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

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ABSTRACT We introduce the consideration of human 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 attributable to migration from 23 disaster-affected areas in the United States before, during, and after some of the most costly 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 the economic resources that migrants take with them. Finally, we consider the implications of these losses for changing spatial inequality in the United States. While disaster-affected areas and their populations 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, these changes primarily reflect changes in out-migration (vs. the economic resources that migrants take with them), and these losses briefly disrupt the status quo by temporarily reducing spatial inequality.

KEYWORDS Climate • Disaster • Migration • Vector • Losses

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 (NOAA National Centers for Environmental Information (NCEI) 2021; Wisner et al. 2004). In 2017, the United States set a new record of $322 billion in losses from 16 unique 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

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serious concerns about what the future holds in store under current and projected climate and environmental change (Intergovernmental Panel on Climate Change (IPCC) 2012, 2018, 2021; U.S. Global Change Research Program 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 climate and environmental change more broadly (Black et al. 2011; Hunter et al. 2015; McLeman 2014). Actors' migration decisions and behaviors ultimately cumulate into place-based migration flows from disaster-affected areas. As we advance and explore in this study, 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 Bank of New York/Equifax Consumer Credit Panel (Lee and van der Klaauw 2010; Whitaker 2018), we start by documenting the size of economic losses attributable to migration from each of 23 disaster-affected areas before, during, and after three types of extreme weather disasters: hurricanes, tornadoes, and wildfires. Next, recognizing that economic losses from migration reflect the loss of both people 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 U.S. places. We conclude by summarizing the key findings and contributions of our work, followed by describing several next steps for continued study in this under-researched yet critical area.

Background

Economic Losses From Extreme Weather Disasters

According to data from the National Oceanic and Atmospheric Administration's National Centers for Environmental Information (NCEI 2021), 285 distinct 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 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 (ASU 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, NCEI's (2021) estimates of economic losses from billion-dollar extreme weather disasters use data from the U.S. 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 U.S. 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 et al. 2017; Hsiang and Sobel 2016; 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).

Migration as Adaptation Requiring Economic Resources

A common feature of estimates of economic losses from extreme weather disasters described in the previous subsection is 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. To begin, 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 *in situ* strategies have been exhausted and tolerances (for stress, etc.) exceeded—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 2014, 2018; Nawrotzki and DeWaard 2016; Scoones 1998; Stark and Bloom 1985). The Intergovernmental Panel on Climate Change (IPCC 2012:556) 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 article is on the resources—specifically, economic resources—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; DeWaard, Hunter et al. 2022; Fussell 2012; McLeman 2014; 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).

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 that is 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 activities and resources from disaster-affected areas. These resources can include their wages and incomes, state and local tax contributions, consumer spending, charitable donations, and more. Consequently, we argue that migration can 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 property, crop, and other losses described earlier (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 to understand the broader costs of extreme weather disasters. 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 of 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 in that the population of New Orleans fell by more than one half in the year after Hurricane Katrina owing 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 following Hurricane Katrina (English 2015; Fussell, Curtis, and DeWaard 2014).

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 article in which they used 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). 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, Curtis, and DeWaard 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 1970:3; see also Bakewell 2014; Kritz and Zlotnik 1992; Massey et al. 1998). Consequently, one should not expect that a given localized extreme weather disaster such as the Joplin Tornado—the costliest and deadliest U.S. tornado on record that struck Jasper County, Missouri, and nearby areas in May of 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 and attending economic resources connecting Jasper County to other places in the United States.

Research Questions

The preceding background and discussion motivate three foundational and descriptive research questions 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. Prior to detailing these three questions, we note that our focus is on out-migration from disaster-affected areas. In contrast to a different or additional focus on in- or net-migration, we focus on out-migration for the same reason that prior research on economic losses from extreme weather disasters focuses on the dollar value of losses themselves and not also on whether, to what extent, or when losses are offset (a damaged building is restored or rebuilt, new crops are planted and harvested, supply chains are restored, etc.).

Our first research question is the most basic and concerns the size of economic losses attributable to 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 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.

Approach

Cases

As Gray and Wise (2016:556; see also Fussell et al. 2017; Hunter et al. 2015; McLeman 2014) 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 distinct 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, and wildfires from lists provided by the National Hurricane Center (2018; for example) and other sources. These include Hurricanes Katrina in August of 2005 (Louisiana), Harvey in August of 2017 (Texas), and Maria in September of 2017 (Puerto Rico); the Joplin (Missouri), Tuscaloosa–Birmingham (Alabama), and Moore (Oklahoma) Tornadoes in May of 2011, April of 2011, and May of 2013, respectively; and the Carr, Camp, and Nuns Wildfires (California) in July of 2018, November of 2018, and October of 2017, respectively. For each of these nine extreme weather disasters, we then used information from SHELDUS to select places that incurred the greatest total or per capita economic losses due to property damage (ASU CEMHS 2019). Figure A1 in the online appendix provides maps of the 23 disaster-affected areas selected for analysis.

[1] In Louisiana, counties are referred to as "parishes." The U.S. 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."

Data

In selecting these 23 disaster-affected areas, 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 study (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 to study 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, Hauer et al. 2022; Kaplan and Schulhofer-Wohl 2012).

