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Migration as a Vector of Economic Losses from Disaster-Affected Areas in the United States

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In this paper, we infuse consideration of migration into research on economic losses from extreme weather disasters. Taking a comparative case study approach and using data from the Federal Reserve Bank of New York/Equifax Consumer Credit Panel, we document the size of economic losses via migration from 23 disaster-affected areas in the United States after the most damaging hurricanes, tornadoes, and wildfires on record. We then employ demographic standardization and decomposition to determine if these losses primarily reflect changes in out-migration or changes in the economic resources that migrants take with them (greater economic losses per migrant). Finally, we consider the implications of these losses for changing spatial inequality in the United States. While disaster-affected areas and those living in them differ in their experiences of and responses to extreme weather disasters, we generally find that, relative to the year before an extreme weather disaster, economic losses via migration from disaster-affected areas increase the year of and after the disaster, that these changes primarily reflect changes in out-migration (vs. the economic resources that migrants take with them), and that these losses briefly disrupt the status quo by temporarily reducing spatial inequality.

Keywords: Natural Disaster, Migration, Consumer Credit, Decomposition, Spatial Inequality
JEL classification: R23, Q54, D12, J60

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1 Introduction

Economic losses from so-called “billion-dollar weather and climate disasters,” which are defined as situations where extreme weather hazards overwhelm the capacity of people, populations, and places to adapt and result in at least $1 billion in losses, have increased substantially in recent years and decades (NCEI 2021; Wisner 2004). In 2017, the United States set a new record of $322 billion in losses from 16 billion-dollar extreme weather disasters. This far surpasses the previous record of $228 billion set in 2005, with the majority of losses that year due to Hurricane Katrina. These and other estimates of economic losses from extreme weather disasters raise serious concerns about what the future holds in store under current and projected climate and environmental change (IPCC 2012, 2018, 2021; USGCRP 2018).

Despite the rich array of data and methods used to produce estimates of economic losses from extreme weather disasters (Gall et al. 2009; Kousky 2014; Smith and Katz 2013; Smith and Matthews 2015), these estimates are incomplete because they do not factor in the important role of human migration (Hsiang et al. 2017). At the level of actors (e.g., individuals and households), migration is a well-documented adaptation strategy for mitigating the destructive and destabilizing impacts of extreme weather disasters and of climate and environmental change more broadly (Black et al. 2011; Hunter et al. 2015; McLeman 2013). Actors’ migration decisions and behaviors ultimately cumulate into place-based migration flows from disaster-affected areas. Therefore, and as we advance and explore in this paper, migration is a vector of economic losses from disaster-affected areas.

We break new ground and attempt to gain some empirical purchase on this idea by examining three aspects of migration as a vector of economic losses from disaster-affected areas in the United States. Using data from the Federal Reserve System/Equifax Consumer Credit Panel (Lee and van der Klaauw 2010; Whitaker 2018), we start by documenting the size of economic losses via migration from 23 disaster-affected areas before, during, and after three types of extreme weather disasters: hurricanes, tornadoes, and wildfires. Next, recognizing that economic losses via migration reflect the loss of both people (i.e., migrants) and their attending economic resources, we use Das Gupta’s (1993) demographic standardization and decomposition procedures to decompose economic losses via migration from disaster-affected areas to determine whether and to what extent these losses primarily reflect underlying demographic or economic changes. Finally, given that migration necessarily connects places to one another, we consider the implications of economic losses via migration from disaster-affected areas for changing spatial inequality in the United States insofar as migration stands to reshuffle the distribution of economic resources across US places. We conclude by summarizing the key findings and contributions of our work, followed by describing several critical next steps for continued study in this under-researched area.

2 Background

2.1 Economic Losses from Extreme Weather Disasters

According to data from the National Centers for Environmental Information in the National Oceanic and Atmospheric Administration (NCEI 2021), 285 billion-dollar extreme weather disasters have resulted in $1.88 trillion in economic losses since 1980, with slightly less than one-half of these totals—135 disasters and $890 billion in losses—accrued in just the last 10 years. Clearly, and importantly, these totals exclude the majority of extreme weather disasters that result in less than $1 billion each in economic losses.

Estimates of economic losses from extreme weather disasters are provided by several sources. To name a few, these include the Storm Events Database provided by the NCEI, the Spatial Hazard Events and Losses Database for the United States (SHELDUS) from Arizona State University's Center for Emergency Management and Homeland Security (CEMHS), the Natural Hazards Assessment Network (NATHAN) provided by Munich Re, and the Emergency Events Database (EM-DAT) from the Centre for Research on the Epidemiology of Disasters. These estimates summarize direct losses (e.g., property and crop losses) and, in some cases, indirect losses (e.g., business interruptions due to breakdowns in supply chains) using data from multiple sources (Gall et al. 2009; Kousky 2014). For example, the NCEI's (2021) estimates of economic losses from billion-dollar extreme weather disasters use data from the US Census Bureau's American Housing Survey, the Federal Emergency Management Agency's Presidential Disaster Declaration and National Flood Insurance Programs, ISO Property Claims Services, the US Department of Agriculture's Risk Management Agency, and other federal, state, and local agencies (Smith and Katz 2013; Smith and Matthews 2015).

In addition to using data from multiple sources, estimates of economic losses from extreme weather disasters are produced using an array of methods (Auffhammer et al. 2013;

Carleton and Hsiang 2016; Hsiang 2016; Hsiang and Jina 2015; Hsiang and Sobel 2016; Hsiang et al. 2017; Kousky 2014; Smith and Katz 2013; Smith and Matthews 2015). In different ways, these methods attempt to deal with three key methodological issues: determining the appropriate spatial and temporal scales, avoiding and correcting for double-counting, and incorporating uncertainty (Cochrane 2004; Kousky 2014; Hsiang 2016; Hsiang et al. 2017; Rose 2004). To date, one of the most comprehensive attempts to deal with these issues and produce highly detailed estimates of economic losses is by Hsiang et al. (2017; see also Hsiang 2016), who developed the Spatial Empirical Adaptive Global-to-Local Assessment System (SEAGLAS). SEAGLAS combines and integrates insights and tools from climate science, econometrics, and process models to produce highly detailed probabilistic estimates of economic damage for local areas (e.g., counties) in the United States by and across sectors (e.g., agriculture).

2.2 Migration as Adaptation Requiring Economic Resources

A common feature of estimates of economic losses from extreme weather disasters described in the previous subsection is that they do not include any consideration of migration and, more broadly, the mobility of economic resources (Hsiang et al. 2017). We argue that this is problematic for at least three interrelated reasons that we discuss here and in the next two subsections. First, it is well-documented in prior research that migration is an adaptation strategy—one of many such strategies and often one of last resort after available insitu strategies have been exhausted and tolerances (for stress, etc.) exceeded—that is employed by actors to mitigate economic uncertainty and risk, including that associated with the destructive and destabilizing impacts of extreme weather disasters (Adams and Kay 2019; Black et al. 2011; Hunter et al. 2015; McLeman 2013, 2018; Nawrotzki and DeWaard 2016; Scoones 1998; Stark and Bloom 1985). The Intergovernmental Panel on Climate Change (IPCC 2012:556, emphasis ours) defines the capacity to adapt to extreme weather disasters as the "*resources* available to an individual, community, society or organization…that can be used to prepare for and undertake actions to reduce adverse impacts, moderate harm, or exploit potential beneficial opportunities." According to Black et al. (2011), these resources are of three basic types: economic, social, and political.

Although our focus in this paper is on the resources—specifically, the economic resources—that actors have at their disposal to adapt to extreme weather disasters by migrating, it is important to point out that another key dimension of actors' migration decisions and behaviors is their migration intentions and, ultimately, their agency (Black and Collyer 2014; Carling 2002; de Haas 2021; Fussell 2012; McLeman 2013; Schewel 2020). As rightly noted by the International Organization for Migration (IOM 2014:6), “Migration can take many forms: sometimes forced, sometimes voluntary, often…in a grey zone somewhere in between.” This helps to explain why some scholars have opted for more nuanced descriptions such as “displacement and migration” (McLeman and Gemenne 2018). For our part, while we recognize and appreciate the continuum of actors’ migration intentions, we nonetheless follow the IOM and use the term *migration* to refer to actors who “are obliged to leave their homes or choose to do so, either temporarily or permanently” (IOM 2014:6).

2.3 Migration as a Vector of Economic Losses from Disaster-Affected Areas

The second reason that it is problematic that estimates of economic losses from extreme weather disasters exclude migration is that migration is not merely an adaptation strategy employed by actors to mitigate the destructive and destabilizing impacts of extreme weather disasters. As economic actors, at least in part, migrants individually and collectively take with them a myriad of economic resources from disaster-affected areas. These resources include, for example, their wages and incomes, state and local tax contributions, consumer spending, charitable donations, and more. Consequently, we argue that migration must also be conceptualized as a vector of economic losses from disaster-affected areas.

While economic losses via migration from disaster-affected areas are clearly different in kind from the sorts of losses described at the beginning of this section (Gall et al. 2009; Hsiang et al. 2017; Kousky 2014; Smith and Katz 2013; Smith and Matthews 2015), they are important to study in their own right in order to understand their magnitude and change over time. Economic losses via migration from disaster-affected areas can also help to shed light on other, related changes after extreme weather disasters. To take one prominent example, it is well-documented that, after Hurricane Katrina in August 2005, consumer spending in the city of New Orleans and in surrounding disaster-affected areas fell sharply (Dolfman et al. 2007). While some of this decline reflected real changes in economic behavior in the form of consumers spending less, another important factor was demographic in nature and consisted of the fact that the population of New Orleans fell by more than one-half in the year after Hurricane Katrina due to out-migration (Vigdor 2008). In other words, there were simply fewer consumers in New Orleans after Hurricane Katrina, and the city’s economic recovery depended, in part, on recovery migration to and population growth in New Orleans in the years and decade after Hurricane Katrina (English 2015; Fussell et al. 2014).

2.4 Implications for Changing Spatial Inequality

The third reason that it is problematic that estimates of economic losses from extreme weather disasters exclude migration involves the inherently spatial nature of migration insofar as it necessarily connects places to one another (Rogers 1975; Roseman 1971). Recalling our having conceptualized migration as a vector of economic losses from disaster-affected areas, migration connects disaster-affected areas to other places, some of which might not have been directly impacted by the extreme weather disaster in question. As Hsiang et al. (2017:1369, emphasis ours) noted at the end of their paper using SEAGLAS to estimate economic losses in local areas in the United States, "The bulk of economic damage from climate change will be borne outside of the United States, and impacts outside of the United States will have indirect effects on the United States through trade, *migration*, and possibly other channels." The same can be said of within-country impacts.

To generalize the previous statement, as a vector of economic losses from disaster-affected areas, migration stands to reshuffle the spatial distribution of economic resources across places and thereby reshape the landscape of spatial inequality (Howell and Elliott 2018, 2019; Logan et al. 2016; Raker 2020; Smiley et al. 2018). However, several recent papers on migration in response to extreme weather disasters and to climate and environmental change more broadly suggest that this redistribution takes place within existing—largely local and regional—networks of migration flows (Curtis et al. 2015; DeWaard et al. 2016; Fussell et al. 2014; Hauer 2017). These migration networks are aggregate manifestations of underlying and often highly stable migration systems consisting of a set of "interacting elements" ranging from individuals and households to governments and other institutions that are defined by both "their attributes and relationships" with one another (Mabogunje 1970; see also Bakewell 2014; Kritz and Zlotnik 1992; Massey et al. 1999). Consequently, one should not expect that a given localized extreme weather disaster such as the Joplin tornado—the costliest and deadliest US tornado on record that struck Jasper County, MO, and nearby areas in May 2011 (Gregg and Lofton 2011)—will alter the spatial distribution of economic resources and reshape the landscape of spatial inequality for the United States as a whole. However, one might expect that the Joplin tornado was sufficient to affect a substantial change within the existing network of migration flows connecting Jasper County to other places in the United States.

3 Research Questions

The preceding background and discussion motivate three foundational and descriptive research questions that are intended to break new ground and gain some empirical purchase on the idea of migration as a vector of economic losses from disaster-affected areas. Our first research question is the most basic and concerns the size of economic losses via migration from disaster-affected areas before, during, and after extreme weather disasters. Next, recognizing that economic losses via migration from disaster-affected areas involve the loss of both people (i.e., migrants) and their attending economic resources, our second research question concerns the relative magnitudes of each. Specifically, we want to know if economic losses via migration from disaster-affected areas primarily reflect changes in out-migration (i.e., more people having left) or changes in the economic resources that migrants take with them (i.e., greater economic losses per migrant). Finally, transitioning from the characteristics to the consequences of economic losses via migration from disaster-affected areas, our third and final research question is concerned with whether and to what extent these losses affect changes in the spatial distribution of economic resources, and thus spatial inequality, within disaster-affected areas' networks of migration flows connecting them to other places.

