Federal Reserve Bank of Cleveland Working Paper Series

Effects of Wildfire Destruction on Migration, Consumer Credit, and Financial Distress

Kathryn McConnell, Stephan Whitaker, Elizabeth Fussell, Jack DeWaard,
Katherine Curtis, Kobie Price, Lise St. Denis, and Jennifer Balch

Working Paper No. 21-29

December 2021

Suggested citation: McConnell, Kathryn, Stephan Whitaker, Elizabeth Fussell, Jack DeWaard, Katherine Curtis, Kobie Price, Lise St. Denis, and Jennifer Balch. 2021. "Effects of Wildfire Destruction on Migration, Consumer Credit, and Financial Distress." Working Paper No. 21-29. Federal Reserve Bank of Cleveland. https://doi.org/10.26509/frbc-wp-202129.

Federal Reserve Bank of Cleveland Working Paper Series
ISSN: 2573-7953

Effects of Wildfire Destruction on Migration, Consumer Credit, and Financial Distress

Kathryn McConnell,[*] Stephan Whitaker,[†] Elizabeth Fussell,[‡] Jack DeWaard,[§] Katherine Curtis,[¶] Kobie Price,[‖] Lise St. Denis,[**] Jennifer Balch[††]

The scale of wildfire destruction has grown exponentially in recent years, destroying nearly 25,000 buildings in the United States during 2018 alone. However, there is still limited research exploring how wildfires affect migration patterns and household finances. In this study, we evaluate the effects of wildfire destruction on in-migration and out-migration probability at the Census tract level in the United States from 1999 to 2018. We then shift to the individual level and examine changes in homeownership, consumer credit usage, and financial distress among people whose neighborhood suffered damaging fires. We pair quarterly observations from the Federal Reserve Bank of New York/Equifax Consumer Credit Panel with building destruction counts from the US National Incident Management System/Incident Command System database of wildfire events. Our findings show significantly heightened out-migration probability among tracts that experienced the most destructive wildfires, but no effect on in-migration probability. Among the consumer credit measures, we find a significant drop in homeownership among those treated by major fires. This is concentrated in people over the age of 60. Measures of credit distress, including delinquencies, bankruptcies, and foreclosures, improve rather than deteriorate after the fire, but the changes are not statistically significant. While wildfire effects on migration and borrowing are measurable, they are not yet as large as those observed following other natural disasters such as hurricanes.

Keywords: Wildfire, Migration, Consumer Credit

JEL classifications: R23, Q54, D12

The views expressed herein are those of the authors and do not necessarily represent the views of the Federal Reserve Bank of Cleveland or of the Federal Reserve System.

[*]Yale University
[†]Federal Reserve Bank of Cleveland
[‡]Brown University
[§]University of Minnesota - Twin Cities
[¶]University of Wisconsin - Madison
[‖]University of Minnesota - Twin Cities
[**]University of Colorado Boulder
[††]University of Colorado Boulder

1 Introduction

The expanding spatial extent and intensity of wildfires are making large regions of the United States increasingly risky to live in (Balch et al., 2017; Abatzoglou and Williams, 2016). Since the 1970's, burn area, length of fire season, and total number of large fires have all increased in the United States (Abatzoglou and Williams, 2016; Schoennagel et al., 2017). While fires have long played an important role in ecosystem functioning (Pausas and Keeley, 2019) and have been used for thousands of years by Indigenous peoples (Mason et al., 2012), the intensifying levels of wildfire damage now pose major threats to human populations. Between 2014 and 2020, wildfire damage to the built environment in the United States began to rise exponentially, with nearly 25,000 buildings destroyed during 2018 alone (Figure 1). Such impacts are projected to increase in the coming decades (Barbero et al., 2015). These destructive wildfires have the potential to rapidly reshape not just forests and grasslands, but the built environments of cities, subdivisions, and towns.

Despite their growing impacts, there remains limited environmental mobility scholarship on wildfires, with recent review articles in the field citing no wildfire-focused work (Hunter, Luna, and Norton, 2015; Millock, 2015; Piguet, Kaenzig, and Guélat, 2018; Hoffmann et al., 2020). Similarly, the impacts of natural disasters on individuals' finances have been explored for each type of disaster except wildfires. This gap in the literature is just beginning to be filled; within the past year, scholars have documented wildfire-related evacuations (Jia et al., 2020) and the migration impacts of different subsets of extreme wildfires (Sharygin, 2021; Winkler and Rouleau, 2020). We build on these efforts in an attempt to develop a more systematic understanding of how wildfires affect migration patterns and household finances, drawing from a full population of all documented wildfires in the United States. Given the well-established heterogeneity in strength and direction of environment-migration relationships (Hoffmann et al., 2020; Hunter, Luna, and Norton, 2015) and disaster-financial relationships (Bleemer and van der Klaauw, 2019; Gallagher and Hartley, 2017; Billings, Gallagher, and Ricketts, Forthcoming) it is critical to empirically evaluate the impacts of wildfires, rather than assuming that their effects operate the same as other, better-documented environmental hazards.

The existing literature relating household finances to natural disasters focuses mostly on hurricanes. Researchers have found mixed results with evidence of temporary negative shocks in some measures, long-lasting disadvantages in other measures, and even some improvements in financial health for individuals who experienced moderate storm impacts but benefited from federal recovery programs (Deryugina, Kawano, and Levitt, 2018; Gallagher and Hartley, 2017; Bleemer and van der Klaauw, 2019). In the particular cases of hurricanes Katrina and Rita, the federal government responded with several multi-billion-dollar recovery packages for the Gulf Coast region (Boyd and Gonzales, 2012; FEMA, 2013; Internal Revenue Service (IRS), 2006). Our research will provide an important complement to those studies by investigating fires known to have destroyed many homes and businesses, but in a manner mainly covered by standard homeowners' or commercial property insurance policies (not supplemental flood insurance) and not subject to any unique federal response programs. If we find that individuals appear to benefit from experiencing a major fire, this may prompt a consideration of the appropriate insurance levels to avoid incentivizing unnecessary risk.

