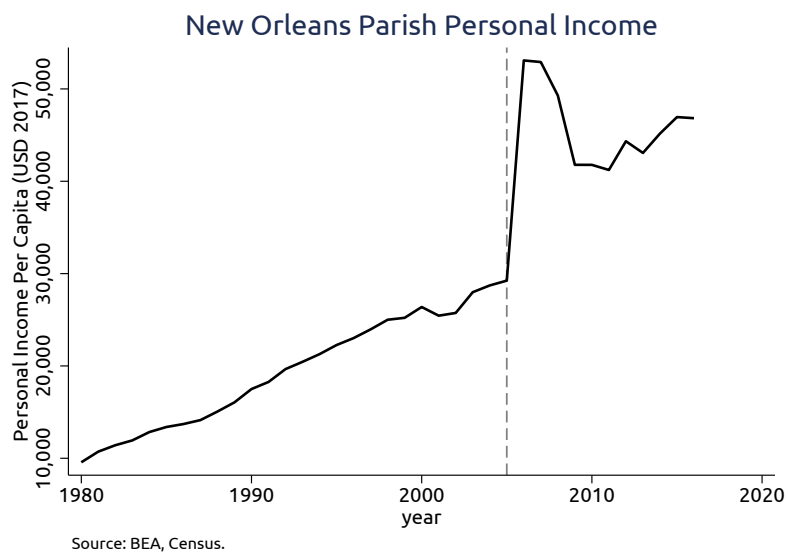
Note: These plots show the IRFs from estimating equation (4), where the percentile lines reflect the model predictions given the per capita damage distributions for all county-month observations with FEMA disaster declarations. All variables are observed at the county level and modeled as cumulative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

Figure A11: Effects by Wind Speed Percentile – Using HURDAT2 data



Source: FEMA, SHELDUS, HURDAT2, BLS, Census, BEA, CoreLogic, and [Anderson et al \(2020a, 2020b\)](#).
 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 A12: Historical Per Capita Personal Income in New Orleans



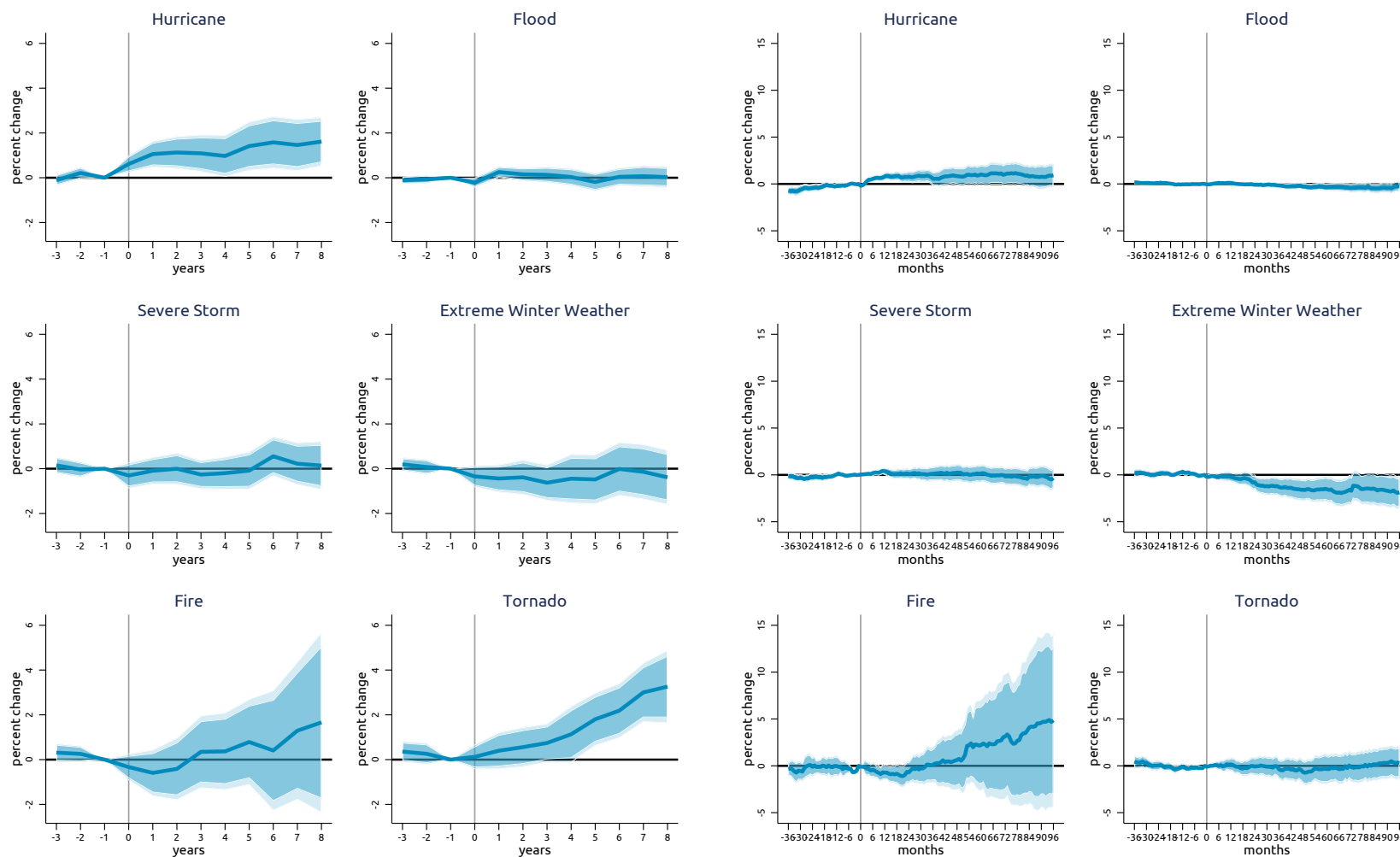
Source: BEA and Census.

Note: Vertical red line indicates 2005, the year of Hurricane Katrina.

Figure A13: Effects By Disaster Type

(a) Personal Income (per capita)