For these reasons, we turn to a nonpublic 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 U.S. 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; the panel nature of the CCP derives from the fact that the same preselected numbers are used each quarter. 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 are 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% of U.S. 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 U.S. 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; DeWaard, Johnson, and Whitaker 2020; Ding et al. 2016; Molloy and Shan 2013).[2] Given the construction of the CCP, after weighting each person in the sample by 20, this information can then be aggregated up to study migration at different time intervals (semiannually, annually, etc.) and spatial scales (census tracts, counties, etc.), which is one of the main strengths of the CCP (DeWaard et al. 2019).

[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 COVID-19 pandemic, the contract was recently amended to provide monthly data since January 2020.

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 nonmortgage 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 important to point out that debt reflects the accumulation of past economic activities and is positively correlated with consumption, income, and wealth (Baker 2018; Brown et al. 2013; Charron-Chénier and Seamster 2018; Stavins 2020; Tudela and Young 2005). Whitaker (2018), for example, documented a strong positive association between household debt and household income, controlling for household type and age of householder. Debt indicates past, usually recent, purchases of homes, automobiles, and various consumer goods and services, with past consumption being highly predictive of future consumption (Gorbachev 2011; Jappelli and Pistaferri 2010). The existence of a debt balance also tends to indicate that borrowers believe they will have the income to repay the debt (Brown et al. 2008). Before extending credit, especially mortgage and auto credit, lenders likewise verify borrowers' incomes and payment histories (Anderson et al. 2011; Furfine 2020). For these reasons, we use total debt balance in the CCP as our measure of total economic losses via migration from disaster-affected areas.

While total debt balance is a valid proxy for the economic resources that migrants take with them from disaster-affected areas, this measure is not without limitations. For example, total debt balance is likely to be more strongly correlated with some economic activities and resources (income, consumer spending, etc.) than others (e.g., charitable donations). If so, then this measure would understate the true extent of economic losses in disaster-affected areas. The measure of total debt balance also raises questions about exactly which debts should qualify as economic losses, as well as under what conditions. For example, if a person who has a mortgage and an auto loan sells their home and migrates from a disaster-affected area, taking the financed car with them in the process, does the original mortgage and auto debt reflect economic losses in the disaster-affected area? The answer is that it depends. One on hand, these debts might not be economic losses if one privileges the idea that what matters is the object of the debt (e.g., a car, which is portable, and a home, which is presumably paid off prior to migrating). On the other hand, and this is the tack that we take in the current study, if one privileges the idea that what matters is the economic activity that initially generated the debt, activity that will necessarily cease in the disaster-affected area after the person in question migrates, then the original mortgage and auto debt would reflect economic losses in the disaster-affected area.

Methods

To answer our first research question and document the size of economic losses attributable to 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, Fussell et al. 2020; 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 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 Eq. (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.[3] For substantive clarity and notational simplicity, we rewrite Eq. (1) as follows, where L_p is the 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 Eq. (2) as inputs to develop standardized estimates of T_p. To briefly walk through this, given information on each of the quantities in Eq. (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:

$$T_{1.2}^{L.M,N} = \left[\frac{M_2 N_2 + M_1 N_1}{3} + \frac{M_2 N_1 + M_1 N_2}{6} \right] L_1. \tag{3}$$

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

[3] While it is possible to include interaction terms, we follow Das Gupta (1993:3), whose techniques work "not by ignoring [these] parts," but, rather, by "distributing the so-called interactions among the main effects" for the purpose of "easier and simpler interpretation of the results."

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 Eq. (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:

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

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 foregoing equations. Following Das Gupta (1993), for any number of periods ($p = 1, 2, \ldots, P$), 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 ($q = 1, 2, \ldots, Q$) as follows:

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

Similar estimates (not shown) can be calculated for each of the remaining periods, as well as for the other two quantities in Eq. (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:

$$\Delta T_{p,q} = \Delta T_{p_*^*q^*}^{L^*} + \Delta T_{p_*^*q^*}^{M^*} + \Delta T_{p_*^*q^*}^{N^*}. \tag{7}$$

On the right-hand side of Eq. (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):

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

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, 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 Eq. (8) as follows, where $T_{ij,p}$ is the total debt balance of migrants from a disaster-affected area i to receiving area j:

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

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.

Results

Size of Economic Losses via Migration From Disaster-Affected Areas

As a place to start, in Figure 1 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 hence differ across graphs. On the x-axes, Year 0 refers to the quarter and year that 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