Many have posited a future of large-scale mobility in response to amplifying climate impacts (Lustgarten, 2020; Rigaud et al., 2018; Hauer, 2017), and there is indeed evidence of preemptive movement away from environmental hazards (Keenan, Hill, and Gumber, 2018). Analysis of disaster-scale wildfires further suggests that the most extreme wildfires may be associated with increased out-migration (Winkler and Rouleau, 2020). Yet, there are also reasons to expect that wildfires will *not* cause large-scale movement out of fire-affected regions. For one, the characteristics of a place that heighten its risk of wildfire damage are often simultaneously the very environmental amenities that draw people to live there in the first place. As a result, it is not clear whether local wildfire destruction would be significant enough to alter the amenity draw of such regions. For instance, the characteristics that improve a a house's amenity draw - such as its location in a low-density development in close proximity to wildlands, perhaps at the top of a slope to better overlook a scenic viewshed - are also characteristics that increase the house's risk of fire damage (Syphard et al., 2019, 2012). In fact, in recent decades there has been an enormous expansion of both population and housing stock within the wildland-urban interface, the land use type considered to be at the highest risk of fire damage (Radeloff et al., 2018). Amenity migration into these regions is driven in large part by retirees seeking less urbanized settings with greater access to environmental amenities and affordable housing (Plane, Henrie, and Perry, 2005). Even if large-scale wildfire destruction occurs, the impact may not be great enough to overwhelm the ongoing amenity draw into the same place.

A number of studies further suggest that, while slow-onset changes to conditions such as temperature and rainfall tend to increase migration, rapid-onset events such as landslides, earthquakes, and cyclones have relatively little effect (Kaczan and Orgill-Meyer, 2020; Robalino, Jimenez, and Chacón, 2015; Bohra-Mishra, Oppenheimer, and Hsiang, 2014; Lu et al., 2016; Mueller, Gray, and Kosec, 2014). This may be in part because such rapid-onset events reduce a household's resources with which to migrate (Kaczan and Orgill-Meyer, 2020), and possibly even open up opportunities for in situ adaptation (Mockrin, Fishler, and Stewart, 2018; Schumann et al., 2020). Finally, growing scholarship on immobility documents the various reasons why households may *not* move away in the face of growing hazard risk, including cultural attachments to place and embeddedness in local social and economic networks (Adams, 2016; Schewel, 2020; Adger et al., 2013). Some residents may further lack the capacity to migrate away, constituting what some have termed "trapped populations" (Black et al., 2013).

Given the dual amenity-disamenity character of many wildfire-prone regions, how do migration patterns respond to wildfire events? Does wildfire destruction cause heightened out-migration and lowered in-migration as residents respond to reduced housing stock and potential future fire damage? Or do residents remain in place in the face of wildfire destruction? Do households experience financial hardship and lose the resources necessary to relocate? Or is their insurance adequate so that their financial situation remains steady, and they have no financial incentive to relocate?

We investigate these questions by analyzing the effects of wildfire building destruction on migration flows and household financial measures in the United States between 1999 and 2018. To do so, we utilize building destruction data from the US National Incident Command System Incident Status Summary Forms (St. Denis et al., 2020), which is an exhaustive data set of all reported wildfires that destroyed at least one building within the United States. These fire incidents are paired with migration data from the Federal Reserve Bank of New York/Equifax Consumer Credit Panel, from which we calculate quarterly estimates of migration and household financial health (Lee and van der Klaauw, 2010; Whitaker, 2018). In doing so, we are able to describe the effects of all wildfires on migration patterns and borrowing during a time period of increasingly destructive wildfire seasons.

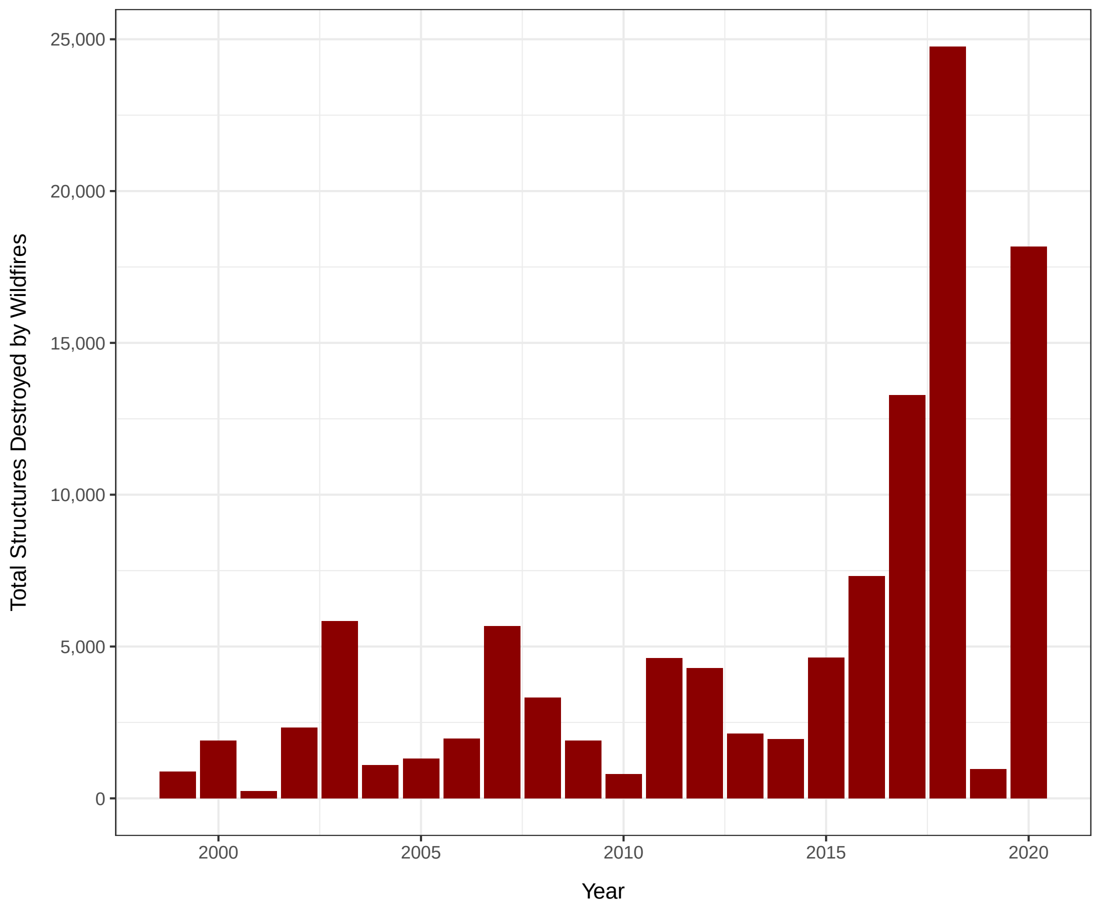

Figure 1: Destruction caused by wildfires from 1999 to 2020, taken from the US National Incident Management System (St. Denis et al., 2020).

2 Literature

Although the economic literature on natural disasters is substantial and growing, none of it has yet to address the impact of wildfires on household outcomes as we do in this paper.