(b) Total Nonfarm Employment

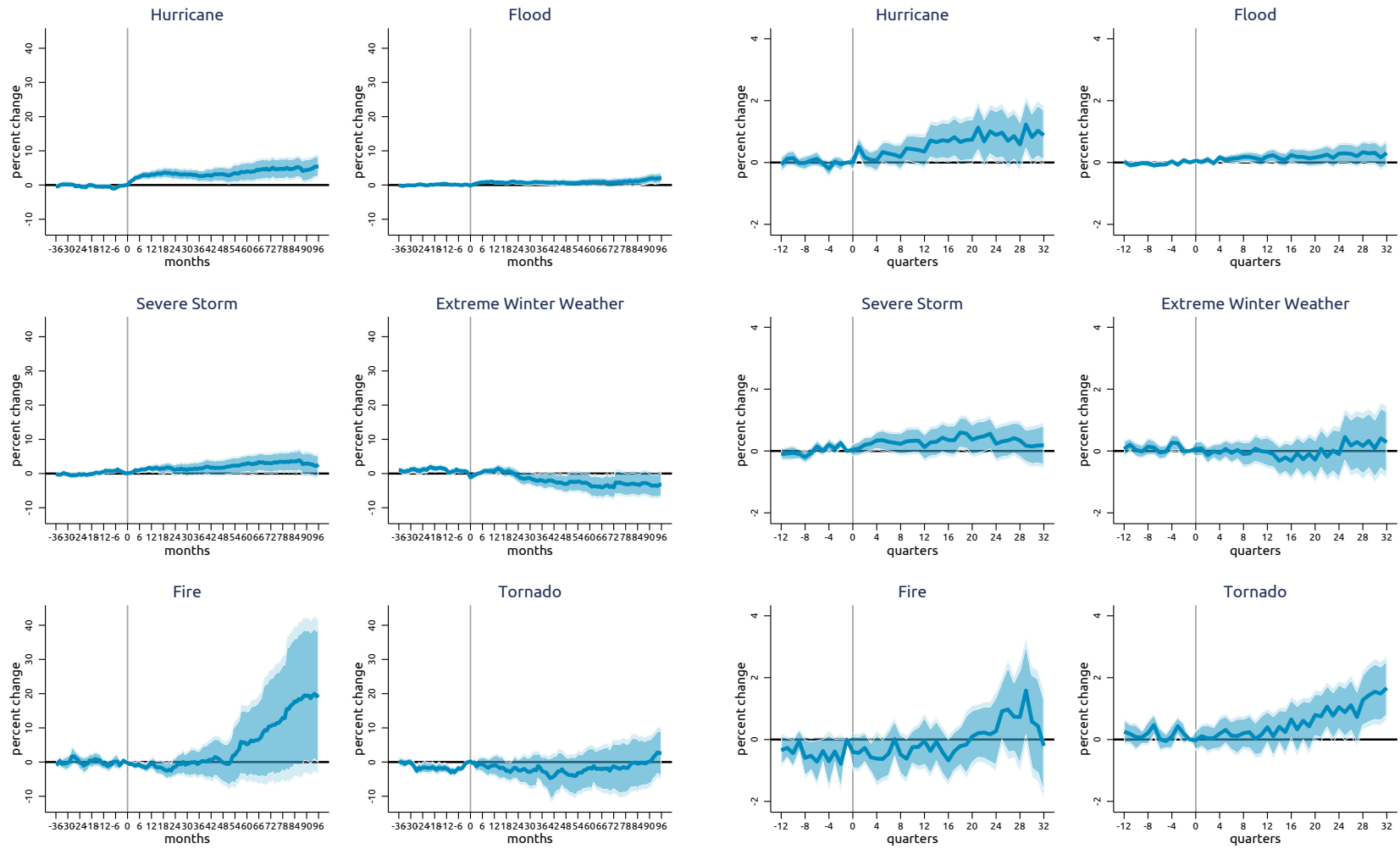


See notes at end of figure.

Figure A13: Effects By Disaster Type (continued)

(c) Construction Employment

(d) Average Weekly Wages



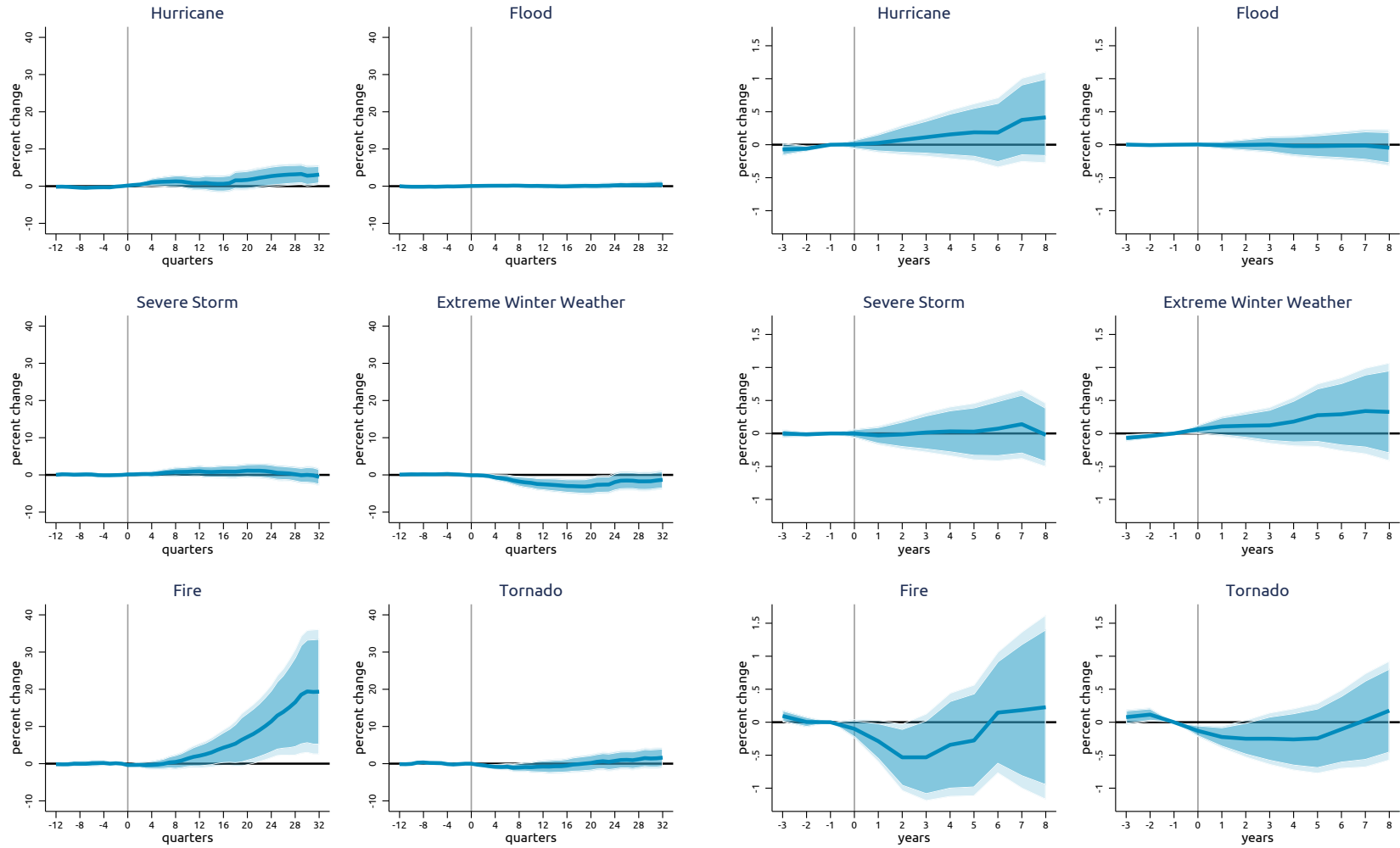
39

See notes at end of figure.

Figure A13: Effects By Disaster Type (continued)

(e) Home Prices

(f) Population

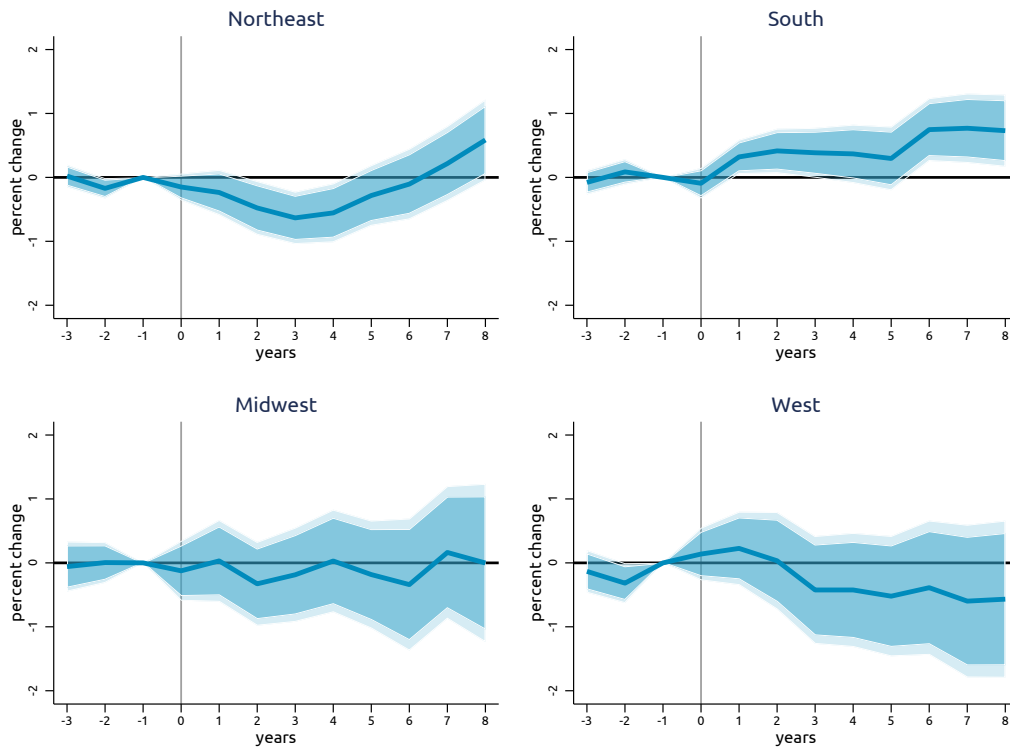


79

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 A14: Impacts of Disasters on Personal Income (p.c.)
Differentiated by Census Division