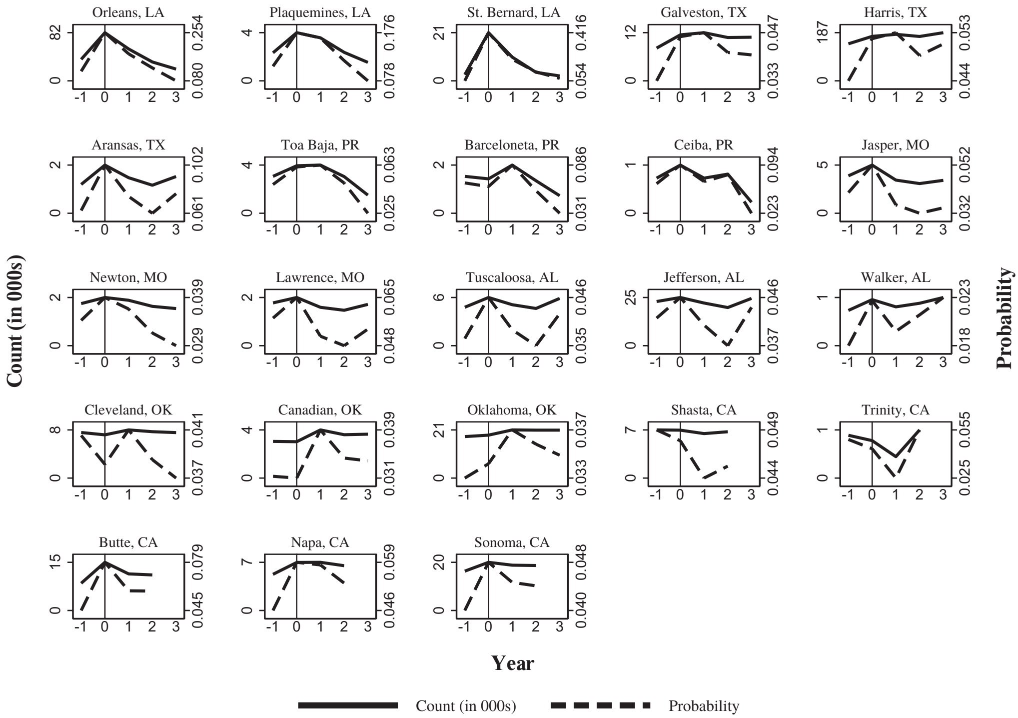

Fig. 1 Out-migration from disaster-affected areas. From left-to-right and top-to-bottom, graphs are organized by hurricane (Katrina, Harvey, and Maria), tornado (Joplin, Tuscaloosa–Birmingham, and Moore), and wildfire (Carr, Camp, and Nuns). For ease of display, scales of *y*-axes range from zero to the maximum value observed for each place and differ across graphs. Year is centered on the quarter-year in which the extreme weather disaster occurred, such that Year −1 refers to one year prior to the disaster, Year 0 refers to the year of and after the disaster, and Years 1–3 refer to the 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.

Q3-2008, and Q3-2008 to Q3-2009, respectively). 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.

Consistent with the idea that places and their populations are differentially vulnerable to extreme weather disasters, we find 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 following three years. Looking across the 23 graphs displayed in Figure 1, absolute levels of out-migration ranged from 420 persons in Trinity County, California, to 172,560 persons in Harris County, Texas, during the year of and after the Carr Wildfire and Hurricane Harvey, respectively. In relative terms, out-migration probabilities ranged from .023 in Walker County, Alabama, to .416 in St. Bernard Parish, Louisiana, after the Tuscaloosa–Birmingham Tornado and Hurricane Katrina, respectively.

Of these 23 disaster-affected areas, five experienced a decrease in out-migration during the year of and after the extreme weather disaster compared with the year before the disaster. The largest absolute magnitudes of these decreases ranged from

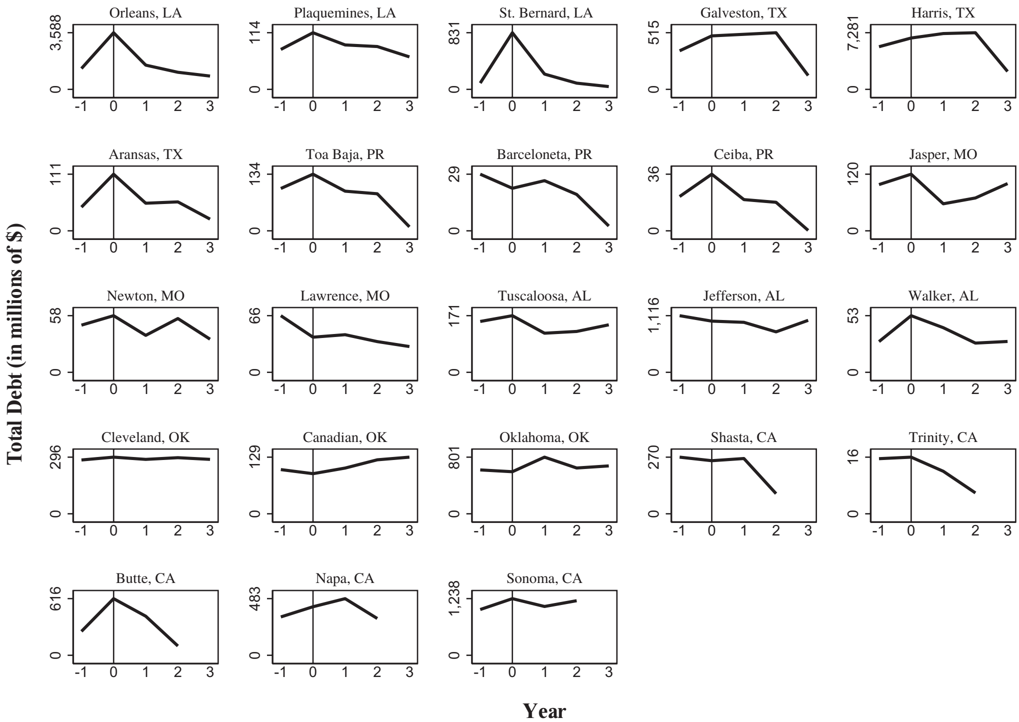

Fig. 2 Total debt balance of migrants from disaster-affected areas. For details, see Figure 1 legend.