4 Approach

4.1 Cases

As Gray and Wise (2016:556; see also Fussell et al. 2017; Hunter et al. 2015; McLeman 2018) noted, research shows that there is no "monolithic and unidirectional migratory response to climatic variation." Given heterogeneity in the relationship between extreme weather disasters and migration, we therefore take a case-specific approach and focus our analysis on 23 places—20 counties in the contiguous United States and three municipios in Puerto Rico—that experienced one of three types of extreme weather disasters: a hurricane, a tornado, or a wildfire.[1] We selected these places, first, by identifying the most costly hurricanes, tornadoes,

[1] In Louisiana, counties are referred to as "parishes." The US Census Bureau treats municipios in Puerto Rico as county equivalents. Hereafter, unless referring to a specific county, parish, or municipio by name, we use the generic terms "places" and "areas."

and wildfires from lists provided by the National Hurricane Center (e.g., see NHC 2018) and other sources. These include Hurricanes Katrina in August 2005, Harvey in August 2017, and Maria in September 2017; the Joplin, Tuscaloosa-Birmingham, and Moore Tornadoes in May 2011, April 2011, and May 2013, respectively; and the Carr, Camp, and Nuns wildfires in July 2018, November 2018, and October 2017, respectively. For each of these nine extreme weather disasters, we then used information from SHELDUS to select places that incurred the greatest total and/or per capita economic losses due to property damage (CEMHS 2020). Figure 1 provides maps of the 23 disaster-affected areas selected for analysis.

4.2 Data

In selecting the 23 disaster-affected areas described in the previous subsection, we were mindful that publicly available migration data from the American Community Survey (ACS), the Current Population Survey (CPS), and the Internal Revenue Service (IRS) are limited in several respects that undermine their utility in the current paper (DeWaard et al. 2019). First, publicly available migration data are limited with respect to their spatial scale. Excluding the IRS data, the small sample sizes of the CPS and, to a lesser extent, of the ACS prohibit producing [accurate] estimates of migration at finer spatial scales (e.g., for an individual county). Second, publicly available migration data such as those provided by the IRS are not up-to-date enough to be useful in studying the three counties and three municipios that experienced Hurricanes Harvey and Maria, respectively, as well as the five counties that experienced the Carr, Camp, and Nuns wildfires. Finally, several recent papers have raised questions and concerns about the quality and accuracy of publicly available migration data, particularly the CPS and the IRS data (DeWaard et al. 2021; Kaplan and Schulhofer-Wohl 2012).

For these reasons, we turn to a non-public data source to study economic losses via migration from each of the 23 disaster-affected areas selected for analysis: the Federal Reserve Bank of New York/Equifax Consumer Credit Panel (CCP). The CCP is a sample panel of over 10 million adults that is updated quarterly from the complete set of Equifax credit records on 240 million US adults (Lee and van der Klaauw 2010; Whitaker 2018). This is achieved by, first, preselecting five random two-digit numbers. If the last two digits of a person's Social Security number match one of these five preselected numbers, they are included in the CCP sample. The same five preselected numbers are used every quarter, so matched individuals appear in each quarterly sample from the first quarter in which they borrow. This results in "a 5% random sample that is representative of all individuals in the US who have a credit history and whose credit file includes the individual's Social Security number" (Lee and van der Klaauw 2010:3). The data is anonymized, removing names, Social Security numbers and street addresses, before they are provided by Equifax to the Federal Reserve Bank of New York. A random but consistent identification number links individuals' records from quarter to quarter in the sample, building individual panels. Clearly, one of the main weaknesses of the CCP is that it excludes the roughly 10-11 percent of US adults who do not have a credit history (Brevoort et al. 2016). The CCP is therefore a sample of relatively older and more financially established US adults.

It is straightforward to use the CCP to study migration, as the data contain quarterly geocoded information on each person's census block of residence (DeWaard et al. 2019; Ding et al. 2016; Molloy and Shan 2013).[2] This information can then be aggregated up to study migration at different time intervals (semi-annually, annually, etc.) and spatial scales (census tracts, counties, etc.), which is one of the main strengths of the CCP (DeWaard et al. 2019). As noted in the previous subsection, we focus on annual migration from each of 23 disaster areas in the contiguous United States and Puerto Rico.

With respect to measuring economic losses via migration from disaster-affected areas, it would be ideal to have one or more measures of current or lifetime consumption, income, or wealth so that we could directly gauge the total amount of economic losses via migration from disaster-affected areas. While the CCP does not provide these sorts of measures, it does contain information on each borrower's total debt balance. Specifically, the CCP contains information on the total dollar value of all debt, including both mortgage and non-mortgage debt, as well as other information, such as one's credit score and delinquency status (Lee and van der Klaauw 2010). While there are extensive literatures on rising debt levels and the worrisome consequences of debt (Dwyer 2018; Joseph 2014), it is also important to point out that debt reflects the accumulation of past economic activities and is positively correlated with

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[2] Per the contract between the Federal Reserve Bank of New York and Equifax, the CCP data have historically—since 1999—been provided quarterly and at the census block level. To facilitate tracking the impact of the pandemic, the contract was recently amended to provide monthly data since January 2020.

consumption, income, and wealth (Baker 2018; Charron-Chénier and Seamster 2018; Stavins 2020; Whitaker 2018). For example, debt indicates past, usually recent, purchases of homes, automobiles, and various consumer goods and services, with past consumption highly predictive of future consumption (Gorbachev 2011; Jappelli and Pistaferri 2010). The existence of a debt balance also indicates that borrowers believe they will have the income to repay the debt. Before extending credit, especially mortgage and auto credit, lenders likewise verify borrowers' incomes and payment histories. For these reasons, we use total debt balance in the CCP as our measure of total economic losses via migration from disaster-affected areas in the current paper. While not a perfect measure, total debt balance is nonetheless a strong proxy for the economic resources that migrants take with them from disaster-affected areas.

4.3 Methods

To answer our first research question and document the size of economic losses via migration from each of the selected 23 disaster-affected areas, we start by writing the total debt balance of migrants from a disaster-affected area in period p as T_p. We then examine T_p the year before the extreme weather disaster, the year of the disaster, and for each of up to three years after the disaster.

To answer our second research question and determine whether and to what extent economic losses via migration from disaster-affected areas primarily reflect underlying economic or demographic changes, we employ demographic standardization and decomposition techniques (Das Gupta 1993; see also DeWaard et al. 2020a; Sana 2008). Specifically, we decompose change over time in T_p into one economic component and two demographic components. The economic component is the average debt balance per migrant from the disaster-affected area, and the demographic components are the probability of migration from and population size in the disaster-affected area. With these components defined, there are three steps involved in demographic standardization and decomposition. The first step is to rewrite T_p as a function of the above three components as follows:

$$T_p = \frac{T_p}{MIG_p} \times \frac{MIG_p}{POP_p} \times POP_p \tag{1}$$

The first term on the right-hand side of Equation 1 is the ratio of T_p to total migration from the disaster-affected area in period p, MIG_p, or the average debt balance per migrant. The second term is the ratio of MIG_p to the total number of persons living in the disaster-affected area at the start of period p, POP_p, or the probability of out-migration. The third term captures population size in the disaster-affected area at the start of the period. For substantive clarity and notational simplicity, we rewrite Equation 1 as follows, where L_p is average debt balance per migrant, M_p is the probability of out-migration, and N_p is population size:

$$T_p = L_p \times M_p \times N_p \tag{2}$$

The second step is to use the quantities in Equation 2 as inputs to develop standardized estimates of T_p. To briefly walk through this, given information on each of the quantities in Equation 2 for two and only two periods ($p = 1, 2$), we can calculate a standardized estimate of T_p for the first period as follows:

$$T_{1.2}^{L.M,N} = \left[\frac{M_2N_2+M_1N_1}{3} + \frac{M_2N_1+M_1N_2}{6}\right] L_1 \tag{3}$$

The quantity, $T_{1.2}^{L.M,N}$, summarizes the total debt balance of migrants from a disaster-affected area in the first period that would have been observed had only the average debt balance per migrant changed between these two periods. In other words, this quantity is standardized by the probability of out-migration from and the size of the population in the disaster-affected area in these two periods. A similar standardized estimate can be written for the second period as follows:

$$T_{2.1}^{L.M,N} = \left[\frac{M_2N_2+M_1N_1}{3} + \frac{M_2N_1+M_1N_2}{6}\right] L_2 \tag{4}$$

Equations 3 and 4 can be rewritten to generate standardized estimates of the total debt balance of migrants from a disaster-affected area in the first and second periods that reflect changes in the other two inputs in Equation 2: the probability of out-migration from ($T_{1.2}^{M.L,N}$ and $T_{2.1}^{M.L,N}$) and population size in ($T_{1.2}^{N.L,M}$ and $T_{2.1}^{N.L,M}$) the disaster-affected area.

The third step is to use these standardized estimates to decompose the change in the total debt balance of migrants from a disaster-affected area between these two periods as follows:

$$T_2 - T_1 = \left[T_{2.1}^{L.M,N} - T_{1.2}^{L.M,N}\right] + \left[T_{2.1}^{M.L,N} - T_{1.2}^{M.L,N}\right] + \left[T_{2.1}^{N.L,M} - T_{1.2}^{N.L,M}\right] \tag{5}$$

In Equation 5, the change in the total debt balance of migrants, $T_2 - T_1$, is the sum of an average debt balance effect, $T_{2.1}^{L.M,N} - T_{1.2}^{L.M,N}$, an out-migration probability effect, $T_{2.1}^{M.L,N} - T_{1.2}^{M.L,N}$, and a population size effect, $T_{2.1}^{N.L,M} - T_{1.2}^{N.L,M}$.

Going beyond two periods requires further adapting the above equations. Following Das Gupta (1993), for any number of periods ($p = 1, 2, \dots, P$), we can calculate the total debt balance of migrants from a disaster-affected area in the first period had only the average debt balance of migrants changed between the first period and all other periods ($q = 1, 2, \dots, Q$) as follows:

$$T_{1^*}^{L^*} = T_{1.2,3,\dots,P}^{L.M,N} = \frac{\sum_{q=2}^{P} T_{1.q}^{L.M,N}}{P-1} + \frac{\sum_{p=2}^{P}\left[\sum_{q\neq 1,p}^{P} T_{p.q}^{L.M,N} - (P-2) * T_{p.1}^{L.M,N}\right]}{P(P-1)} \quad (6)$$

Similar estimates (not shown) can be calculated for each of the remaining periods, as well as for the other two quantities in Equation 2—the probability of out-migration from and population size in the disaster-affected area—for each period. Using the resulting standardized estimates, we can then decompose the change in the total debt balance of migrants from a disaster-affected area between any two periods *p* and *q* as follows:

$$\Delta T_{p,q} = \Delta T_{p^*,q^*}^{L^*} + \Delta T_{p^*,q^*}^{M^*} + \Delta T_{p^*,q^*}^{N^*} \quad (7)$$

On the right-hand side of Equation 7, $\Delta T_{p^*,q^*}^{L^*}$ is the effect of the average debt balance of migrants, $\Delta T_{p^*,q^*}^{M^*}$ is the effect of the probability of out-migration, and $\Delta T_{p^*,q^*}^{N^*}$ is the effect of population size. Recalling our second research question, we are interested in the magnitude of $\Delta T_{p^*,q^*}^{L^*}$ relative to the magnitude of $\Delta T_{p^*,q^*}^{M^*}$ while also accounting for $\Delta T_{p^*,q^*}^{N^*}$.

To address our third research question and determine whether and to what extent the total debt balance of migrants from a disaster-affected area affects changes in spatial inequality within the area's existing network of migration flows that connect them to other places, we use a variant of the Gini index developed by Plane and Mulligan (1997). This index, $G_{i,p}$, measures "spatial focusing," and thus spatial inequality, among a set of migration flows. Specifically, it summarizes inequality "for region-specific out-migration" and is calculated for each disaster-affected area as follows (Bell et al. 2002:455):

$$G_{i,p} = \frac{\sum_{j\neq i}\sum_{l\neq i,j}\left|M_{ij,p} - M_{il,p}\right|}{2(n-2)\sum_{i\neq j} M_{ij,p}} \quad (8)$$

In the numerator, each migration flow from disaster-affected area i to migrant-receiving area j in period p, $M_{ij,p}$ is compared to each and every other migration flow from i, $M_{il,p}$. The denominator ensures that $G_{i,p}$ ranges from zero (i.e., no inequality because there is a migration flow from disaster-affected area i to each and every other place in i's migration network of the exact same size) to one (i.e., maximum inequality because migration from disaster-affected area i is entirely concentrated along a single flow to just one place in i's migration network). Recalling our third research question, rather than flows of people (i.e., migrants), we focus on flows in the form of the total debt balance of migrants from a disaster-affected area. We therefore rewrite the Gini index in Equation 8 as follows, where $T_{ij,p}$ is the total debt balance of migrants from a disaster-affected area i to receiving area j:

$$G_{i,p} = \frac{\sum_{j \neq i} \sum_{l \neq i,j} |T_{ij,p} - T_{il,p}|}{2(n-2) \sum_{i \neq j} T_{ij,p}} \tag{9}$$

With these estimates in hand, we examine levels of $G_{i,p}$ the year before the extreme weather disaster, the year of the disaster, and for each of up to three years after the disaster.