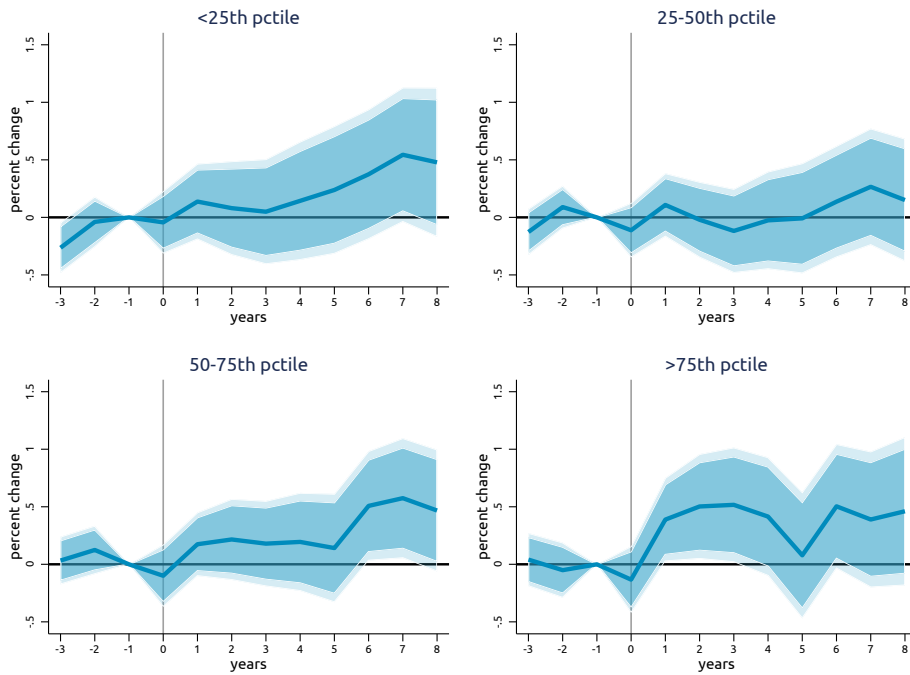


Source: FEMA, SHELDUS, BLS, Census, BEA, and CoreLogic.

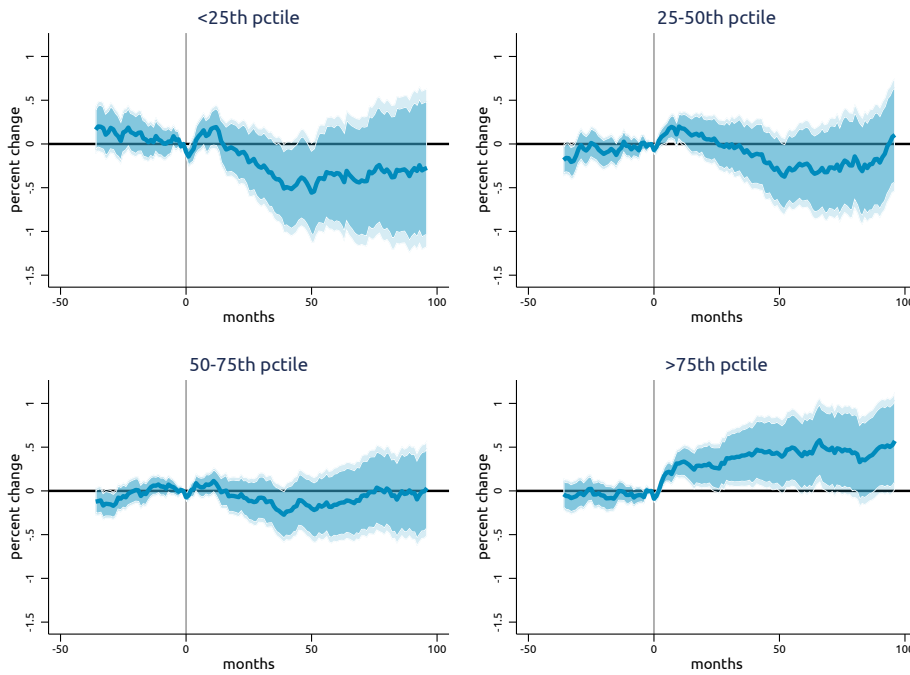
Note: These plots show the IRFs from estimating equation (1) but interacting the disaster indicator with separate indicators for each of the four Census divisions. The inner shaded regions indicate the 90 percent confidence intervals, and the lighter outer shaded regions indicate the 95 percent confidence 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 A15: Effects By Initial Personal Income Per Capita

(a) Personal Income (per capita)