Boustan, Kahn, and Rhode (2012) estimated the long-run migration responses to natural disasters using linked Censuses from the early 20th century. They find significant declines in in-migration to counties struck by floods and hurricanes, but they do not address wildfires. Similarly, Hornbeck and Naidu (2014) examine the case of the Great Mississippi Flood of 1927 and find a migration response and an increase in capital investment.

In this paper, we follow very closely the analyses in Bleemer and van der Klaauw (2019), as well as Gallagher and Hartley (2017) and Deryugina, Kawano, and Levitt (2018). Each of these papers looks at the impact of Hurricane Katrina on households. The first two also use the CCP and therefore have access to the same outcome measures that we do. Gallagher and Hartley disaggregated the New Orleans residents by the level of flooding they experienced. They find a massive migration response with only a partial return to the city. They find declines in flood victims' credit scores and increases in their delinquent balances after the flood, but these dissipate over the next year. Homeownership drops dramatically at the time of the flood and has not recovered three years later. The authors attribute this to homeowners using flood insurance to pay off their mortgage balances, rather than rebuilding. Bleemer and van der Klaauw look for household recoveries over the longer run, using 11 years of CCP data from the storm in 2005 through 2016. They find that individuals in the most badly damaged New Orleans neighborhoods still have higher levels of bankruptcy years later, and they are less likely to own homes than people in adjacent neighborhoods with similar pre-hurricane finances. Both of these papers must consider not only the separate flood insurance market, but also the massive federal programs that specifically targeted the regions impacted by Hurricane Katrina. In our paper, we assume that mortgagees will have the common homeowners' insurance policies required by lenders that cover fire damage for all properties, rather than those in zones (such as 100-year flood planes) specified by federal agencies. We will look for a contrast in the decisions to rebuild in wildfire-prone regions, which often have high housing values in contrast to the low-demand areas most impacted by Hurricane Katrina

The household financial health measures in our study are, of course, impacted by people's ability to earn and service their debts. Two papers have considered the evolution of income for people impacted by Hurricane Katrina: Deryugina, Kawano, and Levitt (2018) and Do Yun and Waldorf (2016). Deryugina et al. found that flood-impacted individuals experienced a drop in earnings immediately after the flood, but their income, as reported to the IRS, had recovered within two years. Using American Community Survey data in an endogenous switching model, Do Yun and Waldorf observed income declines specifically among people who migrated away from hurricane-impacted areas. They found more detrimental impacts for low-income individuals. If our findings are consistent with these studies, we should see a deterioration of individual financial well being soon after the storm, worse outcomes among migrants, and possibly recoveries in personal finances in the later quarters.

Researchers have studied another component of the household balance sheet: property values. Mueller, Loomis, and González-Cabán (2009) estimate that a house's value declines by 10 percent when it is exposed to a wildfire and the value drops by 23 percent if it is exposed to a second wildfire . McCoy and Walsh (2018) document a significant but short-lived decline in property values for properties that have a wildfire scar in their viewshed. This shock could put some of the individuals in our study who have low equity into a negative equity situation. We would predict that these individuals would be less likely to move, more likely to surrender their homes in foreclosure, and less likely to increase their home-secured debts via home equity loans or cash-out refinancing.

Several authors have addressed the issue of wildfire mitigation. Homeowners can clear vegetation from their properties, making it less likely that fires will spread to neighboring homes. Because part of the benefit of this mitigation accrues to neighbors, theory predicts homeowners will invest less in this mitigation than would be socially optimal (Champ et al., 2020; Busby, Amacher, and Haight, 2013; Shafran, 2008). Wibbenmeyer, Anderson, and Plantinga (2019) and Baylis and Boomhower (2019) consider the public good aspects of communities' investments in fire suppression capabilities. Donovan, Champ, and Butry (2007) used the release of fire risk estimates for properties in the Boulder, Colorado, area to measure people's responses to an information shock. Before the estimates were released, property prices were positively correlated with fire risk because locations with desirable surroundings and views are often more vulnerable to fire damage. After the estimates were released, buyers and sellers capitalized the risk into home prices, and the positive correlation went away. For the purposes of our study, we are assuming that both private mitigation and public fire suppression investments are similar in our treatment and control groups. Both types of individuals would have access to similar information and insurance markets, and they would face similar incentives, so the treatment by the wildfire is an exogenous shock.

3 Data and Methods

3.1 Migration and Consumer Credit Data

For migration and consumer credit measures, we utilize the Federal Reserve Bank of New York/Equifax Consumer Credit Panel (CCP). The CCP is a 5 percent random sample of the credit histories maintained by Equifax. It reports the Census block of residence for over 12 million individuals each quarter. The panel nature of the data allows us to observe when someone has migrated and is living in a Census block different from the one they lived in at the end of the preceding quarter. Equifax receives individuals' addresses, along with reports of debt balances and payments, from creditors each month (mortgage lenders, credit card issuers, student loan servicers, etc.). An algorithm maintained by Equifax considers all the addresses reported for an individual and identifies the individual's most likely current address. Equifax anonymizes the data before they are added to the CCP, removing names, addresses, and Social Security Numbers (SSNs). Equifax creates a unique anonymous identifier to enable researchers to build individuals' panels (Whitaker, 2018).

With a quarterly spatial scale already finer than what is available through the widely used Internal Revenue Service's County-to-County Migration database (IRS), the CCP also offers the ability to aggregate individual-level data to the desired spatial unit, such as a tract, county or state. With a much larger sample size than alternative migration data sources such as the American Community Survey or the Current Population Survey, analyses at fine-grained spatial and temporal scales are possible (DeWaard, Johnson, and Whitaker, 2019).

Like the IRS migration data, the CCP is not representative of all individuals in the United States. The CCP is representative of US adults who have a Social Security Number (SSN) and a credit history. Coverage excludes the estimated 10-11 percent of adults who do not have a formal credit history (Brevoort, Grimm, and Kambara, 2016). This means that younger and financially disadvantaged people are less likely to be fully represented in the data. Also, international migrants do not appear in the data until they obtain an SSN and begin using credit in the US. This limitation means that the dataset is not appropriate for all studies, especially for those that target groups underrepresented in the data. Because our research is not focused on a particular subpopulation, we find that the data's benefits outweigh their limitations.

3.2 Wildfire Destruction Data

The US National Incident Management System/Incident Command System (ICS) is a reporting framework operated by the US Department of Homeland Security that centralizes information on a range of hazards, including wildfires. While these data have been publicly available for years, they have only recently been processed into an accessible format by St. Denis et al. (2020), and, therefore, have not yet been widely used.