5 Results

5.1 Size of Economic Losses via Migration from Disaster-Affected Areas

As a place to start, in Figure 2, we display a graph for each disaster-affected area to provide a sense of the overall magnitude of total out-migration before, during, and after the extreme weather disaster in question. For ease of display, the scales of the y-axes range from zero to the maximum value observed for each disaster-affected area and, as a result, differ across graphs. On the x-axes, Year 0 refers to the quarter and year in which the extreme weather disaster occurred. For example, Hurricane Katrina made landfall in the third quarter of 2005 (Q3-2005), impacting Orleans, Plaquemines, and St. Bernard Parishes. Accordingly, in the graphs for these three parishes, Year -1 refers to the one-year period between Q3-2004 and Q3-2005. Year 0 refers to the year beginning with the quarter in which the disaster occurred, from Q3-2005 to Q3-2006. And Years 1-3 refer to the three years after that (Q3-2006 to Q3-2007, Q3-2007 to Q3-2008, and Q3-2008 to Q3-2009, respectively). It is also important to note that the Carr, Camp, and Nuns wildfires are recent enough that, at the time of writing, it is not yet possible to observe a full three years after the disaster year.

Given that places and their populations are differentially vulnerable to extreme weather disasters (Cutter 1996; Gray and Wise 2016; Hunter et al. 2015; McLeman 2013), it not surprising that there is considerable heterogeneity in both levels of and changes in out-migration from disaster-affected areas during the year of and after the extreme weather disaster in question, as well as in the years after that. Looking across the 23 disaster-affected areas displayed in Figure 2, absolute levels of out-migration ranged from 420 persons in Trinity County, CA, to 172,560 persons in Harris County, TX, during the year of and after the Carr wildfire and Hurricane Harvey, respectively. In relative terms, out-migration probabilities ranged from 0.023 in Walker County, AL, to 0.416 in St. Bernard Parish, LA, after the Tuscaloosa-Birmingham tornado and Hurricane Katrina, respectively.

Of these 23 disaster-affected areas, five areas experienced a decrease in out-migration during the year of and after the extreme weather disaster compared to the year before the disaster. The largest absolute magnitudes of these decreases ranged from -20 persons in Canadian County, OK, to -400 persons in Cleveland County, OK, following the Moore tornado. And the largest relative magnitudes of these decreases ranged from -0.96 percent in Canadian County, OK, to -11.96 percent in Trinity County, CA, respectively. The remaining 18 disaster-affected areas experienced an increase in out-migration during the year of and after the extreme weather disaster compared to the year before the disaster. The largest absolute magnitudes of these increases ranged from 220 persons in Lawrence County, MO, to 45,700 persons in Orleans Parish, LA, following the Joplin tornado and Hurricane Katrina, respectively. And the largest relative magnitudes of these increases ranged from 3.15 percent in Oklahoma County, OK, to 677.16 percent in St. Bernard Parish, LA, after the Moore tornado and Hurricane Katrina, respectively.

Turning from an overview of out-migration to our first research question regarding the size of economic losses via out-migration from disaster-affected areas, we display the total debt balance of migrants from each disaster-affected area in Figure 3. Focusing on the year of and after the extreme weather disaster, the total debt balance of migrants from disaster-affected areas ranged from $16.4 million in Trinity County, CA, after the Camp wildfire to $6.6 billion in Harris County, TX, after Hurricane Harvey, and, in all but six areas, exceeded corresponding levels from the year before the disaster in question. One to three years after that, the average total debt balance of migrants from disaster-affected areas was generally lower than the corresponding level from the year of the disaster in question and ranged from an average of $9.2 million in Trinity County, CA, after the Camp wildfire to $5.6 billion in Harris County, TX, after Hurricane Harvey.

To put these figures in perspective, consider the case of Jasper County, MO. On account of out-migration from Jasper County in the year of and after the Joplin tornado, Jasper County lost $120 million. While this figure pales in comparison to the estimated $3 billion in economic losses that Jasper County sustained due to property damage (CEMHS 2020; NCEI 2021), as we argued earlier, economic losses via out-migration from disaster-affected areas are nonetheless an important and understudied source of loss that deserve to see the light of day in empirical research if the total costs of extreme weather disasters are to be tallied in a truly exhaustive way (Hsiang et al. 2017).

5.2 Decomposition of Economic Losses via Migration from Disaster-Affected Areas

Recalling our earlier point that economic losses via migration from disaster-affected areasreflect the loss of both people (i.e., migrants) and their attending economic resources, we seek to answer our second research question regarding the relative magnitudes of each by decomposing the total debt balance of migrants from disaster-affected areas into two components—the average debt balance per migrant and the probability of out-migration—while also accounting for a third component of population size. Graphs of these three components, which are the inputs for the demographic standardization and decomposition employed here, are displayed in Figures 4, 5, and 6, respectively.

We encourage readers to closely examine both levels of and changes in these three components in each disaster-affected area. For our part, due to space, we simply wish to note here that we have provided these three figures to revisit and re-emphasize two key points that we made in the previous section. First, changes in these three components displayed in Figures 4-6 jointly determine changes in the total debt balance of migrants from disaster-affected areas (Das Gupta 1993). And, second, the primacy of a given component in determining the total debt balance of migrants from disaster-affected areas can change over time (e.g., see Sana 2008).

Using the three components displayed in Figures 4-6, we generated three sets of standardized estimates of the total debt balance of migrants from disaster-affected areas. These estimates are displayed in Figure 7. The first set of standardized estimates summarizes the total debt balance of migrants from disaster-affected areas the year before the extreme weather disaster, the year of the disaster, and for each of up to three years after the disaster that would have been observed had only the average debt balance of migrants changed over time. That is, these estimates are standardized by changes in the other two components—the probability of migration from and the size of the population in the disaster-affected area. Similarly, the second and third sets of standardized estimates summarize the total debt balance of migrants from disaster-affected areas that would have been observed had only the probability of migration from and the size of the population in the disaster-affected area changed over time, respectively.

The standardized estimates provided in Figure 7 provide important clues about the answer to our second research question, which the decompositions will ultimately reveal. Specifically, the closer the correspondence between changes over time in a given set of standardized estimates and changes over time in the observed total debt balance of migrants from disaster-affected areas shown earlier in Figure 3, the stronger the "effect" of that particular component. To illustrate, consider the case of Butte County, CA. Comparing changes over time between the year before the Camp wildfire and the year during and after this disaster, it is clear that the standardized series reflecting changes over time only in the probability of migration from Butte County most closely corresponds to observed changes over time in the total debt balance of migrants from Butte County that were shown earlier in Figure 3. Consequently, our decomposition for Butte County should reveal a strong migration probability effect relative to the other two effects of the average debt balance of migrants and population size.

To go the next and final step in this portion of our analysis, we turn to our decomposition results. The absolute effects of each of the three components—the average debt balance of migrants, the probability of out-migration, and population size—are displayed in Figure 8. Relative effects, in percentage terms, are displayed in Figure 9. In each graph, Year -1, the year before the extreme weather disaster, is the reference year against which each estimate for the year of and after the disaster, and for up to each of three years after the disaster, is compared. This is why all effects in Year -1 are zero. To walk through an example of how to interpret these estimates, consider the case of Orleans Parish. As we showed earlier in Figure 3, relative to the year before Hurricane Katrina, the total debt balance of migrants increased by about $2.3 billion during the year of and after this disaster. The three absolute effects displayed in Figure 8 sum to this amount, and the relative effects in Figure 9 sum to 100 percent. Migrants' average debt effect is $463 million (20.4 percent). The migration probability effect is 1.7 billion (74.0 percent). And the population size effect is 126 million (5.6 percent). Recalling our second research question, total economic losses via migration from Orleans Parish in the year of and after Hurricane Katrina were therefore clearly driven by out-migration and, to a much lesser extent, the average debt of migrants. Out-migration continued to be the dominant component one year after Hurricane Katrina, with the probability of migration putting upward pressure (664 million and 309 percent) and migrants' average debt putting downward pressure (-$393 million and -183 percent) on the change in the total debt balance of migrants from Orleans Parish. This was followed by reversals in the directions of these effects over the next two years.

Looking across the 23 disaster-affected areas displayed in Figures 8 and 9, during the year of and after each extreme weather disaster, the average debt of migrants from these disaster-affected areas was the dominant component of change in 9 areas, while the probability of out-migration was the dominant component of change in the remaining 14 areas. Thus, while disaster-affected areas and those living in them clearly differ in their experiences of and responses to extreme weather disasters (Fussell et al. 2017; Gray and Wise 2016; Hunter et al. 2015; McLeman 2013), the answer to our second research question concerning whether economic losses via migration from disaster-affected areas primarily reflect changes in out-migration (i.e., more people having left) or changes in the economic resources that migrants take with them (i.e., greater economic losses per migrant) leans slightly in favor of the former.

5.3 Implications for Changing Spatial Inequality

The results in the previous sections clearly show that migration is a vector of economic losses from disaster-affected areas. However, these losses do not disappear into thin air. Instead, they are redistributed within disaster-affected areas' networks of migration flows connecting them to other places, which, in turn, can affect changes in spatial inequality. To examine this idea empirically and answer our third research question of whether and to what extent these losses affect changes in the spatial distribution of economic resources, and thus spatial inequality, within disaster-affected areas' networks of migration flows connecting them to other places, we display modified Gini coefficients, defined in the previous section, for the total debt balance of migrants from disaster-affected areas in Figure 10.

By way of background, it is worth noting that the Gini coefficients displayed in Figure 10 are quite high, ranging from a low of 0.52 to a high of slightly less than 1.00 in Ceiba Municipio, PR. This is because migration, as well as other types of flows, tends to be highly spatially unequal in the sense that a given place within the United States is generally not connected to each and every other place in the country by a migration flow of the same size. Instead, migration flows from a given place tend to be directed toward some—usually just a handful—of other places, and not others, a phenomenon that McHugh (1987) referred to as "channelized migration streams."

Against this backdrop, the results displayed in Figure 10 show that, relative to the year before the extreme weather disaster in question, spatial inequality decreased in all but 9 disaster-affected areas' migration networks during the year of and after the disaster. Substantively, this means that extreme weather disasters often, but not always, temporarily interrupt the highly uneven spatial redistribution of economic resources via migration and slightly reduce spatial inequality. However, in the years after that, our results show that spatial inequality tends to return to the status quo. For example, of the 23 disaster-affected areas in Figure 10, 17 areas returned to the same or higher levels of spatial inequality in the 1-3 years after the disaster in question.

6 Discussion

In this paper, drawing on prior research by Hsiang et al. (2017) and others, we argued that estimates of economic losses from extreme weather disasters are incomplete because they do not factor in the important role of human migration. While most research on climate and environmental migration conceptualizes migration as an adaptation strategy that is employed by actors to mitigate the destructive and destabilizing impacts of extreme weather disasters and of climate and environmental change more broadly (Black et al. 2011; Hunter et al. 2015; McLeman 2013), it is also the case that actors' migration decisions and behaviors cumulate into place-based migration flows that, from the vantage point of disaster-affected areas, represent losses of both people and their attending economic resources that they take with them. As a result, we argued that migration should also be conceptualized as a vector of economic losses from disaster-affected areas, which has important implications for the spatial redistribution of economic resources across places and, thus, spatial inequality.

In addition to conceptualizing migration as a vector of economic losses from disaster-affected areas, another contribution of our work in this paper is our in-depth empirical examination of economic losses via migration from disaster-affected areas from at least four vantage points. First, going beyond a one-size-fits-all approach (Fussell et al. 2017; Gray and Wise 2016; Hunter et al. 2015; McLeman 2013), we took a case-specific approach and focused our analysis on 23 disaster-affected areas in the contiguous United States and Puerto Rico that have experienced some of the most destructive and costly hurricanes, tornadoes, and wildfires in recent years. Second, because research on climate and environmental migration can be and often is constrained by the availability and quality of publicly available migration data (DeWaard et al. 2019, 2021; Fussell et al. 2014), we used the non-public CCP to study economic losses via migration from disaster-affected areas and, in the process, demonstrated some of the utility of these data for studying [climate and environmental] migration that extends prior research (DeWaard et al. 2019, 2021; Ding et al. 2016; Molloy and Shan 2013). Third, in addition to describing levels of and changes in economic losses via migration from disaster-affected areas, we dug below the surface and used the tools of demographic standardization and decomposition to show that these losses primarily, but not exclusively, reflect underlying changes in out-migration from disaster-affected areas. Fourth, and finally, going beyond out-migration as merely a localized place-based attribute of disaster-affected areas, we embraced the idea that migration is an inherently spatial process that connects disaster-affected areas to other places and, in the process, affects changes in the spatial distribution of economic resources and, thus, spatial inequality (Rogers 1975; Roseman 1971).