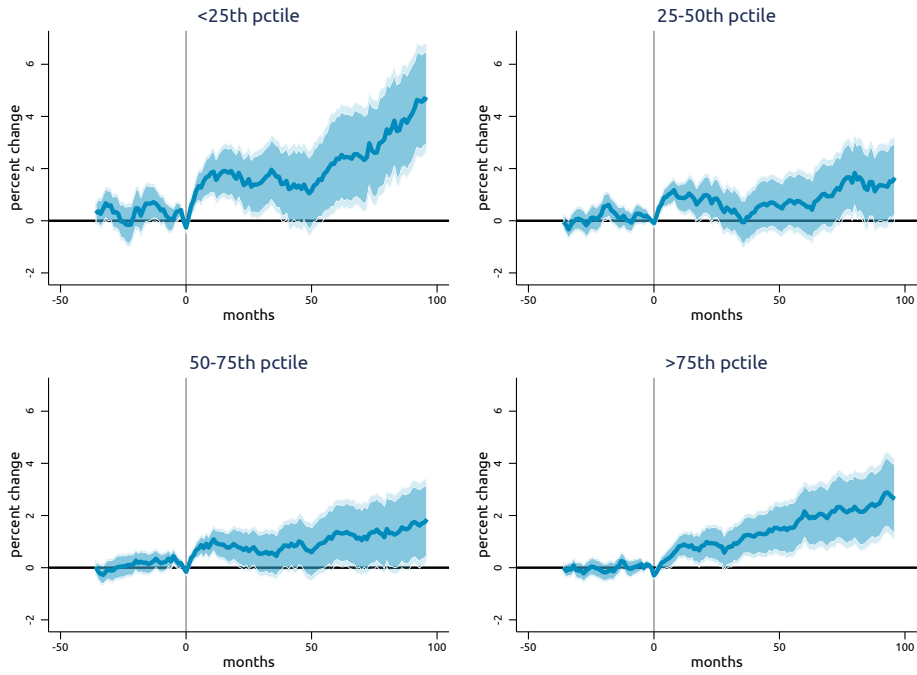
(b) Total Nonfarm Employment



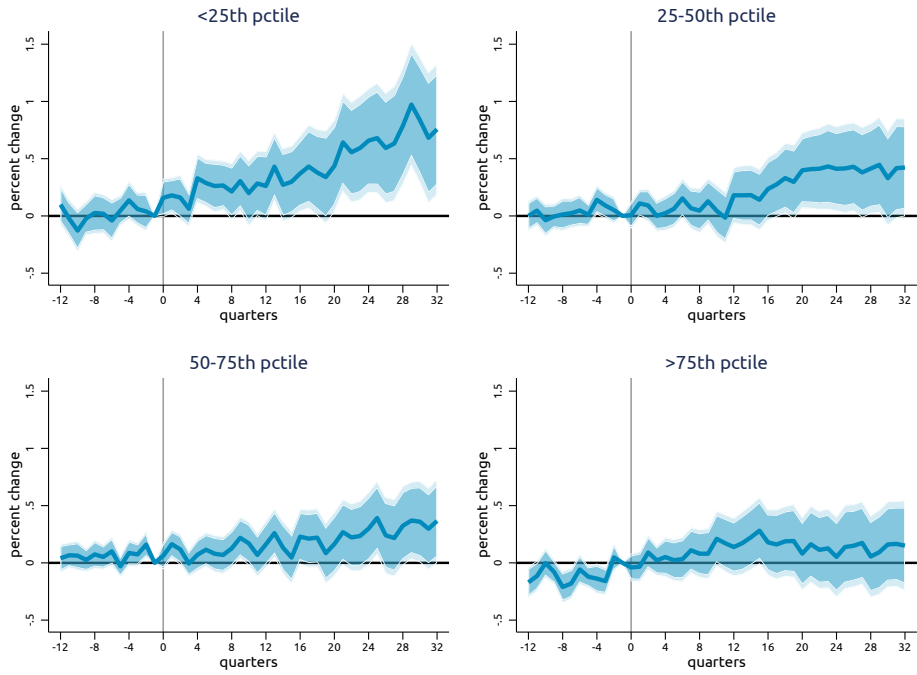
See notes at end of figure.

Figure A15: Effects By Initial Personal Income Per Capita (continued)

(c) Construction Employment



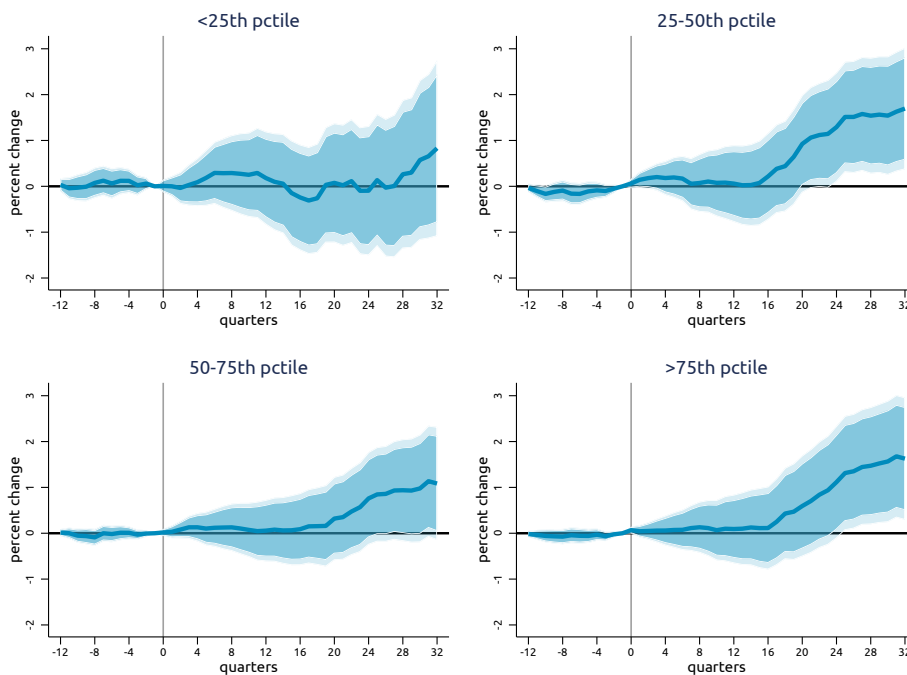
(d) Average Weekly Wages



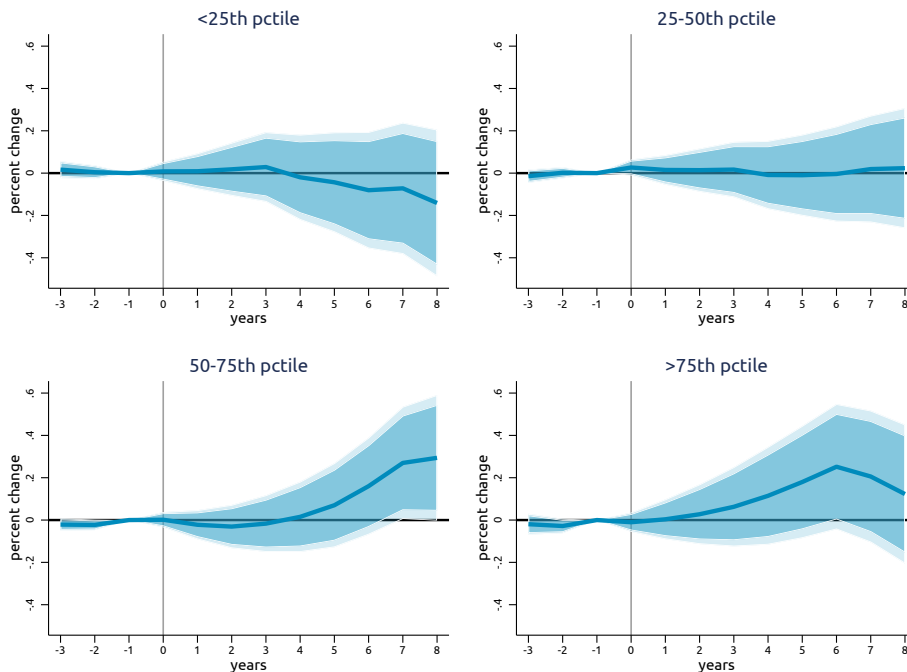
See notes at end of figure.

Figure A15: Effects By Initial Personal Income Per Capita (continued)

(e) Home Prices



(f) Population

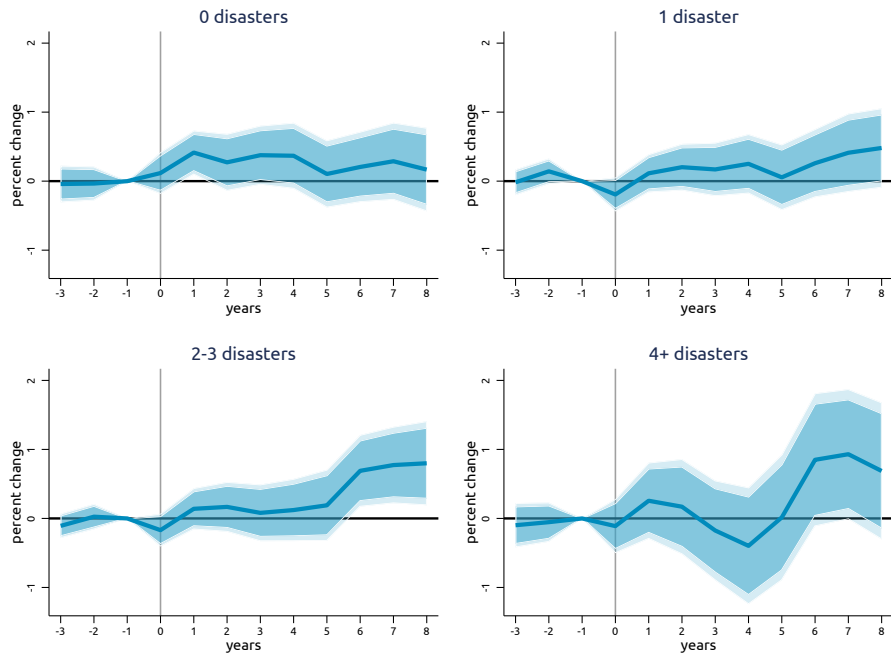


Source: FEMA, SHELDUS, BEA, and Census.