–20 persons in Canadian County to –400 persons in Cleveland County (both in Oklahoma), following the Moore Tornado. The largest relative magnitudes of these decreases ranged from –0.96% in Canadian County to –11.96% in Trinity County, respectively. The remaining 18 areas experienced an increase in out-migration during the year of and after the extreme weather disaster compared with the year before the disaster. The largest absolute magnitudes of these increases ranged from 220 persons in Lawrence County, Missouri, to 45,700 persons in Orleans Parish, Louisiana, following the Joplin Tornado and Hurricane Katrina, respectively. The largest relative magnitudes of these increases ranged from 3.15% in Oklahoma County to 677.16% in St. Bernard Parish, 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 attributable to out-migration from disaster-affected areas, we display the total debt balance of migrants from each area in Figure 2. Focusing on the year of and after the extreme weather disaster, the total debt balance of migrants ranged from \$16.4 million in Trinity County after the Camp Wildfire to \$6.6 billion in Harris County 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 corresponding levels from the year of the disaster in question and ranged from an average of \$9.2 million in Trinity County to \$5.6 billion in Harris County.

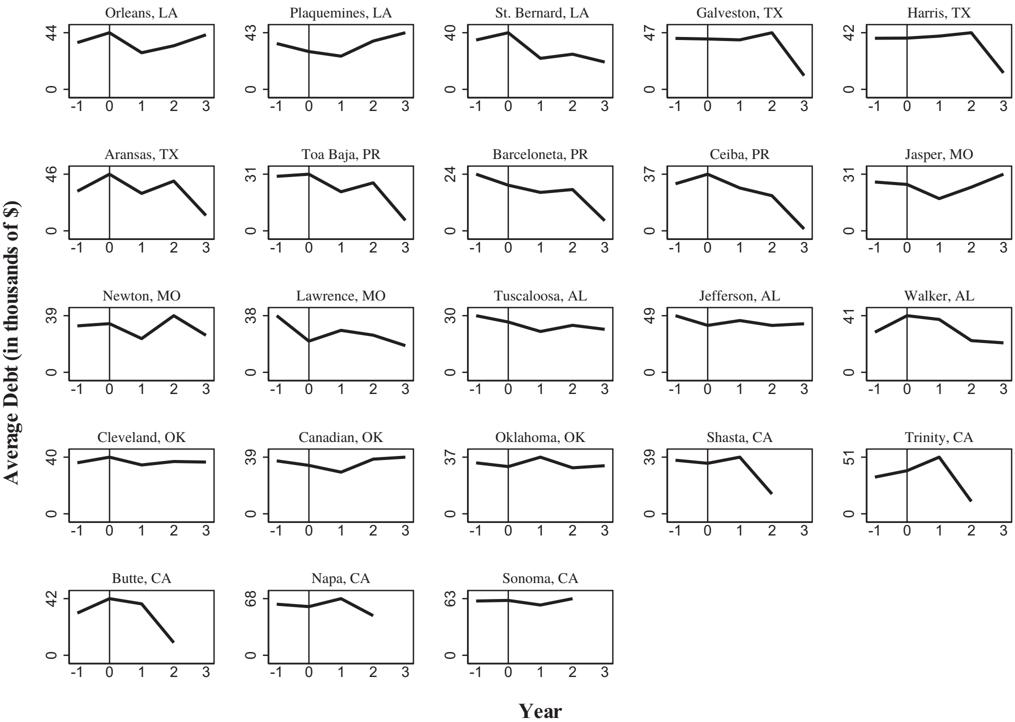

Fig. 3 Average debt balance of migrants from disaster-affected areas. For details, see Figure 1 legend.

To put these figures into perspective, consider the case of Jasper County, Missouri. On account of out-migration from Jasper County in the year of and after the Joplin Tornado, the county lost \$120 million. While this figure pales in comparison to the estimated \$3 billion in economic losses that the county sustained due to property damage (ASU CEMHS 2019), as we argued earlier, economic losses via out-migration from disaster-affected areas are nonetheless an important and understudied source of loss that deserves attention in empirical research if the total costs of extreme weather disasters are to be tallied in a truly exhaustive way.

Decomposition of Economic Losses via Migration From Disaster-Affected Areas

Recalling our earlier point that economic losses from migration from disaster-affected areas reflect the loss of both people 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 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 3, 4, and 5, respectively.

We encourage readers to closely examine both levels of and changes in these three components in each disaster-affected area. Because of space limitations, we simply