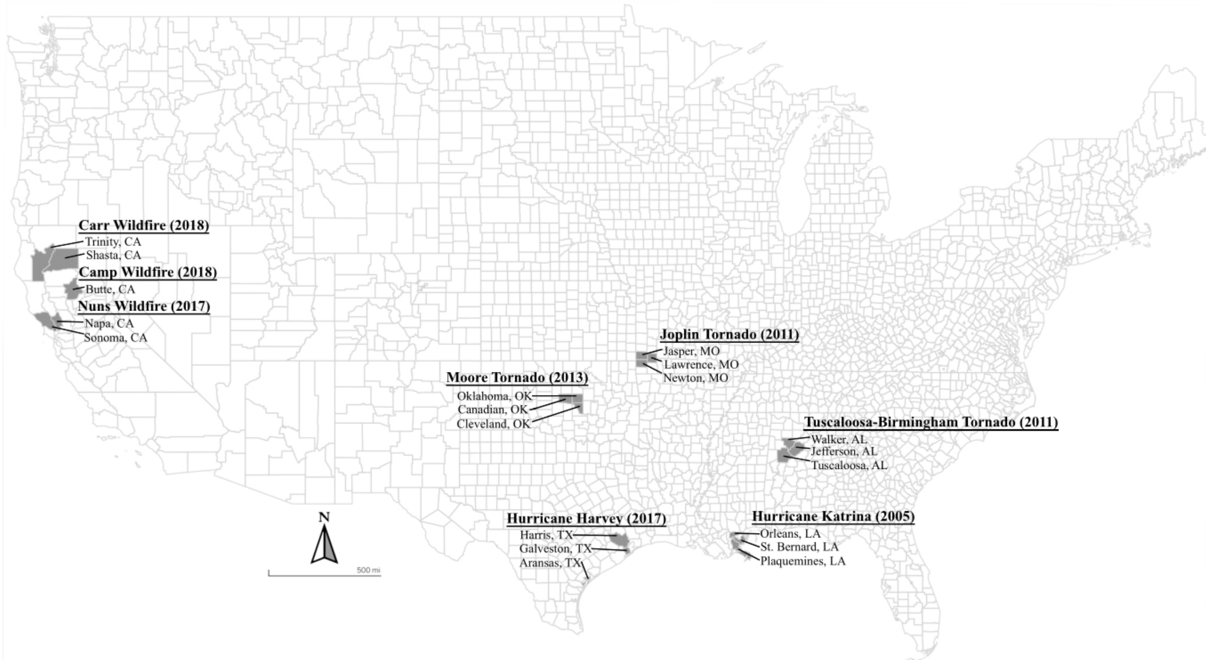
Against this backdrop, at least two limitations of this paper deserve explicit mention. The first limitation is the gap between the concept of economic losses via migration from disaster-affected areas and our operationalization of this concept as the total debt balance of migrants from disaster-affected areas in our empirical analysis. As we noted earlier, total debt balance is a strong, but imperfect measure of the economic resources that migrants from disaster-affected areas take with them. A better measure or set of measures of economic resources would more directly capture current or lifetime consumption, income, or wealth. Accordingly, as scholars have recently done with the case of Hurricane Maria in Puerto Rico (Caraballo-Cueto 2020; DeWaard et al. 2020b; Rivera 2020; Martín et al. 2020), continued efforts and vigilance are needed to identify and incorporate new data sources to study climate and environmental migration, including economic losses via migration from disaster-affected areas.

The second limitation of this paper is broader and concerns our stated aim of providing a detailed descriptive account of economic losses via migration from disaster-affected areas. This is to say, we did not, nor did we intend to, establish any sort of causal link between extreme weather disasters, migration from disaster-affected areas, and corresponding economic losses. While establishing causality in research on climate and environmental migration is an important task (DeWaard and Nawrotzki 2018; Fussell et al. 2014; Hsiang 2016; Piguet 2010), so, too, is establishing a descriptive baseline view of the phenomenon in question (Duncan 2008). Therefore, our work in this paper provides multiple avenues for future research to pursue going forward, one of which is to establish the aforementioned causal linkages.

In addition to examining economic losses via migration from disaster-affected areas, another important avenue for future research is to consider whether and to what extent these losses are offset, partially or even fully, by in-migration and corresponding in-flows of economic resources to disaster-affected areas after extreme weather events. As we noted earlier, there is compelling evidence that the economic decline and subsequent recovery of New Orleans after Hurricane Katrina were due, in part, to the ebb and flow of out- and in-migration (English 2015; Fussell et al. 2014; Vigdor 2008), including actors' spending power and other economic activities associated with these movements (Dolfman et al. 2007). It would therefore be worthwhile for future research to focus on in-migration and replicate what we have done in this paper.

Finally, recalling our starting point in this paper, we hope that our work will help to elevate the importance of economic losses via migration from disaster-affected areas so that estimates of these losses will eventually be incorporated into broader sets of estimates of economic losses from extreme weather disasters, including billion-dollar extreme weather disasters (NCEI 2021). This shift in measurement will help to ensure that future estimates are more exhaustive (Hsiang et al. 2017), as well as more reflective of the important role of migration as an adaptation strategy in the face of extreme weather disasters and climate and environmental change more broadly (Black et al. 2011; Hunter et al. 2015; McLeman 2013).

Figure 1. Disaster-affected areas selected for analysis
Panel A. Contiguous United States



Panel B. Puerto Rico

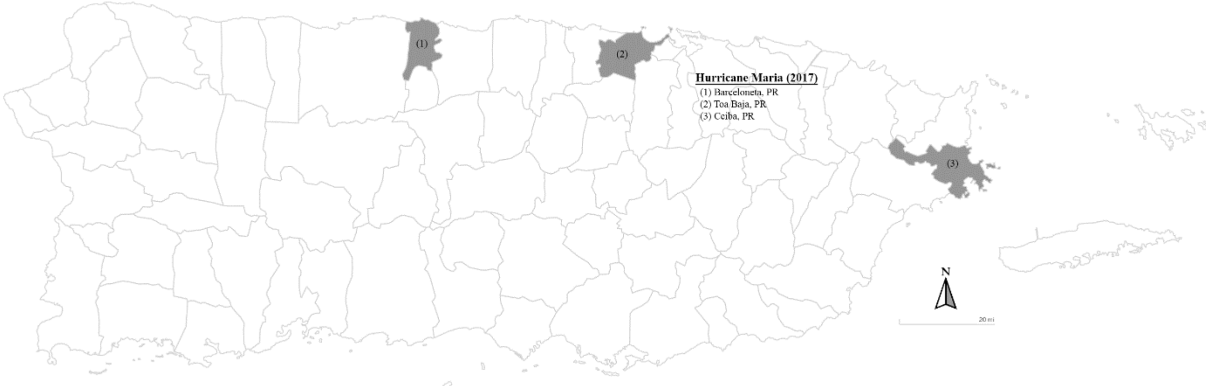
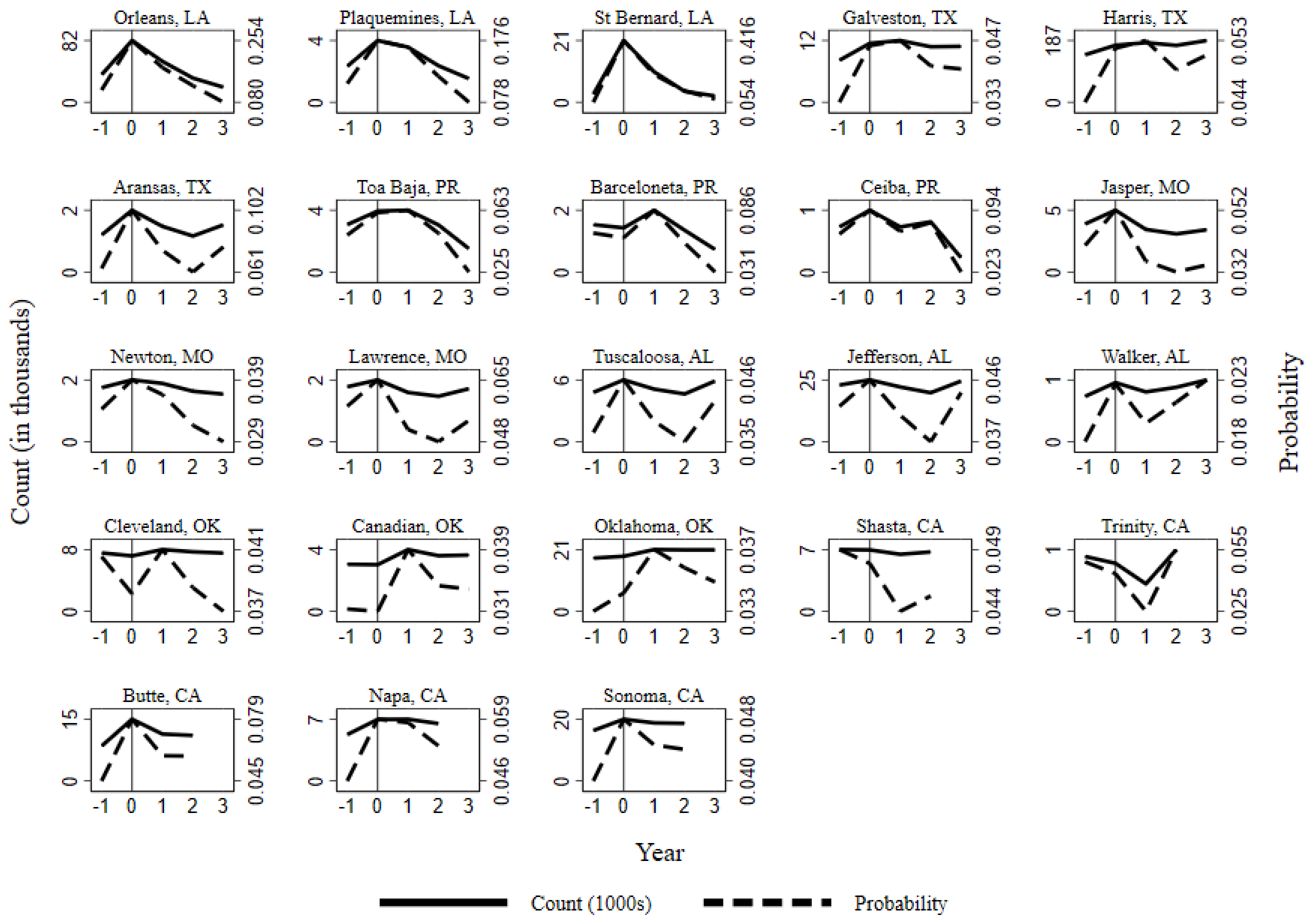
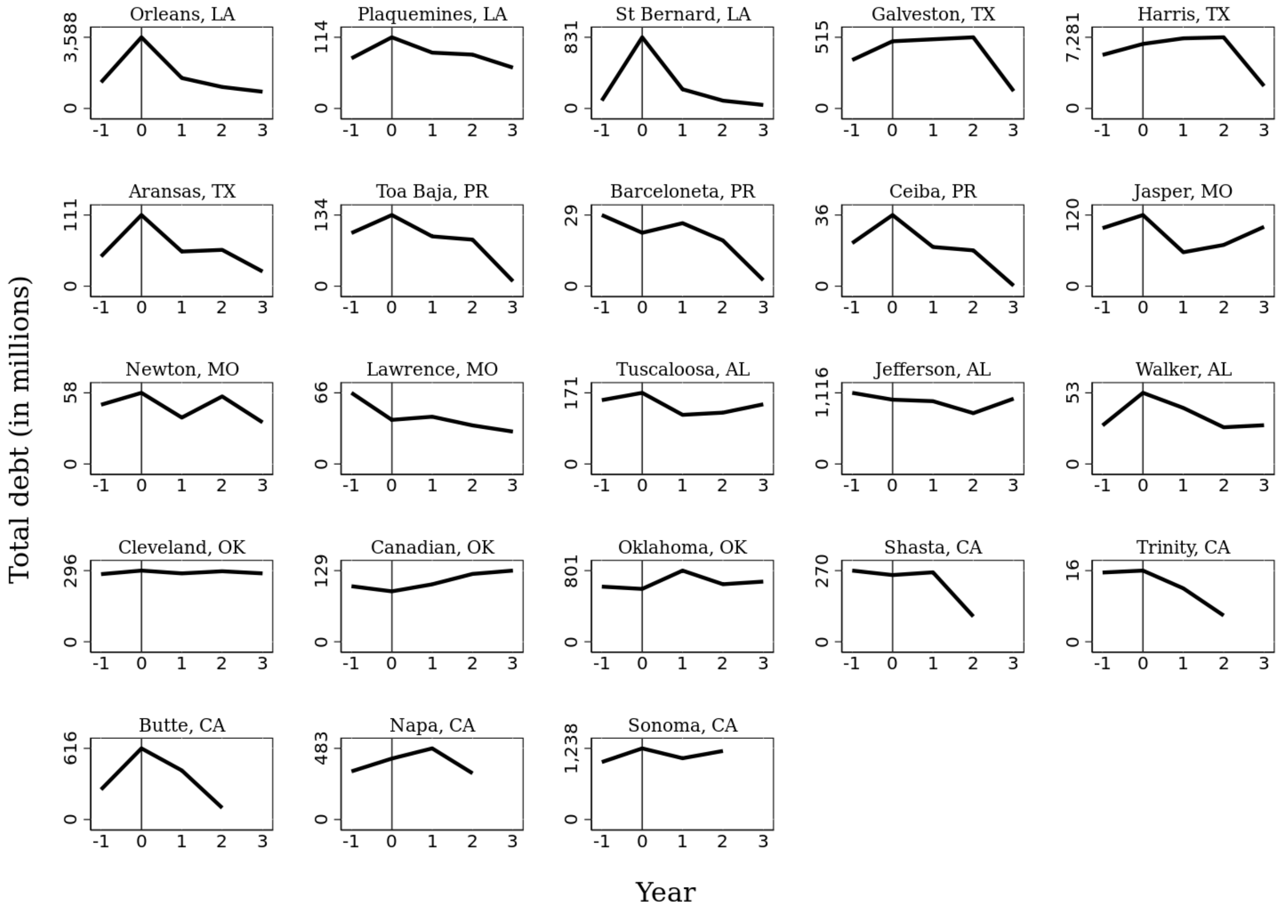