A major benefit of the ICS data set is that it reports direct measures of hazard impact (e.g., counts of structures destroyed or damaged), rather than the dollar value of damaged property. The latter approach to disaster data reporting - adopted, for example, by the widely utilized Spatial Hazards Events and Losses Database for the United States and the NOAA National Centers for Environmental Information - is unable to distinguish between the destruction of a small number of high-value buildings and a high number of low-value buildings. This lack of discrimination in economic-based metrics is a limitation for research such as ours, which seeks to understand the impacts of wildfires on people and not just their assets. As a result, we believe the structure-based metrics offered by the ICS dataset provide for a major improvement in our approach. However, we acknowledge that this measure does not account for wildfire impacts on wildlands and agricultural lands, which could potentially influence migration and household finances via impacts on environment-dependent livelihoods such as forestry or farming.

While the ICS data set includes the full population of all documented wildfires across the United States, we select only fires that have caused at least one building to be destroyed; these fires notably account for only 16 percent of all wildfires. We take advantage of the ICS's detailed spatial and temporal descriptors to reprocess the data from the reported incident level to the Census tract and quarter level. Tracts are selected as our spatial unit because the more commonly used counties are especially large in the western United States, where many destructive wildfires are concentrated. In selecting tracts, we aimed to avoid using an overly coarse spatial unit that would risk Type II error. Quarters are selected as the temporal unit because they allow us to identify shorter-term impacts to migration flows that might similarly go unobserved at the yearly level.

We allocate wildfire impacts across spatial and temporal units through the following procedure. Fire events larger than 1000 acres in the western United States or larger than 500 acres in the eastern United States can be linked to the Monitoring Trends in Burn Severity database (MTBS), which documents spatial footprints of wildfire burn perimeters (Eidenshink et al., 2007). For these events, we calculate the spatial intersection of the fire burn footprint and overlapping Census tracts. Almost all wildfires that are smaller than the MTBS's acreage threshold for inclusion include latitude and longitude points in the ICS database for the fire's point of origin. For these events, we ascribe all damage to the Census tract in which the point is located.

This approach is imperfect in that burn area proportion does not absolutely correspond with the locations in which structures are damaged. Similarly, damage does not necessarily take place equally across each quarter in which a fire burns, which our temporal allocation procedure assumes. Lastly, this process does not identify small fires that may cause damage outside of the Census tract in which their point of origin is reported. However, we believe this procedure provides much greater spatial precision than other commonly used approaches.

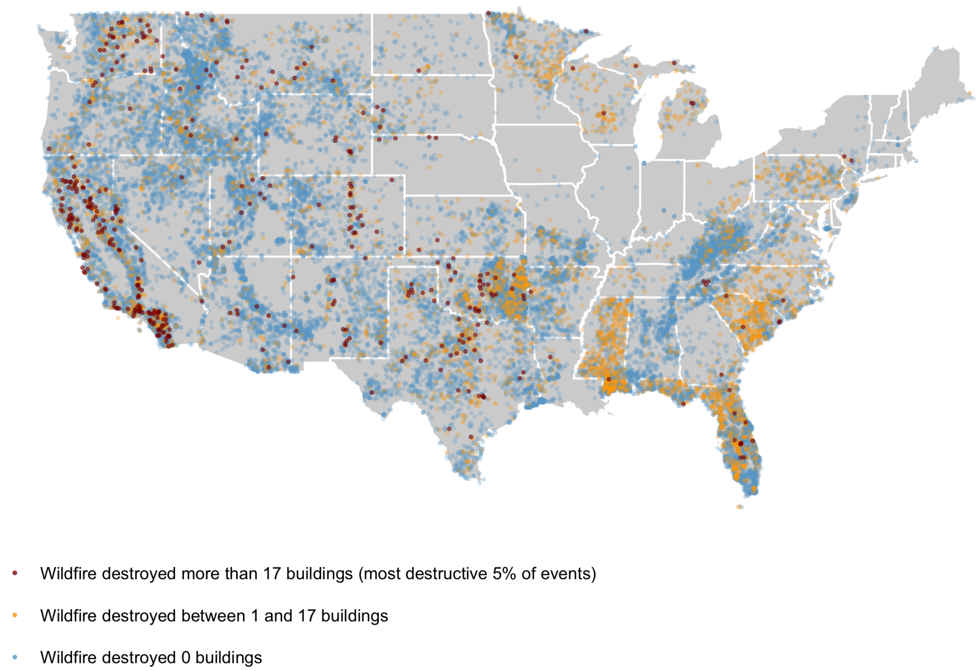

Figure 2: Spatial distribution of all documented wildfires from 1999 to 2020, taken from the US National Incident Management System/Incident Command System (St. Denis et al., 2020). Blue dots indicate fires that caused no structure loss; yellow dots indicate the least destructive 80 percent of wildfires, which destroyed 1-17 structures; and red dots indicate the 20 percent most destructive wildfires which destroyed 17 or more structures.

3.3 Identification Strategies

Our estimates, both at the Census tract and individual levels, are based on difference-in-differences specifications. We assume that trends in the outcomes we measure would be similar for the treated and control groups in the absence of the fire. We test for parallel pre-trends where possible. In the individual analysis, we apply a propensity score weighting to balance the observables of the treatment and control groups. This should increase the balance of any correlated unobservables. However, we find the samples to be close to balanced before the weighting, so our conclusions do not depend on the specification of our propensity score estimation.

3.4 Tract-Level Difference-in-Difference Estimates

Our analytical strategy compares in-migration and out-migration trends in wildfire "treated" tracts (e.g., tracts within which the burn footprint falls) to migration trends in their first-order queen contiguity "control" tracts (e.g., tracts that touch the border or vertex of a treated tract). Eight pre-event quarters are compared with the event quarter and eight post-event quarters. The tract selection procedure is illustrated in Figure 3.