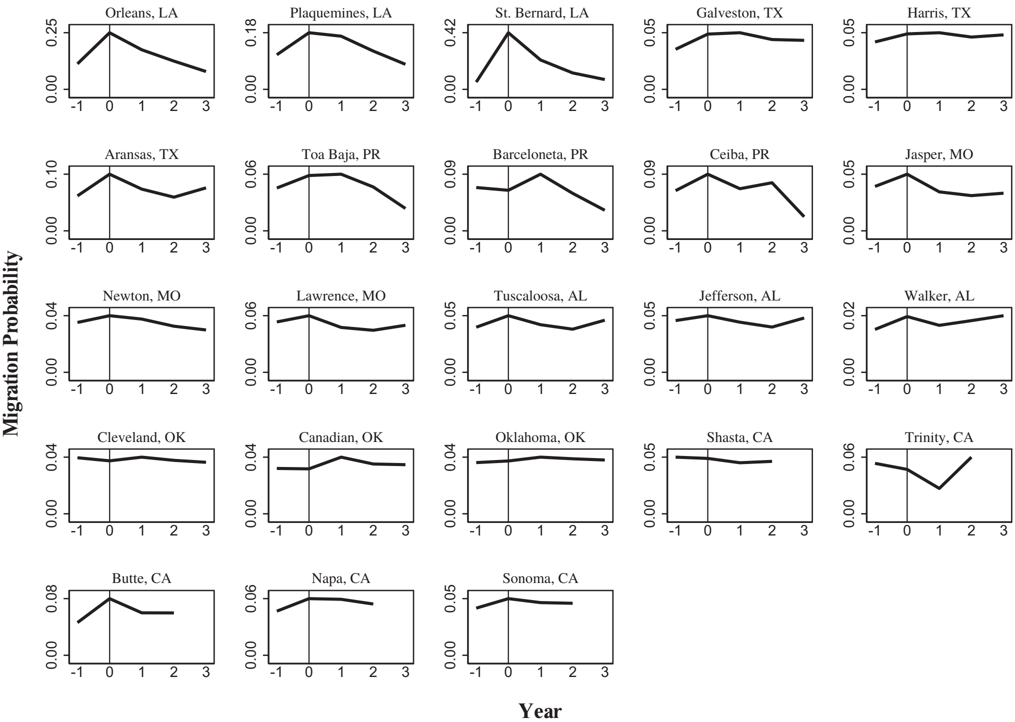

Fig. 4 Probability of out-migration from disaster-affected areas. For details, see Figure 1 legend.

wish to note that we have provided these three figures to revisit and reemphasize two key points from the previous section. First, changes in the three components displayed in Figures 3–5 jointly determine changes in the total debt balance of migrants (Das Gupta 1993). Second, the primacy of a given component in determining changes in the total debt balance of migrants from disaster-affected areas can vary over time (e.g., see Sana 2008).

Using the three components displayed in Figures 3–5, we generated three sets of standardized estimates of the total debt balance of migrants. The first set of standardized estimates, in Figure 6, summarize 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 area. Similarly, the second and third sets of standardized estimates summarize the total debt balance of migrants 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 6 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

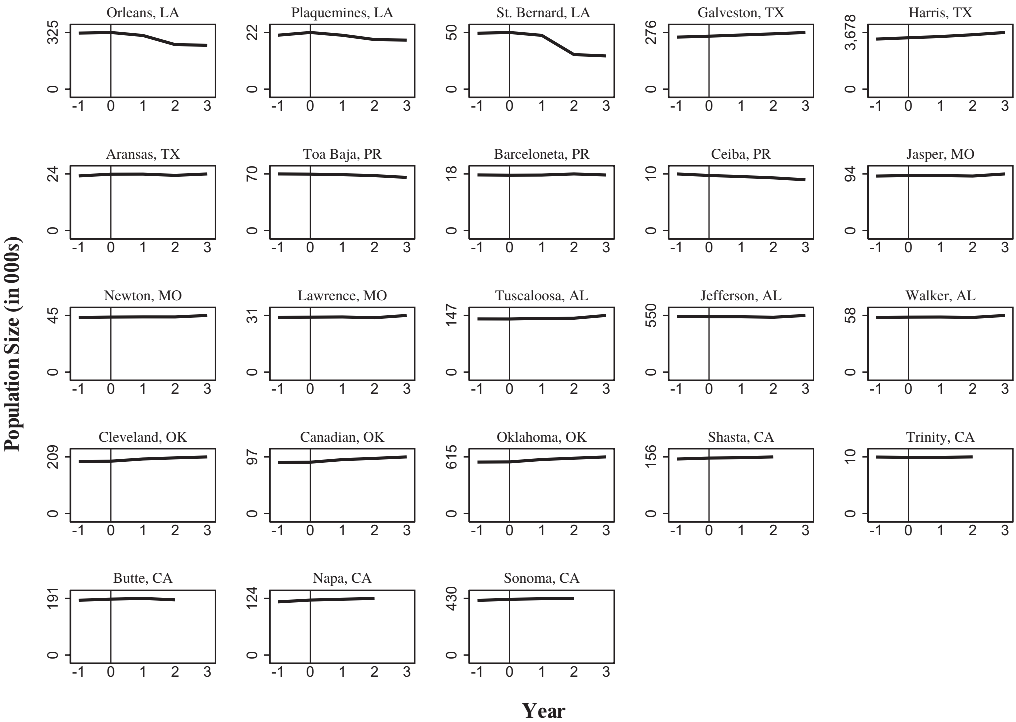

Fig. 5 Population size in disaster-affected areas. For details, see Figure 1 legend.

balance of migrants from disaster-affected areas shown earlier in Figure 2, the stronger the "effect" of that particular component. To illustrate, consider the case of Butte County, California. 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 2. 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. 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 7. Relative effects, in percentage terms, are displayed in Figure 8. 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 2, 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 7