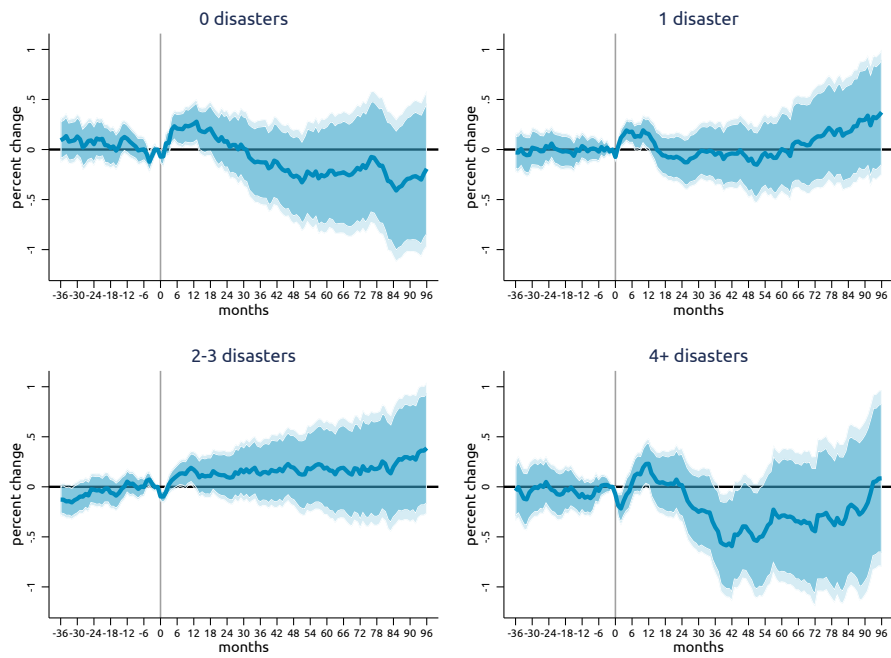
Note: These plots show the IRFs from estimating equation (7), where the shaded regions show the 90 and 95 percent confidence intervals. The quartiles of initial personal income per capita are based on the personal income in year -1 relative to the national distribution in that year. All outcomes are 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 A16: Effects By Local Historical Disaster Exposure

(a) Personal Income (per capita)



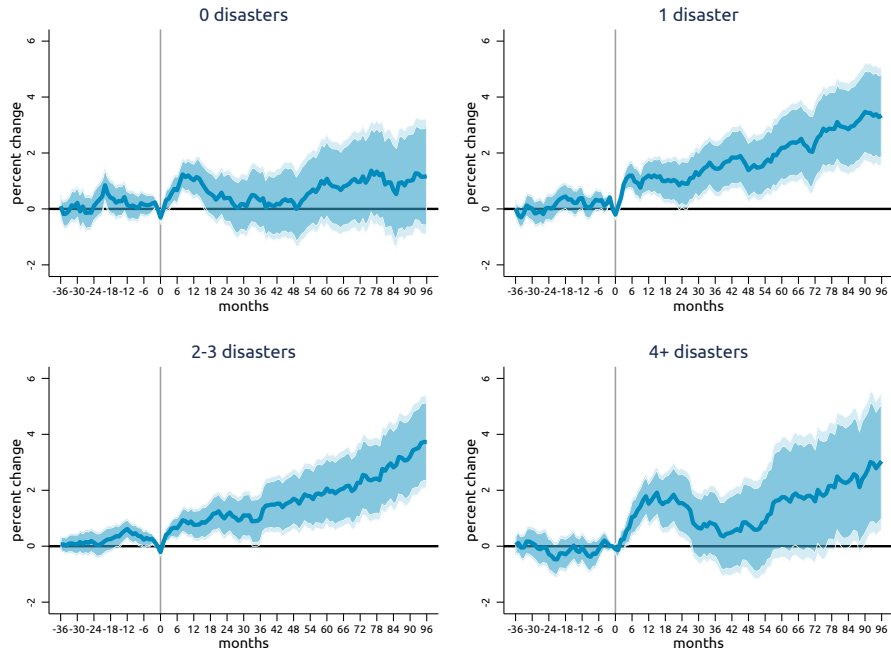
(b) Total Nonfarm Employment



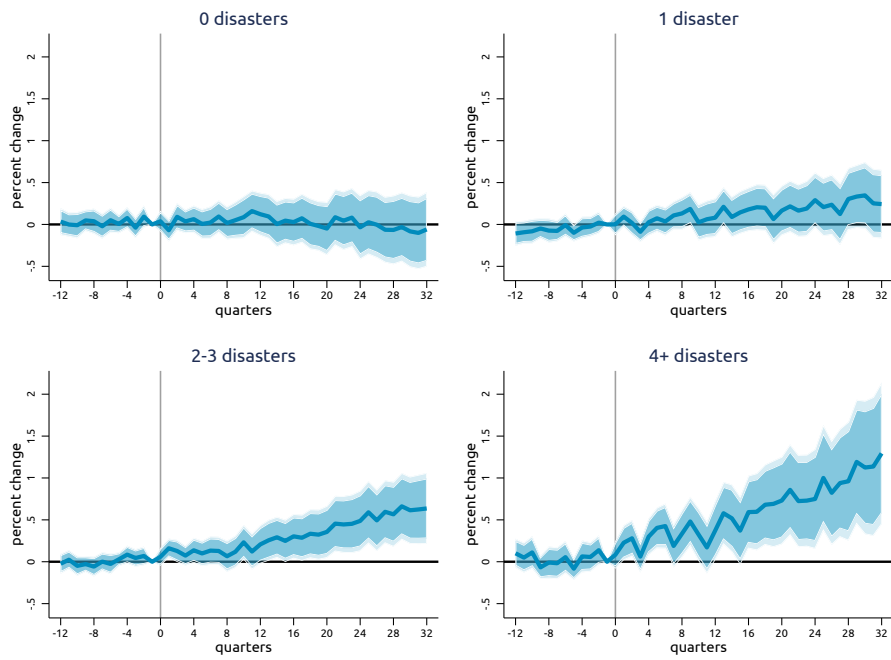
See notes at end of figure.