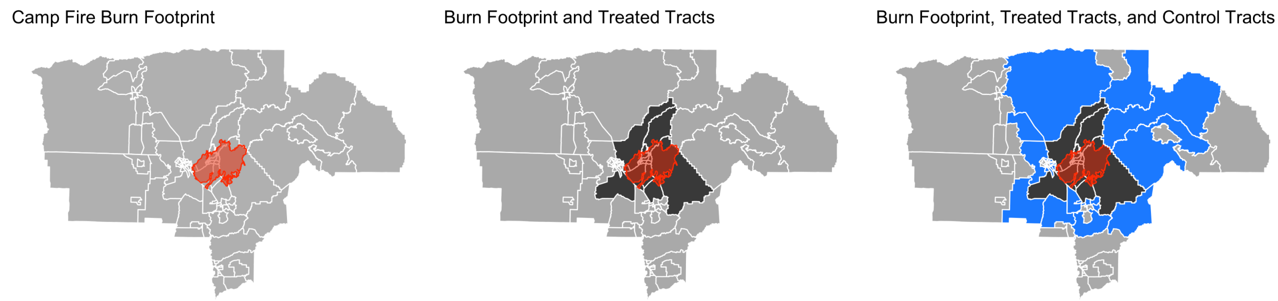

Figure 3: Initial treatment and control Census tract selection process shown for the 2018 Camp Fire in Butte County, California. Red outline indicates burn footprint, dark grey tracts indicate fire-affected treated units, and blue tracts indicate queen contiguity control units.

Rather than focusing exclusively on extreme events, as most disaster scholarship does, we also analyze the full population of all documented wildfires that cause at least one structure to be destroyed (which we term "destructive fires"). The distribution of the count of structures destroyed for individual fires is presented in Figure 4. This broader approach allows us to evaluate whether smaller, but more common, hazards may be influencing population dynamics (Howell and Elliott, 2018). Further, it allows us to identify potential fire severity thresholds at which migratory effects are triggered, which is critical for describing the often non-linear effects of environmental hazards on migration (Kaczan and Orgill-Meyer, 2020) and for developing responsive policy (Bardsley and Hugo, 2010). If such thresholds do exist for wildfires, we anticipate that they would be most likely among destructive events.

To address the likelihood that different scales of wildfire destruction have different effects on migration, we take three different approaches to evaluating the full set of destructive wildfires: global models, damage quintile models, and extreme event models. Each modeling approach pools a different subset of wildfire-affected tracts and their neighboring controls, where the unit of observation is migration probability observed at the tract-quarter. In cases in which a control tract also experienced wildfire damage within the seventeen-quarter observation window, the tract is removed from consideration as a control. If a tract-quarter is defined as a control for multiple fire-affected tracts, it is only counted once within a given pooled model. This results in a sample size of 304,704 tract-quarters for our global models and 5,436 tract-quarters among our extreme event models.

We first conduct global difference-in-differences regressions with all data. Next, building

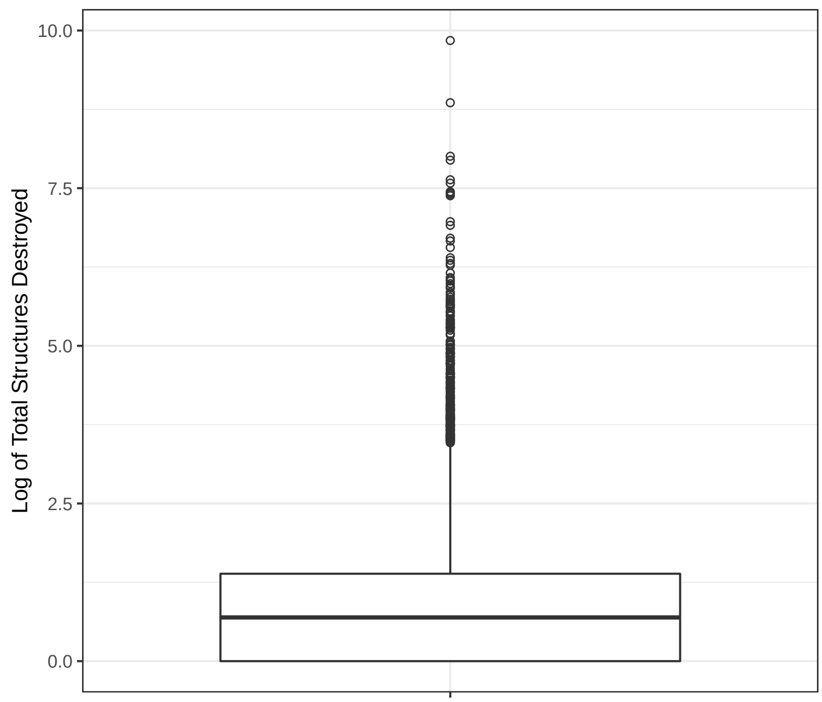

Figure 4: Distribution of structure loss among wildfires that destroyed at least one building, between 1999 and 2018. *Source:* St. Denis et al. (2020).

on the approach of Mueller, Gray, and Kosec (2014), we stratify the data by quintile of fire destruction, where the first quintile includes wildfires with the lowest levels of structure destruction and the fifth quintile includes wildfires with the largest levels of structure destruction. The ICS wildfire data suggest that a small number of wildfires destroy a disproportionately large proportion of all buildings, with the top 10 most destructive fires causing 46.9 percent of all destruction. Notably, 7 of these top 10 wildfires occurred within the most recent five years for which data are available (2013-2018). For this reason, our extreme event models pool only wildfire-affected tracts that experienced the highest 5 percent of destruction from across the full population of destructive wildfires.

In some instances, tracts with small populations show very high or very low migration probabilities. This is likely an artifact of our data's small sample size in low-population tracts, rather than an expression of true migration probability.[1] In the analysis, we weight each tract observation by its observation count (measured in the CCP data set). We further remove observations with an in-migration probability greater than two standard deviations above the full data set's mean in-migration. We also remove observations with an out-migration probability greater than the maximum quarterly out-migration observed following

[1]The Census Bureau designs tracts so that they can be informative to localities. Tract populations have a mean near 4100 people, but they can be as small as a few hundred people. Recalling that the CCP observes 5 percent of adults with credit records, a tract with 500 adults could have fewer than 20 individuals observed. A handful of movers can create the appearance of large migrations in such cases.

the 2018 Camp Fire.

All the tract migration models take a difference-in-differences form that estimates the effects of structure destruction on in-migration probability and out-migration probability. The models take the general form:

$$mp_{it} = \alpha + \beta(d_{it} \cdot y_{it}) + \varepsilon_{it} \tag{1}$$

where mp_{it} is a measure of migration probability in tract t in quarter i, which is defined as the total number of movers divided by the total population at the start of a period within a tract. d_{it} represents a fire destruction indicator (1 or 0), y_{it} represents a post-fire indicator (1 or 0), and ε_{it} represents residual errors. The interaction between these variables is the primary variable of interest; a significant coefficient would indicate that the migration probability of fire-affected units was significantly different in the post-fire period relative to neighboring control tracts. The quarter fixed effects account for unobserved time-varying factors that could affect migration in all tracts in the country, such as the introduction of a national-level policy. The tract fixed effects account for time-invariant characteristics of each spatial unit that may influence in- or out-migration. All models report heteroskedasticity-consistent robust standard errors clustered by tract. We report most models with y_{it}, a binary post-fire time period, but include alternative specifications in the Appendix that document each individual post-fire quarter's interaction with the d_{it}, the wildfire destruction indicator. Summary statistics for treatment and control tracts are also reported in Table 1.