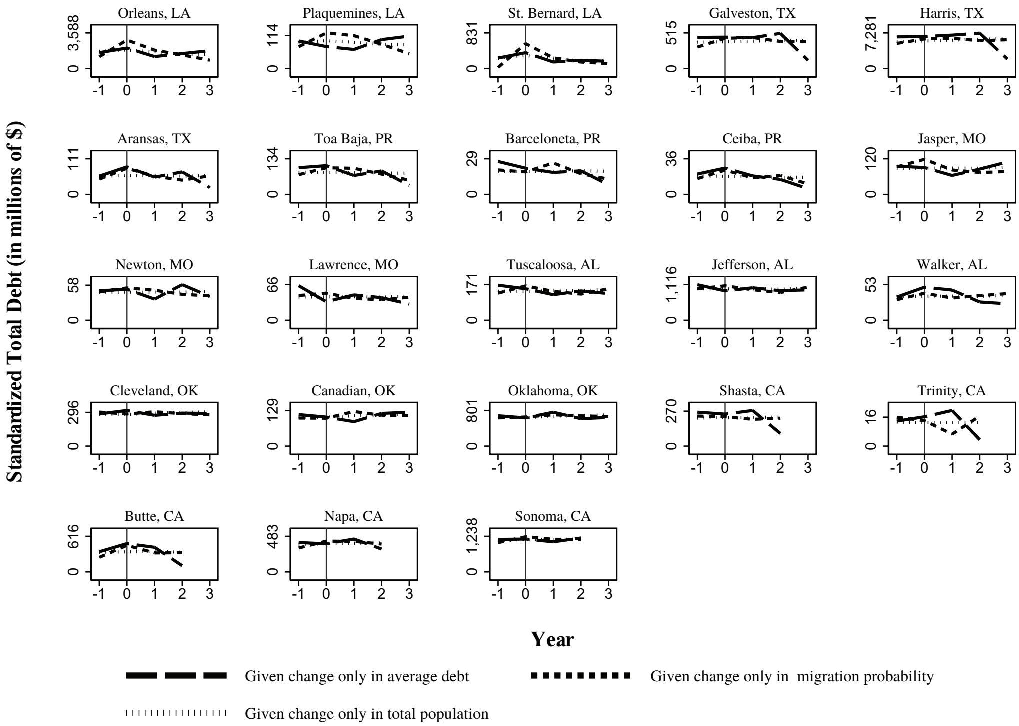

Fig. 6 Standardized estimates of total debt balance of migrants from disaster-affected areas**.** For details, see Figure 1 legend.

sum to this amount, and the relative effects in Figure 8 sum to 100%. Migrants' average debt effect is $463 million (20.4%); the migration probability effect is $1.7 billion (74.0%); and the population size effect is $126 million (5.6%). 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%) and migrants' average debt putting downward pressure (–$393 million and −183%) 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 7 and 8, during the year of and after each extreme weather disaster, the average debt of migrants from these areas was the dominant component of change in nine areas, while the probability of out-migration was the dominant component of change in the remaining 12 areas. Thus, 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.

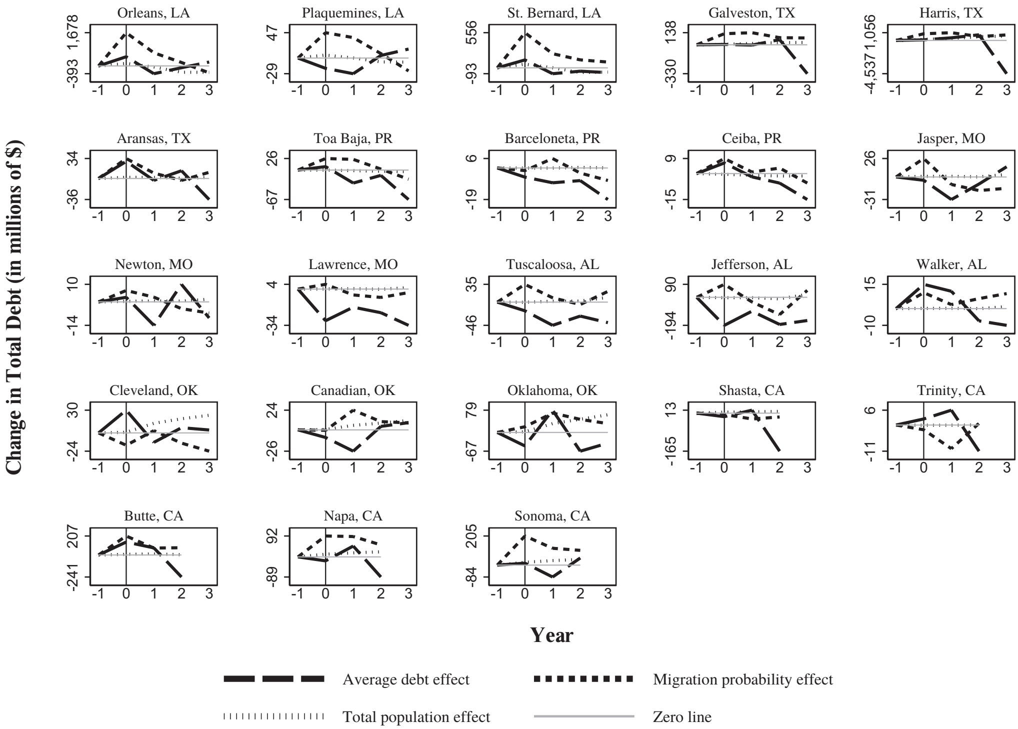

Fig. 7 Decomposition of total debt balance of migrants from disaster-affected areas: Absolute effects. For details, see Figure 1 legend.

Implications for Changing Spatial Inequality

The preceding results clearly show that migration is a vector of economic losses from disaster-affected areas. These losses are then redistributed within disaster-affected areas' networks of migration flows connecting them to other places, which, in turn, translate to other areas' gains and 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, in Figure 9 we display modified Gini coefficients for the total debt balance of migrants from disaster-affected areas.