Figure A16: Effects By Local Historical Disaster Exposure (continued)

(c) Construction Employment



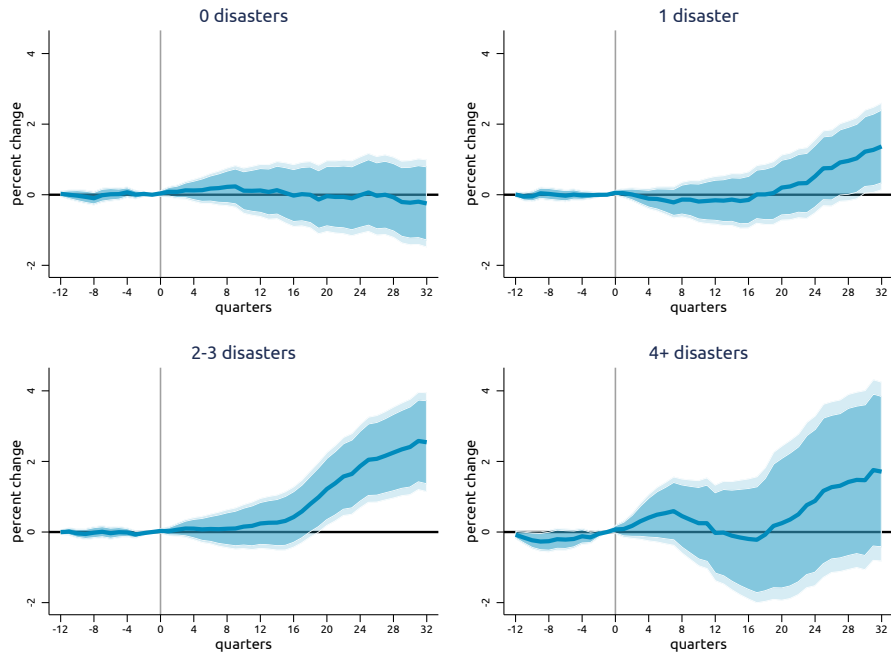
(d) Average Weekly Wages



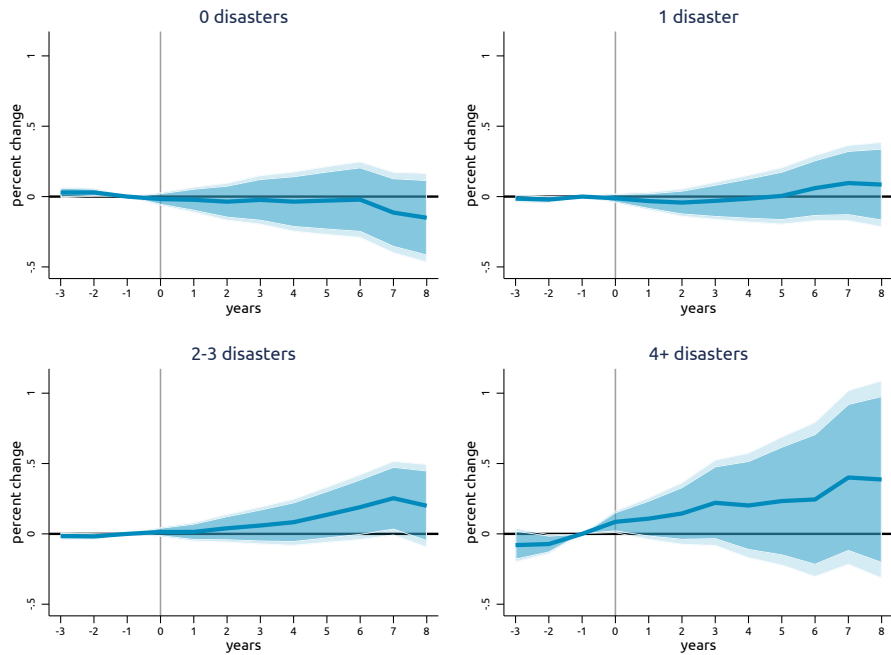
See notes at end of figure.

Figure A16: Effects By Local Historical Disaster Exposure (continued)

(e) Home Prices



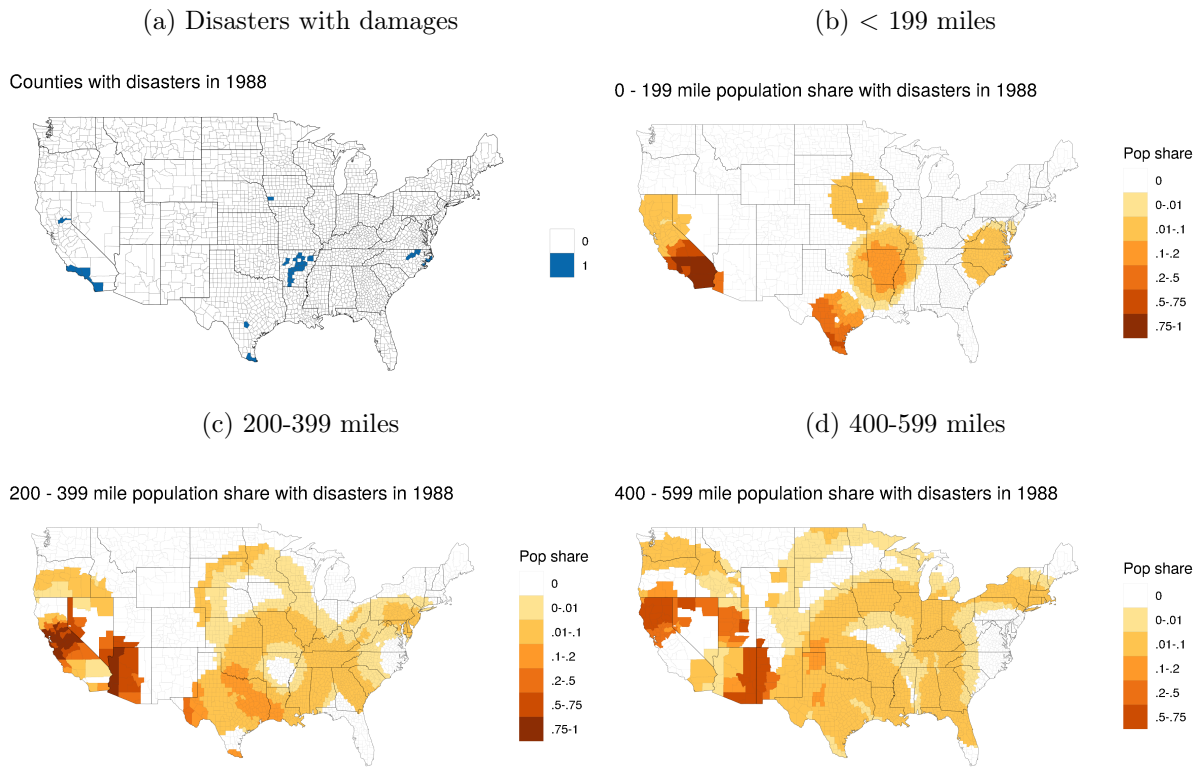
(f) Population



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 A17: Spatial Lags in 1988

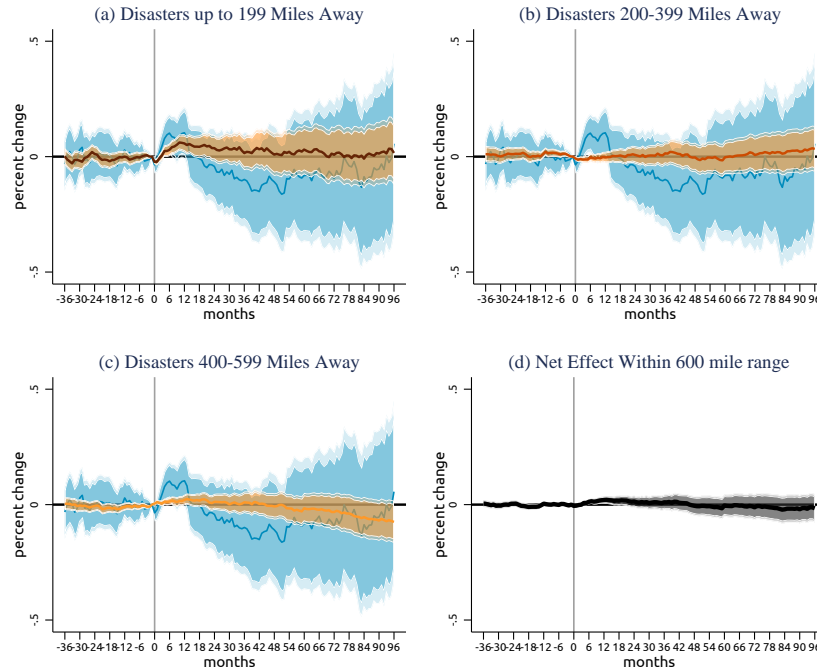


Source: FEMA, SHELDUS.