Parallel trend plots in Figures A1 and A2 illustrate that treatment tracts generally exhibit pre-fire migration trends comparable to those in control tracts, making them an appropriate comparison group for analysis. Additionally, given our access to the spatial details of each wildfire, we can accurately delineate where destruction took place at a fine scale, thereby ensuring that the excludability criterion is met. We acknowledge that the queen contiguity neighbors we have selected as control units may be susceptible to spatial spillovers from the treatment tract. If this is the case, we anticipate that the result would be a dampening of the difference-in-differences estimator (e.g., treatment and control tracts' migratory effects would be similar to each other, minimizing the difference between them). While this is a limitation of our method, we believe that it is a more conservative approach to identifying migratory effects than non-experimental correlation analysis or assuming that treatment effects do spill over.

3.5 Individual-Level Difference-in-Differences Estimates

The results presented in Section 4.5 are plots of the coefficients of interest (β) and their confidence intervals estimated with the difference-in-differences specification in equation 2.

$$Y_{it} = \delta_i + \gamma_{ft} + \sum_{\tau \in \mathrm{T}} K_i 1_{\{t=\tau\}} \beta + \epsilon_{it} \quad (2)$$

Y is the outcome measure for individual i in time t. K is the indicator if individual i was living in a treated tract in the fire quarter. The individual panels allow us to include an individual fixed effect δ. We also include a fire-specific relative quarter fixed effect γ. This term flexibly captures regional economic conditions or unobserved shocks that would change the level or trend of outcomes for both the treated and the control individuals in the region of a specific fire. With this specification, β can be interpreted as the effect of living in an impacted tract in quarter t relative to the fire quarter.

Although our control group individuals are all selected from adjacent small geographies, some differences in their observables exist, and we assume that these are correlated with differences in unobservables. To reduce any potential bias introduced by these differences, we apply a propensity score weighting as described in Abadie (2005). In this, we follow Bleemer and van der Klaauw (2019) and Deryugina, Kawano, and Levitt (2018). We estimate a logit regression with the treatment indicator as the dependent variable. The outcome variables from all eight pre-fire quarters are the independent variables. The regression gives predicted probabilities of treatment or non-treatment. We drop 39 individuals with predicted probabilities that are greater than 1 (no predictions are below zero). We also impose overlapping support by dropping individuals with predicted probabilities outside of the range of the probabilities for the other group. This removes fewer than 10 individuals in total. We weight treated observations with $\frac{1}{Pr(\widehat{K_i=1})}$ and control observations with $\frac{1}{Pr(\widehat{K_i=0})}$. As demonstrated in Abadie (2005), this reweighting enables the difference-in-differences specification to estimate the average treatment effect on the treated.

In Table 8 the means of all of the outcome variables are presented absent the weighting. A few display economically significant differences, with fire-treated individuals displaying higher credit scores and higher mortgage balances, for example. The large sample sizes provide precision; so many of the mean differences are statistically significant, including some unlikely to be economically significant. After the weighting, the means of the outcomes displayed in columns 4 and 5 are mostly equal at the level of precision displayed, and none are significantly different.

4 Results

4.1 All Wildfires

Table 1 describes the distribution of the in-migration and out-migration probabilities for the treatment and control tracts in the full sample. A tract's in-migration is measured as the count of people living in the tract at the end of the quarter who were living in a different

Table 1: Migration Probability Summary Statistics

	Minimum	First Quartile	Median	Mean	Third Quartile	Maximum
In-Migration, Wildfire-Affected Tracts	0	0.016	0.030	0.035	0.048	0.166
In-Migration, Neighboring Tracts	0	0.020	0.035	0.041	0.056	0.166
Out-Migration, Wildfire-Affected Tracts	0	0.015	0.028	0.032	0.043	0.355
Out-Migration, Neighboring Tracts	0	0.018	0.032	0.038	0.051	0.355

Sources: Federal Reserve Bank of New York/Equifax Consumer Credit Panel. St. Denis et al. (2020).

tract at the end of the previous quarter, divided by the total number of all people living in the tract at the end of the quarter. The out-migration measure is the ratio of the number of people who were living in the tract at the end of the previous quarter and are living in a different tract at the end of the quarter, divided by the total count of people living in the tract at the end of the previous quarter. The descriptive statistics show that the tracts in wildfire-prone areas are generally gaining population through migration because the in-migration values are higher than the out-migration values throughout most of the distribution.

For models in which all destructive wildfires are pooled, ranging from just one building destroyed to thousands, we observe significant increases in both in-migration and out-migration probability, though both are small in magnitude. Fire-affected tracts experienced an additional 10 out-migrations ($p < .001$, SE = .0002) and 8 in-migrations ($p < .05$, SE = .0003) per 10,000 residents relative to neighboring tracts in the two-year period following the fire.

Table 2: All-Wildfire Estimates

	Dependent Variables:	
	In-Migration	Out-Migration
	(1)	(2)
Burned Tract	0.0004	0.0002
	(0.0004)	(0.0003)
Post-Fire Period	0.0007***	0.0005***
	(0.0001)	(0.0001)
Burned*Post-Fire	0.0008*	0.0010***
	(0.0003)	(0.0002)
Observations	304704	304704

Note: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$
All models include tract and quarter fixed effects. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel. St. Denis et al. (2020).

4.2 Wildfires by Destruction Quintile

When stratified by destruction quintile, we observe no significant effects of wildfires on in-migration at any level of destruction, but there are significant increases in out-migration at both the highest level of destruction (Quintile 5) and the second-lowest level of destruction (Quintile 2). As with our global models above, the effect size for the Quintile 2 model is fairly small, at 11 additional out-migrations per 10,000 residents ($p < .01$, SE = .0004). The effect size more than doubles among our subset of the most destructive 20 percent of all wildfires, at 26 additional out-migrations per ten thousand residents ($p < .01$, SE = .0009).

Table 3: Structures Destroyed per Wildfire Destruction Subset

Data Subset	Min Structures Destroyed	Max Structures Destroyed
First Quintile (Least destructive 20%)	1	1
Second Quintile	1	2
Third Quintile	2	3
Fourth Quintile	4	17
Fifth Quintile (Most destructive 20%)	17	18804
Extreme Events (Most destructive 5%)	277	18804

Source: St. Denis et al. (2020).