By way of background, it is worth noting that the Gini coefficients displayed in Figure 9 are high, ranging from a low of .52 to a high of slightly less than 1.00 in Ceiba Municipio, Puerto Rico. This is due to the fact that 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 small handful—of possible other places and not others, a phenomenon that McHugh (1987:171) referred to as "channelized migration streams."

Against this backdrop, the results displayed in Figure 9 show that, relative to the year before the extreme weather disaster in question, spatial inequality decreased in

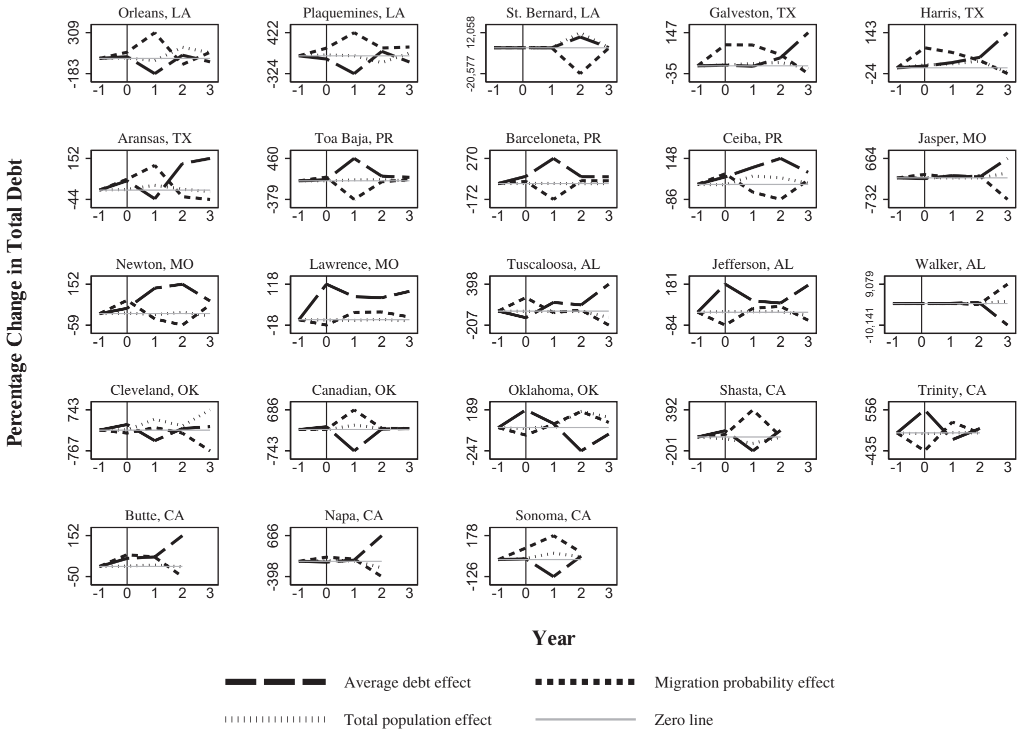

Fig. 8 Decomposition of total debt balance of migrants from disaster-affected areas: Relative effects. For details, see Figure 1 legend.

all but nine 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 9, 17 areas returned to the same or higher levels of spatial inequality in the 1–3 years after the disaster in question.

Discussion

In this study, drawing on prior research on economic losses from extreme weather disasters (e.g., by Hsiang et al. 2017 and others), we argued that migration can be conceptualized as a vector of economic losses from disaster-affected areas. We approached our empirical investigation from 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 2014), 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 is often constrained by the availability and quality of publicly available migration