Figure 2. Out-migration from disaster-affected areas



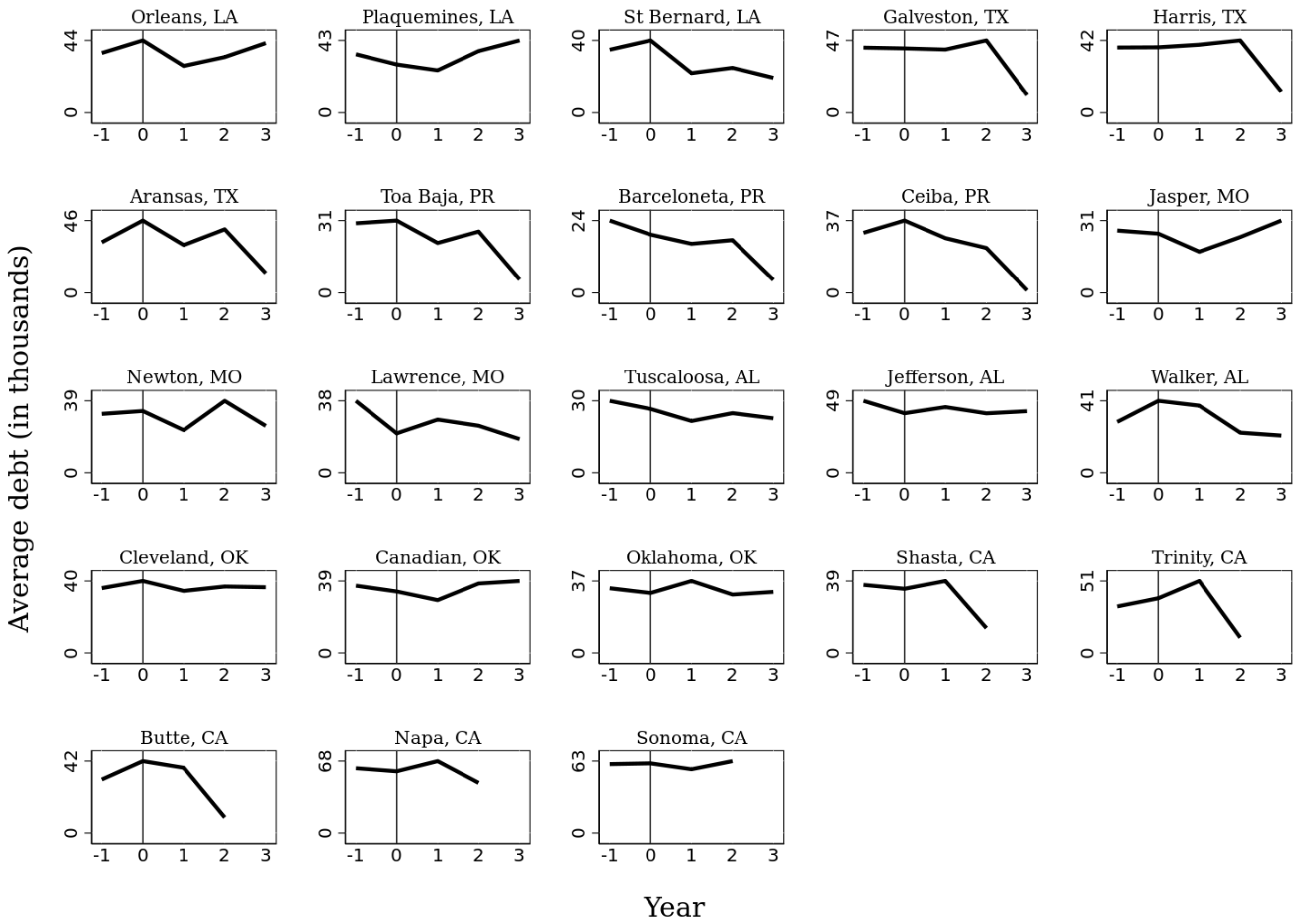
Notes: For ease of display, scales of *y*-axes range from zero to maximum value observed for each place and differ across graphs. Year is centered on quarter-year in which extreme weather disaster occurred, such that Year -1 refers to one year prior to disaster, Year 0 refers to year of and after disaster, and Years 1-3 refer to three years after that. Sources: Federal Reserve Bank of New York/Equifax Consumer Credit Panel, Spatial Hazard Events and Losses Database for the United States (SHELDUS), and authors' calculations.

Figure 3. Total debt balance of migrants from disaster-affected areas



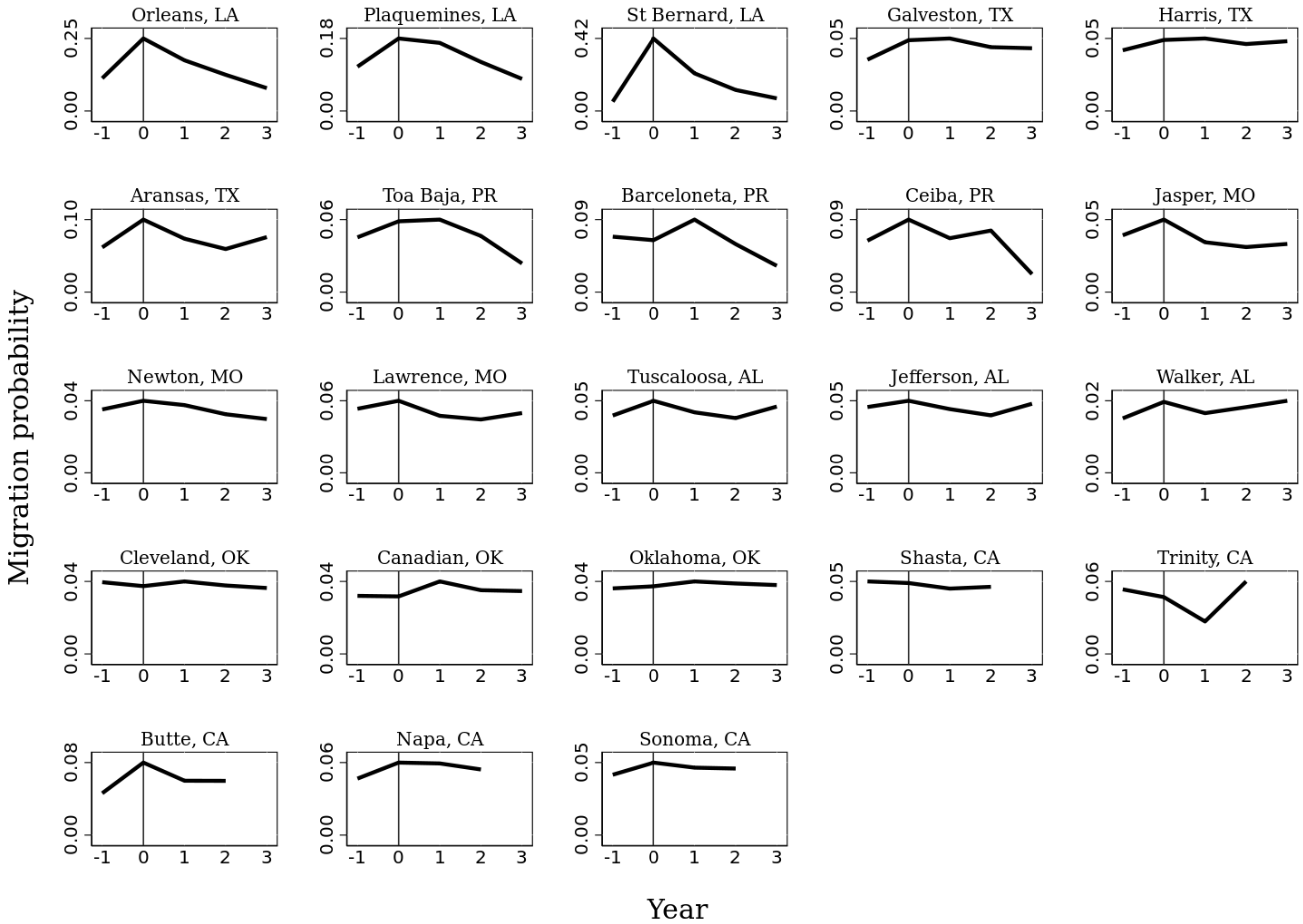
Notes: For ease of display, scales of *y*-axes range from zero to maximum value observed for each place and differ across graphs. Year is centered on quarter-year in which extreme weather disaster occurred, such that Year -1 refers to one year prior to disaster, Year 0 refers to year of and after disaster, and Years 1-3 refer to three years after that. Sources: Federal Reserve Bank of New York/Equifax Consumer Credit Panel, Spatial Hazard Events and Losses Database for the United States (SHELDUS), and authors' calculations.

Figure 4. Average debt balance of migrants from disaster-affected areas



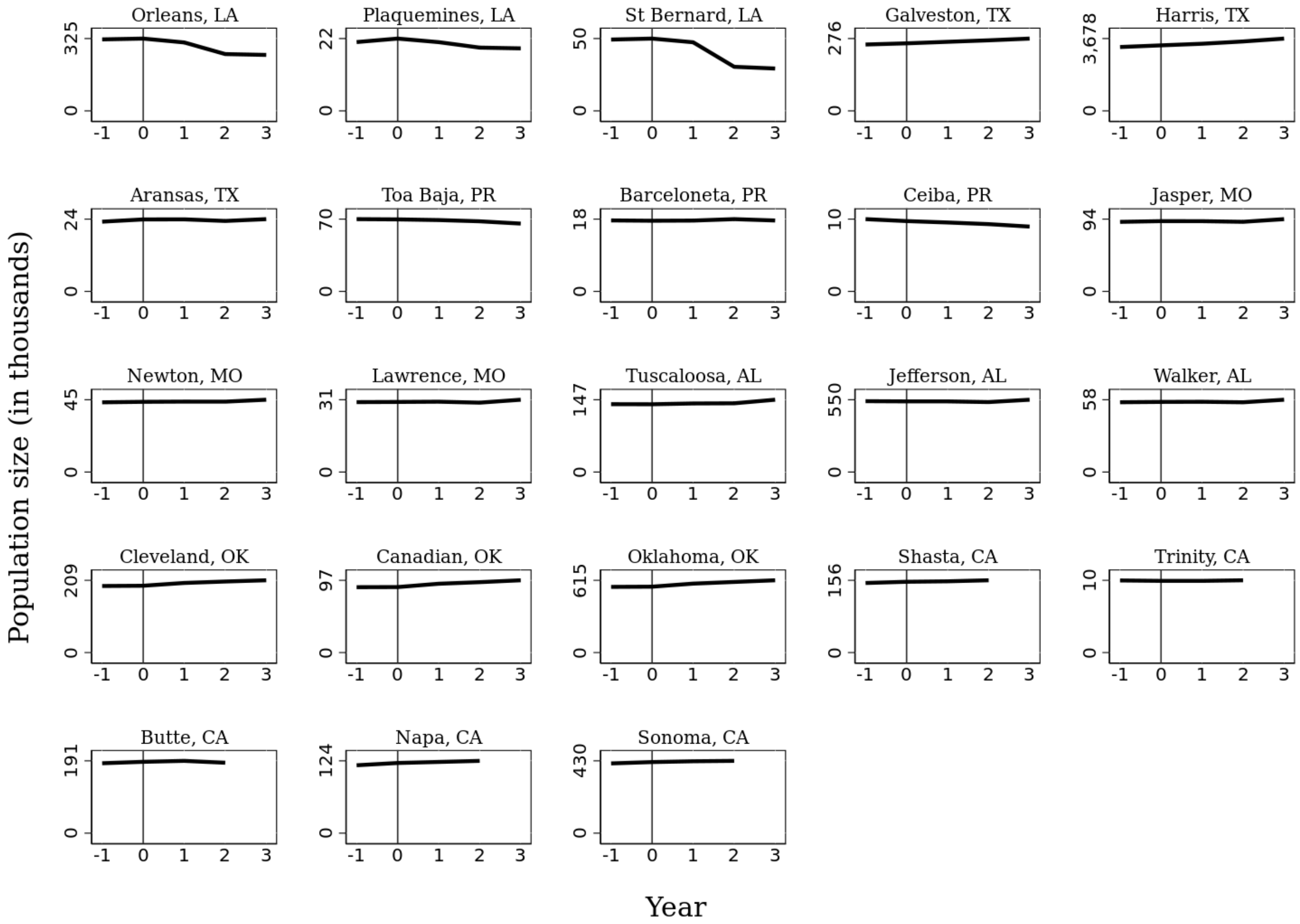
Notes: For ease of display, scales of *y*-axes range from zero to maximum value observed for each place and differ across graphs. Year is centered on quarter-year in which extreme weather disaster occurred, such that Year -1 refers to one year prior to disaster, Year 0 refers to year of and after disaster, and Years 1-3 refer to three years after that. Sources: Federal Reserve Bank of New York/Equifax Consumer Credit Panel, Spatial Hazard Events and Losses Database for the United States (SHELDUS), and authors' calculations.