Table 4: In-Migration by Destruction Quintile

	Dependent variable:				
	In-Migration Probability				
	(Q1)	(Q2)	(Q3)	(Q4)	(Q5)
Burned Tract	0.0005	0.0003	0.0016	−0.0004	0.0005
	(0.0009)	(0.0007)	(0.0009)	(0.0011)	(0.0015)
Post-Fire Period	0.0000	0.0009***	0.0001	0.0007*	0.0009*
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0005)
Burned*Post-Fire	0.0014	0.0002	0.0001	0.0008	0.0002
	(0.0008)	(0.0005)	(0.0007)	(0.0008)	(0.0011)
Observations	67331	71624	68095	57040	34422

Note: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

All models include tract and quarter fixed effects. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel. St. Denis et al. (2020).

Table 5: Out-Migration by Destruction Quintile

	Dependent variable:				
	Out-Migration Probability				
	(Q1)	(Q2)	(Q3)	(Q4)	(Q5)
Burned Tract	0.0004	−0.0004	−0.0002	−0.0003	−0.0016
	(0.0007)	(0.0006)	(0.0007)	(0.0009)	(0.0012)
Post-Fire Period	0.0004	0.0002	0.0005*	−0.0002	0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0004)
Burned*Post-Fire Period	0.0009	0.0011**	0.0003	0.0002	0.0026**
	(0.0005)	(0.0004)	(0.0005)	(0.0006)	(0.0009)
Observations	67331	71624	68095	57040	34422

Note: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$
All models include tract and quarter fixed effects. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel. St. Denis et al. (2020).

4.3 Extreme Wildfires

Finally, among all models that pool multiple wildfires, out-migration effects are strongest among the top 5 percent most destructive wildfires. While there are no observed effects on in-migration, wildfire damage caused an additional 71 out-migrations per 10,000 residents (p < .01, SE = .0025), which is almost three times the magnitude of wildfire effects among wildfires in the fifth destruction quintile.

Table 6: Extreme Events Migration Estimates

	Dependent Variables:	
	In-Migration	Out-Migration
	(1)	(2)
Burned Tract	-0.0036	-0.0029
	(0.0032)	(0.0027)
Post-Fire Period	0.0027	0.0022^{*}
	(0.0015)	(0.0011)
Burned*Post-Fire	0.0011	0.0071^{**}
	(0.0021)	(0.0025)
Observations	5436	5436

Note: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

All models include tract and quarter fixed effects. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel. St. Denis et al. (2020).

4.4 The Camp Fire

This section presents an analysis of the single most destructive wildfire within the data set, the 2018 Camp Fire. This wildfire occurred in Butte County, California, and destroyed more than 18,000 buildings within the town of Paradise and the surrounding unincorporated areas of Magalia, Concow, and Yankee Hill. Out of all wildfires examined, the Camp Fire is the most extreme event, having destroyed more than twice the number of structures as the second-largest fire (a list of the 10 most destructive wildfires is reported in Appendix Figure A7). This analysis is completed at the individual level.

Results indicate that the Camp Fire - the most destructive wildfire in our data set by nearly threefold - caused a significant spike in out-migration, but no identifiable effect on in-migration. Out-migration began to increase during the quarter in which the fire took place (2018 Q4), peaking in the first quarter after the event (2019 Q1). At this point, burned tracts saw an additional 17 out-migrants per 100 residents, relative to their unaffected neighboring tracts. The out-migration rate remained significantly elevated during the full eight quarters measured following the event.

Table 7: 2018 Camp Fire Estimates

	Dependent Variables:	
	In-Migration	Out-Migration
	(1)	(2)
(Intercept)	0.0315***	0.0446***
	(0.0024)	(0.0032)
Burned Tract	0.0103***	−0.0212***
	(0.0026)	(0.0059)
Burned*Event Quarter	−0.0097	0.0954***
	(0.0074)	(0.0197)
Burned*1 Quarter Post	0.0075	0.1728***
	(0.0154)	(0.0331)
Burned*2 Quarters Post	0.0241	0.0959***
	(0.0169)	(0.0144)
Burned*3 Quarters Post	0.0100	0.0720***
	(0.0127)	(0.0191)
Burned*4 Quarters Post	0.0133*	0.0545**
	(0.0060)	(0.0174)
Burned*5 Quarters Post	0.0067	0.0368***
	(0.0082)	(0.0086)
Burned*6 Quarters Post	0.0004	0.0393*
	(0.0090)	(0.0156)
Burned*7 Quarters Post	0.0112	0.0359**
	(0.0059)	(0.0113)
Burned*8 Quarters Post	0.0112	0.0302*
	(0.0086)	(0.0134)
Observations	84600	84600

Note: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

All models include tract and quarter fixed effects. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel. St. Denis et al. (2020).

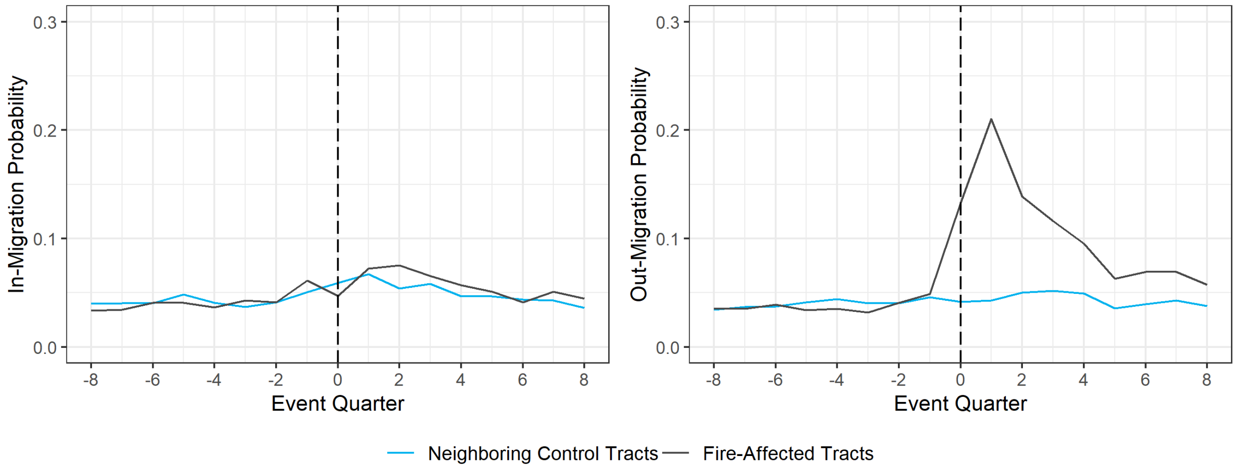

Figure 5: Parallel trend plots illustrate the effects of the 2018 Camp Fire on in-migration and out-migration probability in fire-affected Census tracts relative to their queen contiguity neighboring tracts. Vertical lines indicate the quarter in which the fire occurred. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel. St. Denis et al. (2020).