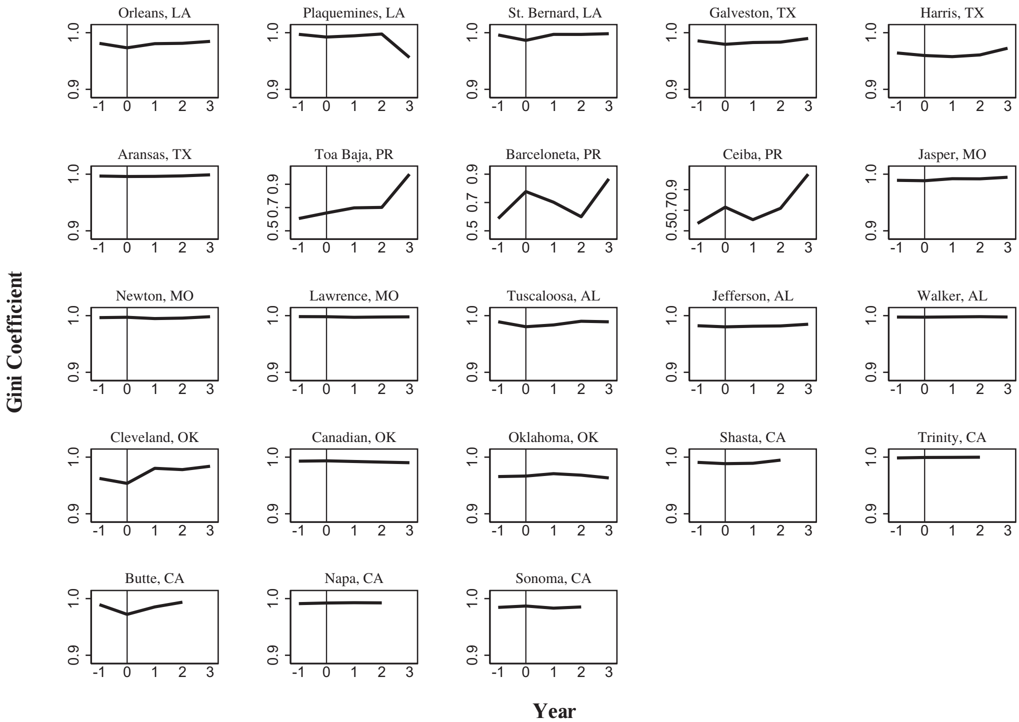

Fig. 9 Gini index for the total debt balance of migrants from disaster-affected areas. For ease of display, excluding municipios in Puerto Rico, scales of *y*-axes range from .9 to 1.0. For details, see Figure 1 legend.

data (DeWaard et al. 2019; DeWaard, Hauer et al. 2022; Fussell, Hunter, and Gray 2014), we used the nonpublic CCP to study economic losses via migration from disaster-affected areas and, in the process, demonstrated the utility of these data for studying climate and environmental migration that extends prior research (DeWaard et al. 2019; DeWaard, Johnson, and Whitaker 2020; Ding et al. 2016; Molloy and Shan 2013). Third, in addition to summarizing levels of and changes in economic losses via migration from disaster-affected areas, we 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. Finally, going beyond out-migration as a localized place-based attribute of disaster-affected areas, we pursued 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).

Our work and findings open up several broader questions and lines of discussion. Despite our case-specific approach, questions remain about whether and to what extent emphasis should be placed on consistency, versus heterogeneity, across cases. While our results suggest that economic losses attributable to migration from disaster-affected areas do not exhibit a "monolithic and unidirectional" pattern (Gray and Wise 2016:556), they might nonetheless still vary in fairly regular and predictable ways by at least three classes of factors. First, while we are limited by our sample size, the type of extreme weather disaster (hurricane, tornado, wildfire, etc.) might be a key organizing factor, as well as related features such as the onset, intensity, and duration of the disaster. Second, following work by Cutter (1996) and others on place vulnerability, features such as geography and elevation might be relevant organizing factors, perhaps in combination with the type and features of the extreme weather disaster. Third, because extreme weather disasters are inherently social phenomena wherein the hazards overwhelm the capacity of people, populations, and places to cope and adapt, pertinent economic, social, and political characteristics and vulnerabilities are also important starting points to consider.

In addition to consistency, versus heterogeneity, across cases, the work and findings of this study raise similar questions about time. As we showed, in the year of and after extreme weather disasters, the 23 cases examined do not tell a single unified story. And while the reasons why might involve one or more of the three classes of factors described above, exactly when changes (if any) occur is also of interest (Curran et al. 2020; Fussell et al. forthcoming). As we foreshadowed at the beginning of this article, precisely when changes occur can reveal much about the availability and quality of *in situ* adaptation strategies to people, populations, and places (Adams and Kay 2019; Black et al. 2011; Hunter et al. 2015; McLeman 2014, 2018; Nawrotzki and DeWaard 2016; Scoones 1998; Stark and Bloom 1985). The timing of changes also stands to inform thinking about and preparations for the various phases of extreme weather disasters, postdisaster recovery and reconstruction, and resilience (Kates et al. 2006).

Beyond these broader questions and discussions, three narrower points, which are both limitations of the current study and potential next steps for future research, deserve mention. First, the reference to time in the preceding paragraph and the potential for changes to unfold over potentially longer (versus shorter) periods suggest that our focus on out-migration and corresponding economic losses via migration from disaster-affected areas could be nuanced by also considering whether and to what extent these losses are offset, partially or even fully, by in-migration and corresponding inflows and net flows of economic resources in disaster-affected areas after extreme weather events. For instance, supplemental analyses (not shown, but available upon request) indicate that 12 of the 23 disaster-affected areas considered experienced higher levels of in-migration during the year of and after the extreme weather disaster compared with the year before the disaster. 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, Curtis, and DeWaard 2014; Vigdor 2008), including actors' spending power and other economic activities associated with these movements (Dolfman et al. 2007). This observation raises similar questions about the implications of considering in-migration for documenting and understanding changes in spatial inequality of the sort displayed in Figure 9, as well as other types of social inequalities. Given the focus of this article and space limitations, we do not pursue this limitation here and leave this as an important extension of our work and next step for future research.

Another limitation and need for future research concerns 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 in our empirical analysis. As noted earlier, total debt balance is a reasonable and potentially strong but imperfect measure of the economic resources that migrants from disaster-affected areas take with them. A more nuanced 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, Johnson, and Whitaker 2020; Martín et al. 2020; Rivera 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.

Third, and finally, in this article we aimed to provide a detailed descriptive account of economic losses via migration from disaster-affected areas. 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, Hunter, and Gray 2014; Hsiang 2016; Piguet 2010), it is equally important to establish a descriptive baseline view of the phenomenon in question (Duncan 2008). This article provides multiple avenues for future research to pursue, one of which is to establish the aforementioned causal linkages. Such efforts might involve, for example, linking geocoded data on the hazards associated with extreme weather disasters to individuals in the CCP to identify causal impacts of the former on out-migration and attending economic losses via migration from disaster-affected areas.

Taken together, our work helps to elevate the importance of economic losses attributable to 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 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 2014). ■

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