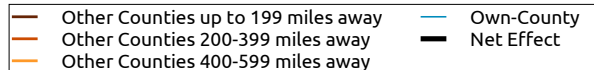
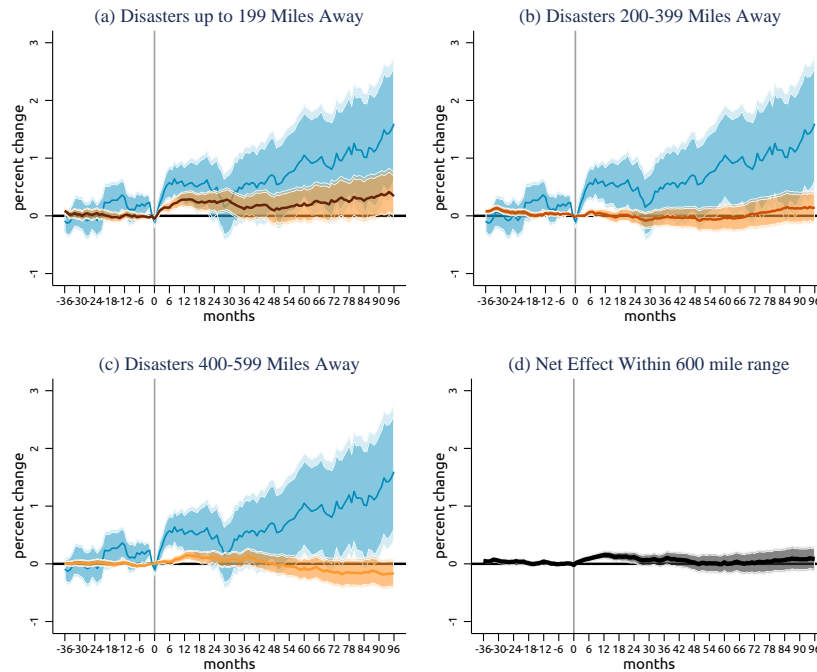
Note: Using 1988 as an example, panel (a) depicts the counties that received major disaster declarations from FEMA with positive damages in SHELDUS. Panels (b)-(c) depict the share of population within each band (50-199, 200-399, and 400-599 miles) of a given county that had disaster declarations with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

Figure A18: Impacts of Own-county Disasters vs. Spatially-Lagged Disasters
Results for spatial lags of varying distance bands

(a) Total Non-Farm Employment



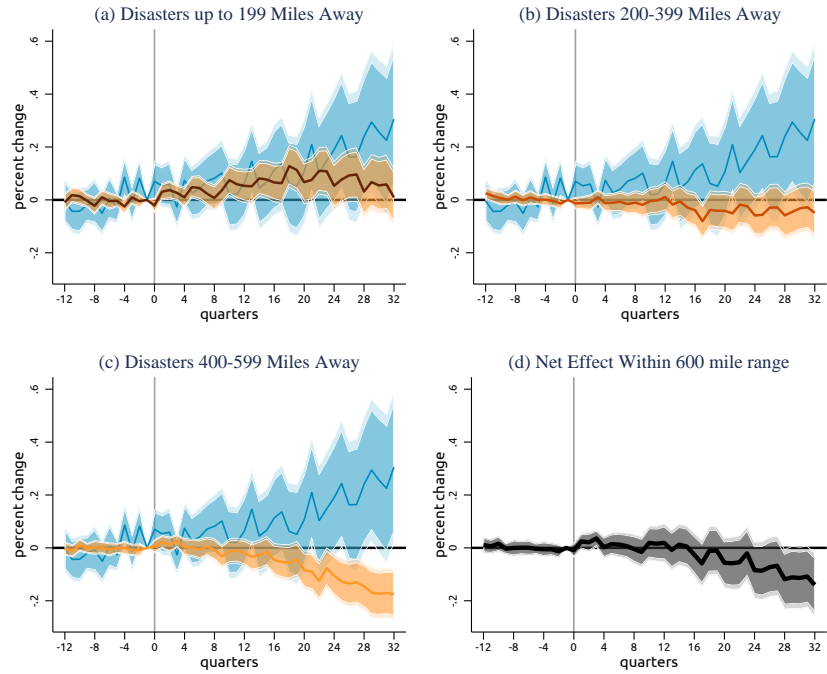
(b) Construction Employment



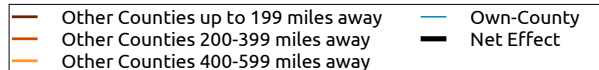
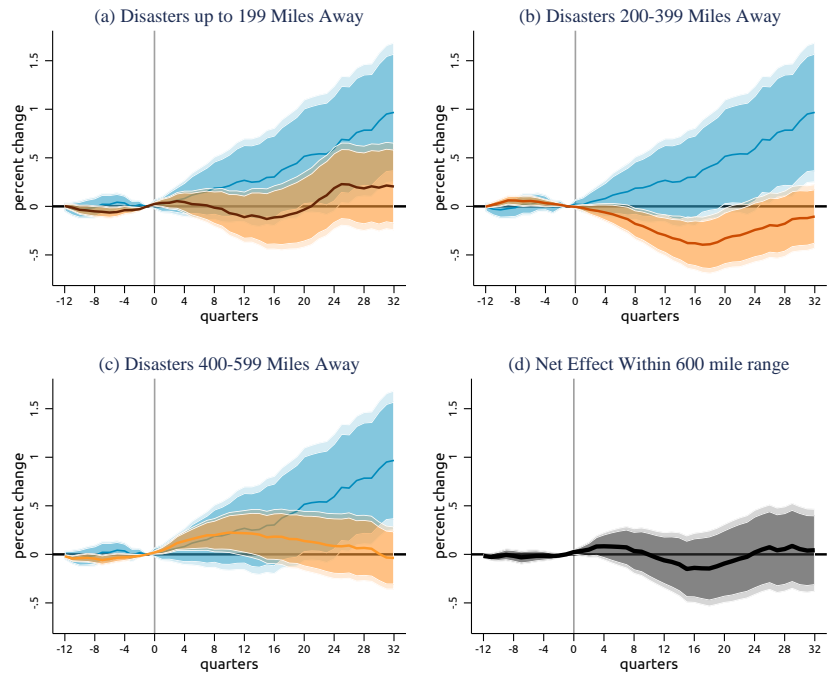
See notes at end of figure.

Figure A18: Impacts of Own-county Disasters vs. Spatially-Lagged Disasters
Results for spatial lags of varying distance bands (Continued)

(c) Average Weekly Wages



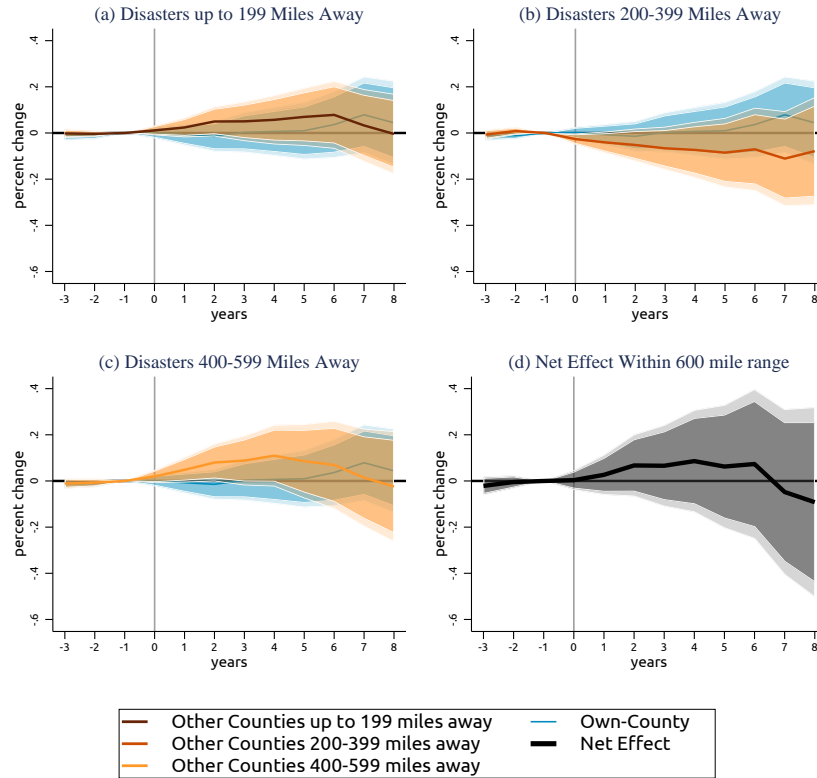
(d) Home Prices



See notes at end of figure.