Figure 5. Probability of out-migration from disaster-affected areas



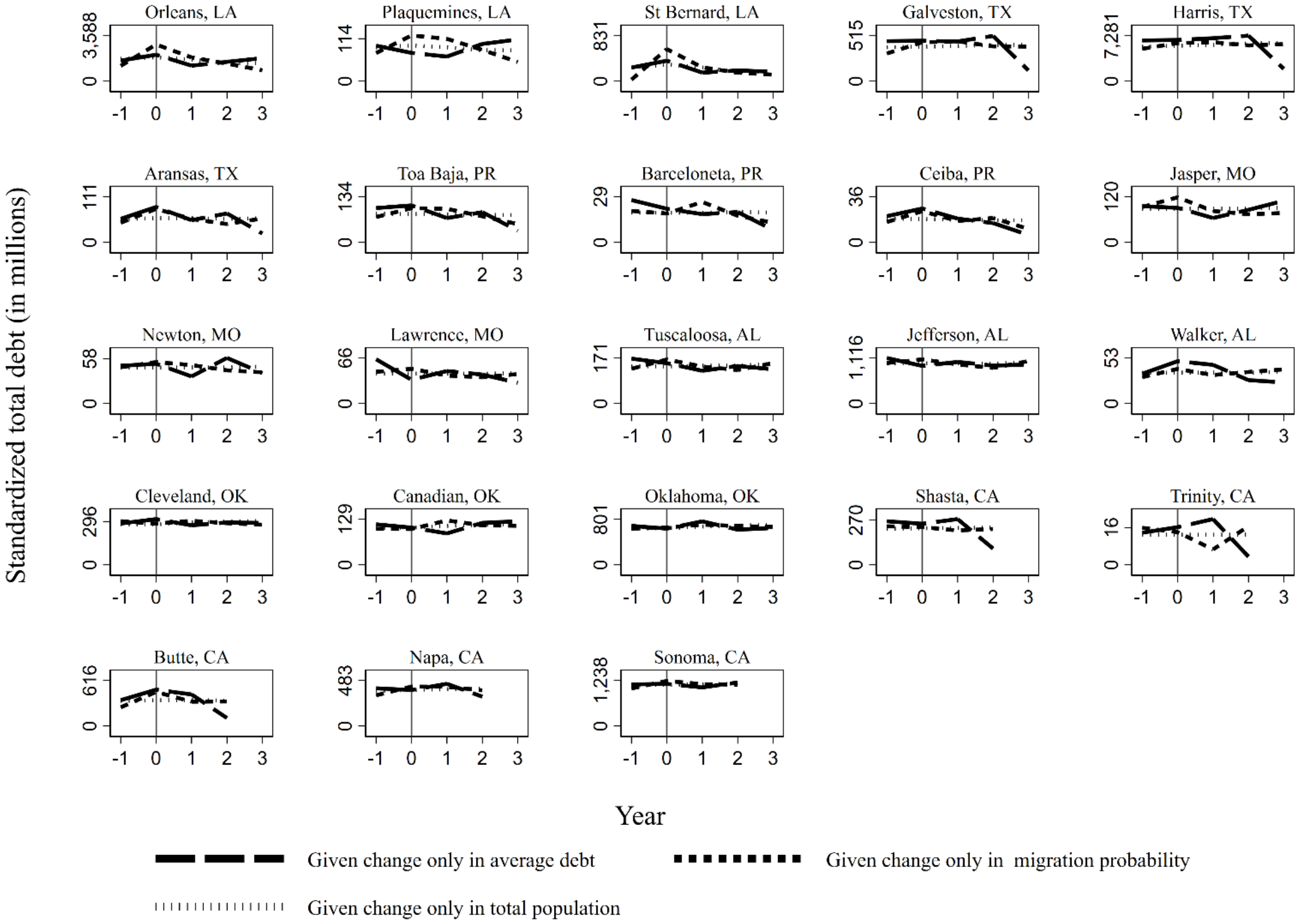
Notes: For ease of display, scales of *y*-axes range from zero to maximum value observed for each place and differ across graphs. Year is centered on quarter-year in which extreme weather disaster occurred, such that Year -1 refers to one year prior to disaster, Year 0 refers to year of and after disaster, and Years 1-3 refer to three years after that. Sources: Federal Reserve Bank of New York/Equifax Consumer Credit Panel, Spatial Hazard Events and Losses Database for the United States (SHELDUS), and authors' calculations.

Figure 6. Population size in disaster-affected areas



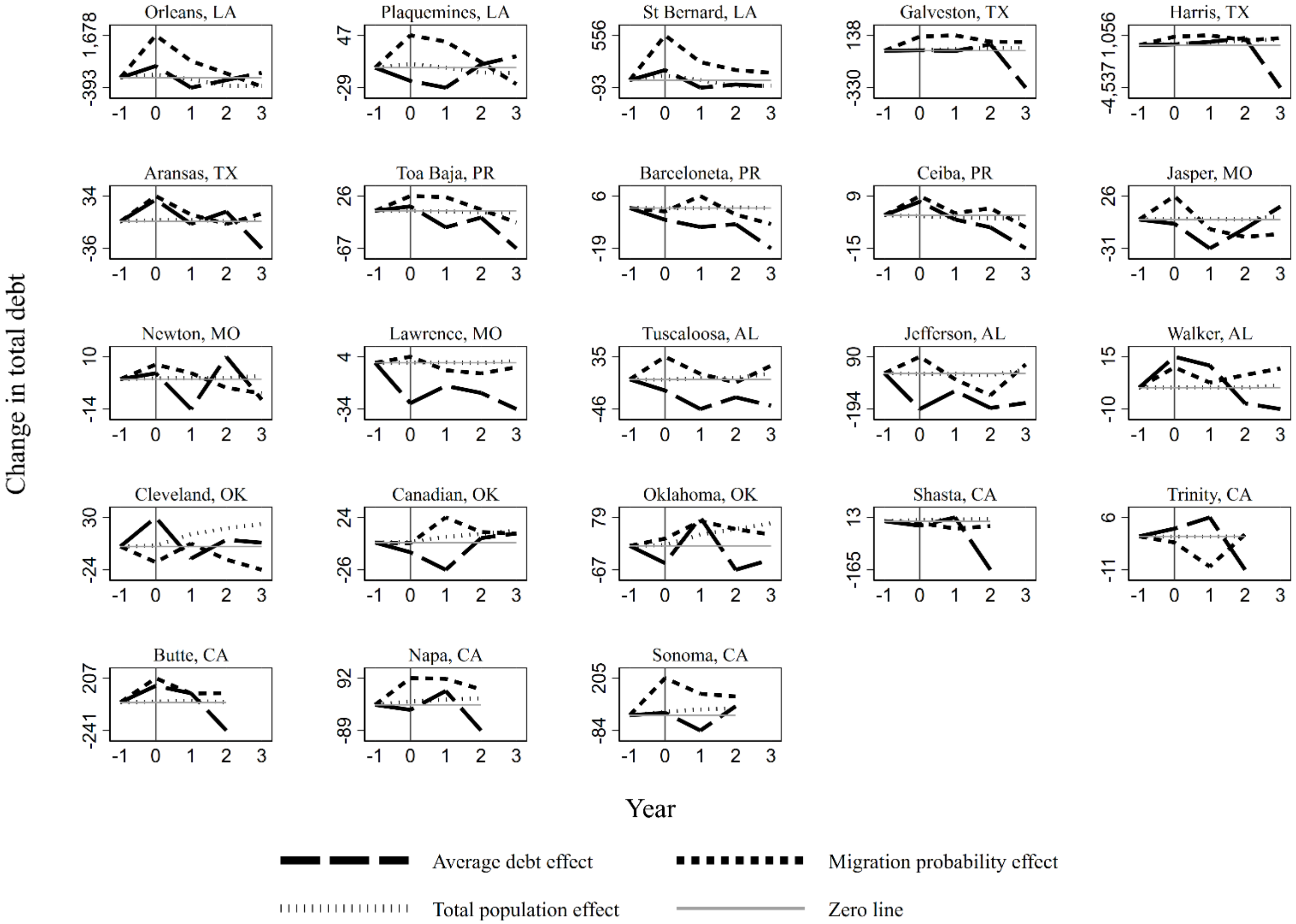
Notes: For ease of display, scales of *y*-axes range from zero to maximum value observed for each place and differ across graphs. Year is centered on quarter-year in which extreme weather disaster occurred, such that Year -1 refers to one year prior to disaster, Year 0 refers to year of and after disaster, and Years 1-3 refer to three years after that. Sources: Federal Reserve Bank of New York/Equifax Consumer Credit Panel, Spatial Hazard Events and Losses Database for the United States (SHELDUS), and authors' calculations.

Figure 7. Standardized estimates of total debt balance of migrants from disaster-affected areas



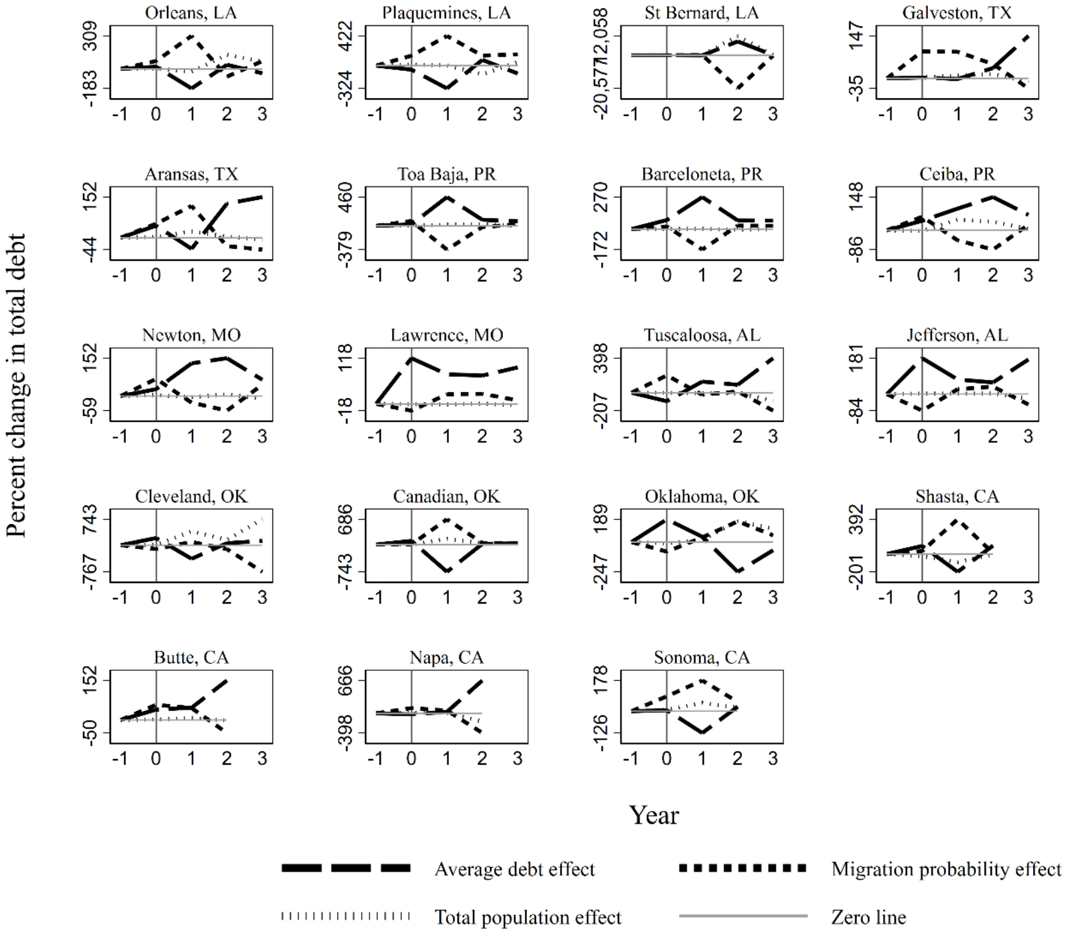
Notes: For ease of display, scales of *y*-axes range from zero to maximum value observed for each place and differ across graphs. Year is centered on quarter-year in which extreme weather disaster occurred, such that Year -1 refers to one year prior to disaster, Year 0 refers to year of and after disaster, and Years 1-3 refer to three years after that. Sources: Federal Reserve Bank of New York/Equifax Consumer Credit Panel, Spatial Hazard Events and Losses Database for the United States (SHELDUS), and authors' calculations.

Figure 8. Decomposition of total debt balance of migrants from disaster-affected areas: Absolute effects



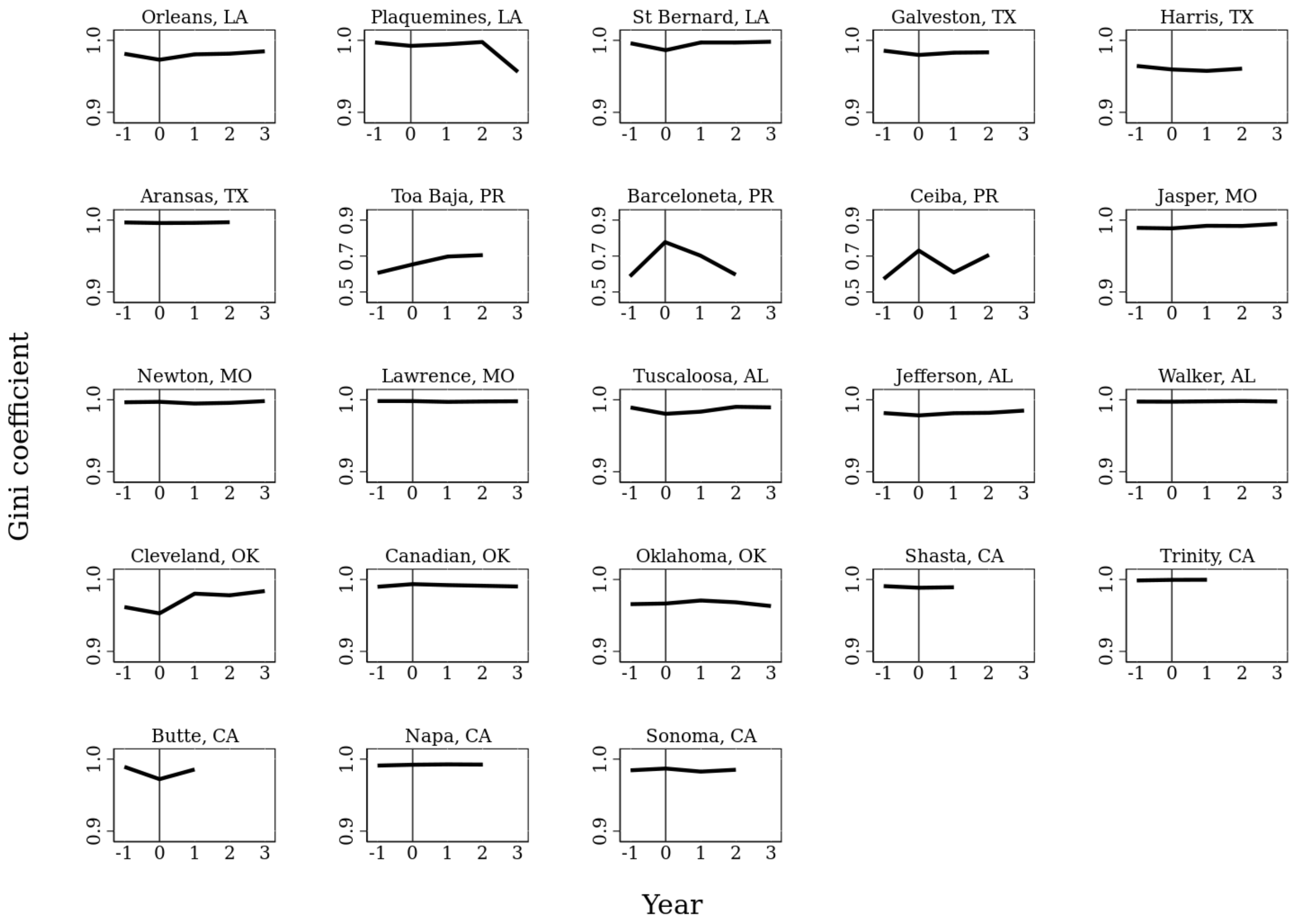
Notes: For ease of display, scales of *y*-axes range from zero to maximum value observed for each place and differ across graphs. Year is centered on quarter-year in which extreme weather disaster occurred, such that Year -1 refers to one year prior to disaster, Year 0 refers to year of and after disaster, and Years 1-3 refer to three years after that. Sources: Federal Reserve Bank of New York/Equifax Consumer Credit Panel, Spatial Hazard Events and Losses Database for the United States (SHELDUS), and authors' calculations.

Figure 9. Decomposition of total debt balance of migrants from disaster-affected areas: Relative effects



Notes: For ease of display, scales of *y*-axes range from zero to maximum value observed for each place and differ across graphs. Year is centered on quarter-year in which extreme weather disaster occurred, such that Year -1 refers to one year prior to disaster, Year 0 refers to year of and after disaster, and Years 1-3 refer to three years after that. Sources: Federal Reserve Bank of New York/Equifax Consumer Credit Panel, Spatial Hazard Events and Losses Database for the United States (SHELDUS), and authors' calculations.

Figure 10. Gini index for the total debt balance of migrants from disaster-affected areas



Notes: For ease of display, excluding municipalities in Puerto Rico, scales of *y*-axes range from 0.9 to 1.0. Year is centered on quarter-year in which extreme weather disaster occurred, such that Year -1 refers to one year prior to disaster, Year 0 refers to year of and after disaster, and Years 1-3 refer to three years after that. Sources: Federal Reserve Bank of New York/Equifax Consumer Credit Panel, Spatial Hazard Events and Losses Database for the United States (SHELDUS), and authors' calculations.

7 Appendix

Table A1. Estimates, standardized estimates, decomposition of total debt, and Gini coefficients for disaster-impacted counties.

County	Year	Migrants' Total Debt ($M)	Per Capita Debt ($K)	Migration Probability	Estimated Migrants	Population (thousands)	Standardized Total Debt	Standardized Migration Probability	Standardized Population	Avg Debt Effect	Mig Prob Effect	Pop Effect	Rel Debt Effect	Rel Mig Prob Effect	Rel Pop Effect	Gini
Aransas, TX	-1	46.6	31.9	0.0629	1460	23.22	57.23	47.78	56.85	0.0	0.0	0.0	0.0	0.0	0.0	0.9967
Aransas, TX	0	111.4	45.6	0.1018	2440	23.96	86.17	81.64	58.78	28.9	33.9	1.9	44.7	52.3	3.0	0.9959
Aransas, TX	1	54.3	30.2	0.0750	1800	24.00	54.04	56.89	58.63	-3.2	9.1	1.8	-41.5	118.5	23.1	0.9962
Aransas, TX	2	56.9	40.1	0.0605	1420	23.46	70.34	44.52	57.32	13.1	-3.3	0.5	127.2	-31.7	4.5	0.9970
Aransas, TX	3	23.1	12.4	0.0773	1860	24.06	21.48	58.23	58.57	-35.7	10.4	1.7	151.6	-44.3	-7.3	0.9989
Barceloneta, PR	-1	28.7	24.3	0.0659	1180	17.90	26.53	19.71	18.66	0.0	0.0	0.0	0.0	0.0	0.0	0.5372
Barceloneta, PR	0	21.5	19.6	0.0617	1100	17.82	21.07	18.12	18.58	-5.5	-1.6	-0.1	76.6	22.2	1.2	0.7273
Barceloneta, PR	1	25.4	16.5	0.0862	1540	17.86	17.70	25.32	18.61	-8.8	5.6	0.0	270.1	-171.6	1.4	0.6523
Barceloneta, PR	2	18.4	17.7	0.0571	1040	18.22	19.01	16.66	19.00	-7.5	-3.0	0.3	73.6	29.8	-3.3	0.5495
Barceloneta, PR	3	2.4	4.4	0.0313	560	17.88	7.74	12.26	18.68	-18.8	-7.4	0.0	71.7	28.4	-0.1	0.8169
Butte, CA	-1	259.6	31.0	0.0455	8380	184.24	347.97	252.08	339.43	0.0	0.0	0.0	0.0	0.0	0.0	0.9893
Butte, CA	0	615.8	41.5	0.0788	14820	188.08	489.64	459.54	346.44	141.7	207.5	7.0	39.8	58.3	2.0	0.9722
Butte, CA	1	424.8	37.7	0.0591	11260	190.52	425.68	327.93	351.01	77.7	75.8	11.6	47.1	45.9	7.0	0.9854
Butte, CA	2	101.2	9.3	0.0589	10940	185.62	107.24	331.49	342.35	-240.7	79.4	2.9	152.0	-50.1	-1.8	0.9937
Canadian, OK	-1	100.5	36.7	0.0313	2740	87.68	113.97	101.33	104.38	0.0	0.0	0.0	0.0	0.0	0.0	0.9929
Canadian, OK	0	91.2	33.5	0.0310	2720	87.88	104.84	100.76	104.84	-9.1	-0.6	0.5	98.8	6.1	-4.9	0.9935
Canadian, OK	1	103.9	28.9	0.0390	3600	92.30	88.39	124.95	109.78	-25.6	23.6	5.4	-742.7	686.0	156.7	0.9923
Canadian, OK	2	122.7	37.9	0.0343	3240	94.48	118.16	111.23	112.52	4.2	9.9	8.1	18.8	44.6	36.6	0.9912
Canadian, OK	3	128.7	39.2	0.0338	3280	96.94	122.60	109.67	115.66	8.6	8.3	11.3	30.5	29.5	39.9	0.9902
Ceiba, PR	-1	21.7	31.0	0.0668	700	10.48	20.49	15.89	18.64	0.0	0.0	0.0	0.0	0.0	0.0	0.5226
Ceiba, PR	0	35.8	37.3	0.0941	960	10.20	26.49	24.42	18.23	6.0	8.5	-0.4	42.5	60.4	-2.9	0.6802
Ceiba, PR	1	19.8	28.2	0.0700	700	10.00	18.61	16.76	17.72	-1.9	0.9	-0.9	96.9	-44.7	47.8	0.5587
Ceiba, PR	2	18.1	23.2	0.0799	780	9.76	15.10	19.02	17.27	-5.4	3.1	-1.4	148.2	-85.8	37.7	0.6691
Ceiba, PR	3	0.3	1.3	0.0234	220	9.40	5.79	10.52	17.29	-14.7	-5.4	-1.4	68.6	25.1	6.3	1.0003
Cleveland, OK	-1	281.5	36.3	0.0404	7760	192.04	282.77	298.72	277.25	0.0	0.0	0.0	0.0	0.0	0.0	0.9624
Cleveland, OK	0	296.2	40.2	0.0382	7360	192.80	313.02	282.34	278.11	30.3	-16.4	0.9	205.3	-111.2	5.8	0.9537
Cleveland, OK	1	284.7	34.7	0.0408	8200	200.84	270.18	301.74	290.03	-12.6	3.0	12.8	-391.3	94.1	397.2	0.9803
Cleveland, OK	2	293.6	37.2	0.0385	7900	205.00	289.68	285.12	296.02	6.9	-13.6	18.8	57.2	-112.5	155.3	0.9780
Cleveland, OK	3	284.6	36.8	0.0371	7740	208.52	286.69	274.43	300.79	3.9	-24.3	23.5	123.6	-766.7	743.0	0.9839
Galveston, TX	-1	350.3	41.9	0.0330	8360	253.38	450.32	310.86	381.85	0.0	0.0	0.0	0.0	0.0	0.0	0.9857
Galveston, TX	0	486.0	41.4	0.0455	11740	257.90	454.25	437.45	387.06	3.9	126.6	5.2	2.9	93.3	3.8	0.9795