Figure A18: Impacts of Own-county Disasters vs. Spatially-Lagged Disasters
Results for spatial lags of varying distance bands (Continued)

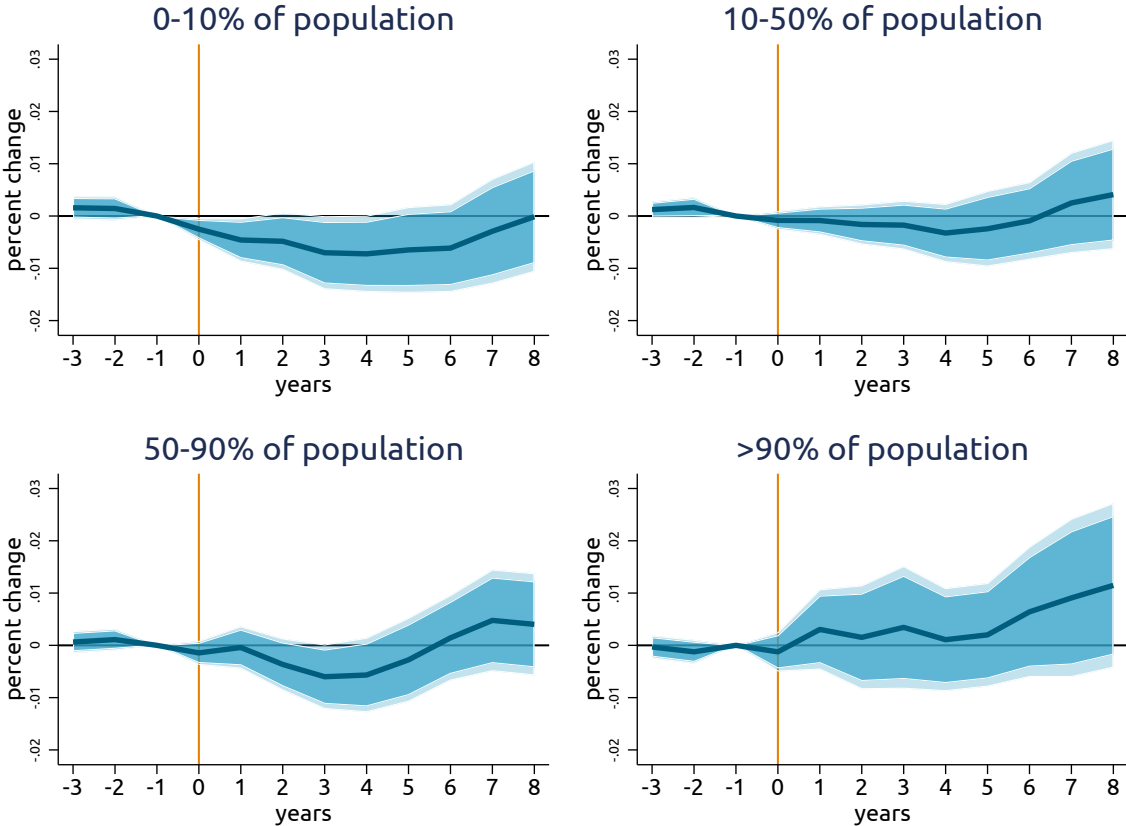
(e) Population



Source: FEMA, SHELDUS, Census, BEA, BLS, and CoreLogic.

Note: Subpanels (a)-(c) for each dependent variable 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. Subpanel (d) for each dependent variable shows the net effect on that dependent variable within these bands, where each coefficient has been rescaled by the variable's unconditional mean. The dependent 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 A19: State-Level Impacts of Disasters on Personal Income (p.c.) with Disasters Differentiated by Geographic Breadth



Source: FEMA, SHELDUS, BLS, Census, BEA, and CoreLogic.
 Note: This figure shows the IRFs from estimating equation (1) on state-aggregated data, but allowing the coefficient on the disaster treatment variable to vary across four geographic breadth indicator variables. These variables indicate what quartile the disaster falls in of the distribution of the share of the state’s population in a county hit with a disaster (with positive damages), conditional on having a disaster. The inner shaded regions indicate the 90 percent confidence intervals, and the lighter outer shaded regions indicate the 95 percent confidence intervals. Personal income is aggregated at the state level and modeled as cumulative differences in logs between the horizon pictured and the period before the disaster ($t = -1$). Standard errors are clustered at the state and at the time-by-division levels.

Appendix B

B1. Poverty Data

The county-level poverty rate data come from the Census Bureau’s Small Area Income and Poverty Estimates (SAIPE) program and cover the years 1989, 1993, 1995, and 1997-2020. We fill in the missing years for each county via linear interpolation between adjacent years. We expect the resulting measurement error to be systematically unrelated to disaster occurrence and hence expect it to inflate standard errors but not to introduce bias.¹

B2. Data for Industry Mix-Implied Wages

We construct a measure of industry mix in order to assess how disasters impact the industry composition of a county’s workforce. Specifically, we construct a variable measuring each county’s expected average wage in a given year based only on its industry composition:

$$w_{ct}^{pred} = \sum_j s_{cjt} w_{jt} ; \quad \sum_j s_{cjt} = 1$$

where s_{cjt} is the employment in industry j in county c in year t and w_{jt} is the national mean wage in industry j in year t .

Data on s_{cjt} come from the Census Bureau’s County Business Patterns (CBP) data. We use Eckert, et al. (2021)’s version of the CBP data, which exploits various adding-up constraints in the raw data to fill in missing values. It imputes some missing values in the raw CBP data by exploiting cross-county (within industry) and cross-industry (within county) totals and adding up constraints. To further minimize missing values, we use the “major sector” NAICS industry level rather than a finer level of industry categorization.

We calculate w_{jt} as the mean wage by NAICS major sector across individuals using the CEPR yearly extracts of the CPS Outgoing Rotation Group micro-data.²

B3. Hurricane Wind Speed Data

For hurricane wind speed data, we use county level data made available via Anderson et al (2020a) and Anderson et al (2020b) using the U.S. National Hurricane Center’s Best Track Atlantic hurricane

¹ Using only 1997-2020 results in too short a sample to estimate the full dynamic pattern from $h = -3$ to 8 with reasonable precision.

² Using the median wage yields qualitatively similar results to the mean.

database (HURDAT2.) We use versions 0.1.1 and 0.1.0 of R packages `hurricaneexposure` and `hurricaneexposuredata`, respectively. Our wind speed measure is the highest maximum sustained wind speed that has a duration of at least 10 minutes. We only include the observed wind speed for a county and event if the maximum gust is at least 64 knots, the maximum sustained wind is at least 50 knots, the daily precipitation is at least 50 mm (about 2 inches), or the total precipitation over the five day period is at least 200 mm (about 8 inches).