Galveston, TX	1	500.1	40.7	0.0466	12300	263.72	447.10	448.87	396.91	-3.2	138.0	15.1	-2.1	92.1	10.1	0.9827
Galveston, TX	2	514.7	46.5	0.0410	11060	269.48	508.91	391.85	406.67	58.6	81.0	24.8	35.6	49.3	15.1	0.9834
Galveston, TX	3	125.7	11.3	0.0403	11140	276.10	120.45	388.71	409.25	-329.9	77.8	27.4	146.9	-34.7	-12.2	0.9899
Harris, TX	-1	5482.2	38.2	0.0442	143680	3248.82	6480.33	5150.74	5507.99	0.0	0.0	0.0	0.0	0.0	0.0	0.9642
Harris, TX	0	6604.3	38.3	0.0518	172560	3333.98	6560.35	6062.18	5638.49	80.0	911.4	130.5	7.1	81.2	11.6	0.9597
Harris, TX	1	7175.5	39.8	0.0528	180420	3414.96	6840.17	6206.36	5785.76	359.8	1055.6	277.8	21.3	62.3	16.4	0.9578
Harris, TX	2	7281.5	42.3	0.0488	172160	3530.82	7249.52	5685.79	6003.00	769.2	535.1	495.0	42.8	29.7	27.5	0.9608
Harris, TX	3	2300.2	12.3	0.0508	186900	3678.26	1943.29	5901.84	6111.85	-4537.0	751.1	603.9	142.6	-23.6	-19.0	0.9726
Jasper, MO	-1	98.3	26.7	0.0408	3680	90.28	95.34	92.93	87.98	0.0	0.0	0.0	0.0	0.0	0.0	0.9892
Jasper, MO	0	120.3	25.4	0.0520	4740	91.18	90.79	118.61	88.88	-4.5	25.7	0.9	-20.6	116.5	4.1	0.9885
Jasper, MO	1	57.5	17.6	0.0358	3260	91.12	63.99	82.57	88.90	-31.3	-10.4	0.9	76.8	25.4	-2.2	0.9921
Jasper, MO	2	69.8	23.9	0.0323	2920	90.32	85.57	74.01	88.18	-9.8	-18.9	0.2	34.3	66.4	-0.7	0.9918
Jasper, MO	3	100.4	31.0	0.0346	3240	93.76	109.55	77.27	91.56	14.2	-15.7	3.6	664.4	-732.0	167.6	0.9946
Jefferson, AL	-1	1115.9	49.4	0.0420	22600	538.74	1113.84	988.88	985.15	0.0	0.0	0.0	0.0	0.0	0.0	0.9822
Jefferson, AL	0	1008.9	40.9	0.0459	24660	537.28	919.86	1078.54	982.48	-194.0	89.7	-2.7	181.3	-83.8	2.5	0.9802
Jefferson, AL	1	985.1	45.1	0.0406	21820	537.30	1017.78	956.73	982.56	-96.1	-32.2	-2.6	73.4	24.6	2.0	0.9813
Jefferson, AL	2	797.6	40.9	0.0367	19520	532.16	926.03	869.24	974.33	-187.8	-119.6	-10.8	59.0	37.6	3.4	0.9819
Jefferson, AL	3	1024.1	42.3	0.0440	24200	549.86	953.32	1036.98	1005.72	-160.5	48.1	20.6	174.8	-52.4	-22.4	0.9849
Lawrence, MO	-1	66.3	38.1	0.0577	1740	30.18	64.25	46.03	43.26	0.0	0.0	0.0	0.0	0.0	0.0	0.9984
Lawrence, MO	0	41.1	21.0	0.0648	1960	30.24	34.45	50.49	43.43	-29.8	4.5	0.2	118.4	-17.7	-0.7	0.9982
Lawrence, MO	1	44.0	28.2	0.0514	1560	30.36	47.20	40.50	43.60	-17.0	-5.5	0.3	76.6	24.9	-1.5	0.9971
Lawrence, MO	2	36.0	25.0	0.0481	1440	29.94	42.01	38.18	43.05	-22.2	-7.9	-0.2	73.4	25.9	0.7	0.9977
Lawrence, MO	3	30.2	18.0	0.0538	1680	31.20	30.10	42.72	44.61	-34.2	-3.3	1.3	94.6	9.2	-3.7	0.9979
Napa, CA	-1	327.5	61.6	0.0458	5320	116.10	398.98	325.32	371.36	0.0	0.0	0.0	0.0	0.0	0.0	0.9912
Napa, CA	0	414.2	58.7	0.0588	7060	120.06	381.56	417.61	383.19	-17.4	92.3	11.8	-20.1	106.4	13.6	0.9923
Napa, CA	1	483.5	68.3	0.0581	7080	121.84	446.87	415.30	389.45	47.9	90.0	18.1	30.7	57.7	11.6	0.9928
Napa, CA	2	314.2	47.7	0.0532	6580	123.68	310.15	378.43	393.74	-88.8	53.1	22.4	665.6	-398.0	-167.7	0.9925
Newton, MO	-1	48.4	31.9	0.0347	1520	43.82	48.83	47.00	46.21	0.0	0.0	0.0	0.0	0.0	0.0	0.9965
Newton, MO	0	58.1	33.4	0.0394	1740	44.16	51.50	53.68	46.56	2.7	6.7	0.3	27.6	68.9	3.6	0.9972
Newton, MO	1	37.9	23.1	0.0370	1640	44.28	35.07	49.76	46.72	-13.8	2.8	0.5	131.2	-26.4	-4.9	0.9949
Newton, MO	2	55.2	38.9	0.0321	1420	44.26	59.09	43.02	46.68	10.3	-4.0	0.5	152.0	-58.9	6.9	0.9957
Newton, MO	3	34.0	25.4	0.0295	1340	45.46	39.42	40.44	47.79	-9.4	-6.6	1.6	65.4	45.6	-10.9	0.9982
Oklahoma, OK	-1	620.8	33.6	0.0331	18500	558.90	682.80	634.29	639.23	0.0	0.0	0.0	0.0	0.0	0.0	0.9657
Oklahoma, OK	0	595.3	31.1	0.0341	19140	560.56	634.59	654.55	641.70	-48.2	20.3	2.5	189.2	-79.5	-9.7	0.9666
Oklahoma, OK	1	801.2	37.3	0.0366	21480	586.66	762.25	703.65	670.80	79.5	69.4	31.6	44.0	38.5	17.5	0.9708
Oklahoma, OK	2	647.9	30.3	0.0356	21380	600.98	615.94	681.01	686.41	-66.9	46.7	47.2	-247.3	172.8	174.5	0.9682
Oklahoma, OK	3	677.2	31.7	0.0348	21380	614.96	644.61	665.84	702.28	-38.2	31.5	63.0	-67.7	55.9	111.8	0.9633
Orleans, LA	-1	1320.6	35.9	0.1144	36740	321.06	1606.04	1198.24	1748.44	0.0	0.0	0.0	0.0	0.0	0.0	0.9812
Orleans, LA	0	3587.7	43.5	0.2538	82440	324.78	2069.24	2875.76	1874.82	463.2	1677.5	126.4	20.4	74.0	5.6	0.9733
Orleans, LA	1	1535.3	28.1	0.1774	54560	307.50	1213.32	1861.81	1692.30	-392.7	663.6	-56.1	-182.9	309.1	-26.1	0.9807
Orleans, LA	2	1082.5	33.5	0.1267	32320	255.18	1513.95	1371.27	1429.36	-92.1	173.0	-319.1	38.7	-72.7	134.0	0.9813
Orleans, LA	3	842.2	41.9	0.0800	20100	251.30	1802.77	847.88	1423.65	196.7	-350.4	-324.8	-41.1	73.2	67.9	0.9847
Plaquemines, LA	-1	80.2	35.2	0.1074	2280	21.22	95.00	75.30	90.28	0.0	0.0	0.0	0.0	0.0	0.0	0.9971
Plaquemines, LA	0	113.7	29.0	0.1758	3920	22.30	75.75	122.56	95.82	-19.2	47.3	5.5	-57.4	140.8	16.5	0.9924
Plaquemines, LA	1	89.2	25.5	0.1651	3500	21.20	65.80	113.37	90.43	-29.2	38.1	0.2	-323.6	421.8	1.8	0.9945
Plaquemines, LA	2	86.0	37.1	0.1189	2320	19.52	99.73	83.59	83.08	4.7	8.3	-7.2	81.3	142.5	-123.8	0.9977

Plaquemines, LA	3	65.2	43.5	0.0778	1500	19.28	111.76	51.27	82.58	16.8	-24.0	-7.7	-112.0	160.6	51.4	0.9563
Shasta, CA	-1	270.4	37.0	0.0485	7300	150.50	262.92	232.79	216.79	0.0	0.0	0.0	0.0	0.0	0.0	0.9908
Shasta, CA	0	253.5	34.9	0.0474	7260	153.08	247.63	227.04	220.99	-15.3	-5.7	4.2	90.8	34.1	-25.0	0.9885
Shasta, CA	1	263.9	39.2	0.0437	6740	154.14	275.91	207.48	222.65	13.0	-25.3	5.9	-201.1	391.8	-90.6	0.9892
Shasta, CA	2	96.3	13.7	0.0449	7020	156.30	97.67	216.27	224.50	-165.3	-16.5	7.7	94.9	9.5	-4.4	0.9947
Sonoma, CA	-1	999.6	60.7	0.0397	16480	415.36	1128.89	1016.96	1100.99	0.0	0.0	0.0	0.0	0.0	0.0	0.9845
Sonoma, CA	0	1237.7	61.3	0.0477	20180	423.22	1142.52	1221.79	1120.59	13.6	204.8	19.6	5.7	86.0	8.2	0.9869
Sonoma, CA	1	1066.3	56.2	0.0443	18980	428.00	1045.07	1135.32	1133.11	-83.8	118.4	32.1	-125.8	177.6	48.2	0.9832
Sonoma, CA	2	1192.7	63.3	0.0438	18840	430.44	1178.88	1120.83	1140.23	50.0	103.9	39.2	25.9	53.8	20.3	0.9853
St Bernard, LA	-1	91.9	34.8	0.0536	2640	49.28	246.31	25.88	244.81	0.0	0.0	0.0	0.0	0.0	0.0	0.9960
St Bernard, LA	0	830.9	39.9	0.4163	20800	49.96	371.59	581.95	302.46	125.3	556.1	57.6	17.0	75.2	7.8	0.9865
St Bernard, LA	1	224.0	21.9	0.2160	10240	47.40	153.69	249.51	245.94	-92.6	223.6	1.1	-70.1	169.2	0.9	0.9971
St Bernard, LA	2	91.3	24.8	0.1207	3680	30.48	193.39	152.21	170.79	-52.9	126.3	-74.0	8619.8	-20577.5	12057.7	0.9970
St Bernard, LA	3	40.9	19.3	0.0724	2120	29.28	170.91	117.15	177.90	-75.4	91.3	-66.9	147.7	-178.8	131.1	0.9983
Toa Baja, PR	-1	100.4	30.1	0.0480	3340	69.64	100.66	74.30	83.43	0.0	0.0	0.0	0.0	0.0	0.0	0.5561
Toa Baja, PR	0	134.2	31.2	0.0620	4300	69.40	108.47	100.43	83.37	7.8	26.1	-0.1	23.1	77.1	-0.2	0.6035
Toa Baja, PR	1	94.0	21.6	0.0634	4360	68.74	71.33	98.47	82.21	-29.3	24.2	-1.2	459.6	-378.8	19.2	0.6475
Toa Baja, PR	2	87.9	26.5	0.0491	3320	67.56	88.61	76.57	80.73	-12.0	2.3	-2.7	96.5	-18.1	21.7	0.6516
Toa Baja, PR	3	9.5	5.8	0.0251	1640	65.38	34.04	53.59	79.90	-66.6	-20.7	-3.5	73.3	22.8	3.9	0.9368
Trinity, CA	-1	15.9	33.2	0.0491	480	9.78	14.16	16.32	13.34	0.0	0.0	0.0	0.0	0.0	0.0	0.9986
Trinity, CA	0	16.4	39.0	0.0432	420	9.72	16.60	14.41	13.25	2.4	-1.9	-0.1	556.1	-435.4	-20.7	0.9995
Trinity, CA	1	12.3	51.2	0.0247	240	9.72	20.15	6.77	13.26	6.0	-9.5	-0.1	-164.6	262.2	2.4	0.9996
Trinity, CA	2	6.0	11.2	0.0551	540	9.80	3.60	16.99	13.36	-10.6	0.7	0.0	106.9	-6.8	-0.1	0.9999
Tuscaloosa, AL	-1	153.4	30.0	0.0370	5120	138.34	168.02	130.01	139.37	0.0	0.0	0.0	0.0	0.0	0.0	0.9892
Tuscaloosa, AL	0	170.8	26.6	0.0464	6420	138.22	150.95	164.79	139.10	-17.1	34.8	-0.3	-97.9	199.5	-1.6	0.9805
Tuscaloosa, AL	1	118.0	21.6	0.0390	5460	139.86	122.47	138.42	141.12	-45.5	8.4	1.7	128.7	-23.8	-4.9	0.9836
Tuscaloosa, AL	2	123.3	24.9	0.0354	4960	140.18	140.62	125.33	141.40	-27.4	-4.7	2.0	91.2	15.6	-6.7	0.9902
Tuscaloosa, AL	3	143.2	22.7	0.0427	6300	147.44	127.75	150.96	148.57	-40.3	20.9	9.2	397.9	-207.0	-90.9	0.9892
Walker, AL	-1	28.8	29.4	0.0176	980	55.72	34.59	30.67	35.77	0.0	0.0	0.0	0.0	0.0	0.0	0.9975
Walker, AL	0	53.1	41.5	0.0229	1280	56.00	49.16	40.25	35.88	14.6	9.6	0.1	60.1	39.5	0.5	0.9974
Walker, AL	1	41.8	38.7	0.0193	1080	56.08	45.00	33.07	35.95	10.4	2.4	0.2	80.1	18.4	1.4	0.9978
Walker, AL	2	27.4	23.2	0.0212	1180	55.70	27.18	36.67	35.76	-7.4	6.0	0.0	526.6	-426.9	0.2	0.9982
Walker, AL	3	28.9	21.6	0.0232	1340	57.72	24.51	39.69	36.92	-10.1	9.0	1.2	-10141.0	9079.2	1161.8	0.9977

Sources: Federal Reserve Bank of New York/Equifax Consumer Credit Panel, Spatial Hazard Events and Losses Database for the United States (SHELDUS), and authors' calculations.

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