4.5 Consumer Credit Results

In this subsection, we present the estimated impact of a destructive wildfire on a variety of measures that can be derived from the CCP, including both an alternative measure of migration and several consumer credit measures. Considering the results in Sections 4.1 through 4.4, we narrow our focus to the largest fires that are likely to have a detectable impact. We take approximately the upper half of the sample used in Section 4.3 as ranked by the buildings destroyed. The sample used in this section includes the 17 largest fires, those destroying over 575 structures. All subsamples, by age, homeownership, etc., are drawn from individuals living near these 17 fires.

The CCP contains measures of most of the items that one finds on a personal credit report. It reports current balances of various types of debt as well as delinquent balances. It contains flags indicating whether the individual has lost a home through a foreclosure proceeding or filed for bankruptcy protection over the last seven years. The outcome measures we explore are derived from this information. We use the debt balances, grouped into four categories. The category labeled "mortgage" contains mortgages and any other debts secured by a home, such as home equity loans. The consumer category contains credit card balances as well as any other debt that doesn't fall into the other three categories. In addition to the intensive measures, we have extensive measures that are binary, taking a value of one if the individual has any positive balance of the debt type or delinquent balance of the debt type. The bankruptcy and foreclosure variables look back over the previous 12 quarters and take a value of one if the bankruptcy or foreclosure flag switches from off to on from any quarter to the next. Subsequent quarters will have the value of one for this measure until three years have passed; these measures should be viewed as the stock of people among the treatment or control group who have recently experienced financial distress. The migration measures are also stocks rather than flows because they look back over the preceding 12 quarters and effectively measure the stock of people who have moved recently. These look-back periods are longer than our post-fire study period, so if the gap between the treated and untreated opens after the fire, and then narrows in later quarters, that would suggest that the fire pulled forward some bankruptcies or residential moves and the untreated group catches up while likely remaining at its pre-fire pace.

The unweighted descriptive statistics show that the treated and untreated individuals are similar in their foreclosure histories, most delinquency measures, and their recent migration. The large sample sizes allow even small differences to be statistically significant. However, there are notable differences in the mean mortgage balances of the treated ($75,093) and untreated ($65,123) and mean credit scores (718 vs 709). It seems that people living in tracts that experience wildfire destruction are in households with better financial health. However, higher balances could also reflect a newer housing stock in these tracts, with fewer residents who have had many years to pay down their mortgage balances.

Table 8: Descriptive Statistics of Individual Outcomes Observable in the Consumer Credit Panel

	Unweighted			*Weighted*	
	Overall	Neighboring	Burned	Neighboring	Burned
State-to-State Migration (3 years)	0.019	0.020	0.017 *	0.019	0.019
County-to-County Migration (3 years)	0.130	0.130	0.130	0.130	0.131
Tract-to-Tract Migration (3 years)	0.290	0.292	0.282	0.290	0.290
Block-to-Block Migration (3 years)	0.363	0.363	0.364	0.363	0.364
Credit Score	711	709	718 *	711	711
Subprime Credit Score	0.242	0.250	0.216 *	0.243	0.242
Bankruptcy (3 years)	0.015	0.015	0.014	0.015	0.015
Foreclosure (3 years)	0.014	0.014	0.013	0.014	0.013
Has Mortgage Debt	0.396	0.388	0.421 *	0.396	0.396
Has Consumer Debt	0.817	0.815	0.823 *	0.817	0.817
Has Auto Debt	0.357	0.358	0.356	0.357	0.358
Has Student Debt	0.090	0.093	0.080 *	0.090	0.089
Mortgage Balance	67416	65123	75093 *	67459	67700
Consumer Balance	12249	11965	13200 *	12253	12285
Auto Balance	4563	4555	4590	4564	4575
Student Balance	1510	1555	1359 *	1509	1494
Has Delinquent Mortgage Debt	0.008	0.008	0.007 *	0.008	0.007
Has Delinquent Consumer Debt	0.090	0.093	0.080 *	0.090	0.090
Has Delinquent Auto Debt	0.018	0.018	0.016	0.018	0.018
Has Delinquent Student Debt	0.011	0.011	0.009 *	0.011	0.011
Delinquent Mortgage Balance	485	517	377 *	488	394
Delinquent Consumer Balance	393	405	355 *	393	391
Delinquent Auto Balance	78	80	72	78	79
Delinquent Student Balance	27	29	21 *	27	26
Number of observations	514,724	396,353	118,371	396,353	118,371
Number of borrowers	30,278	23,315	6,963	23,315	6,963

Note: $^{*}p < 0.01$

Inverse propensity weights are created by a first-stage logistic regression. The credit score variables are based on the Equifax Risk Score. The subprime cut off for this score is 640. The mortgage balances include all home-secured debt, and the "has mortgage" variable indicates a positive value of this sum. Consumer balances include all credit cards, retail cards, and all other debt not secured by a home or automobile. Balances are delinquent if they are more than 90 day past due. The bankruptcy and foreclosure variables indicate filings within the last three years. Sources: Federal Reserve Bank of New York/Equifax Consumer Credit Panel. St. Denis et al. (2020).

In Figure 6 and all those that follow, we present the results by plotting the β coefficients in solid navy lines, and the 95 percent confidence intervals in dashed red lines. The omitted quarter is the observation as of the last day of the quarter that ended before the fire (-1). The fires occur between the end of quarter -1 and the end of quarter 0; so the balances and other outcomes observed on the last day of quarter 0 are the first that could possibly display the impact of the fire.

The mobility measure, which is a binary indicator of whether or not an individual has changed geographies in the last three years, shows significant differences for fire-treated individuals at the block, tract, and county geographies. The pre-fire mean of the block migration measure is .36 and the pre-fire mean for the tract migration measure is .29 (see Table 8). In the first quarters after the fire, the share of people who have moved to a different block in the last three years rises among the fire-treated individuals to be .02 higher than it is among the non-treated. The increase is similar in the block and tract measures, and less than half as large in the county measure. This indicates that the fires are causing people to move to another tract, with most of those destination tracts being in the individual's original county. While there is an increase in departures from the state, its magnitude is very small, at around .001, and it is not statistically significant.

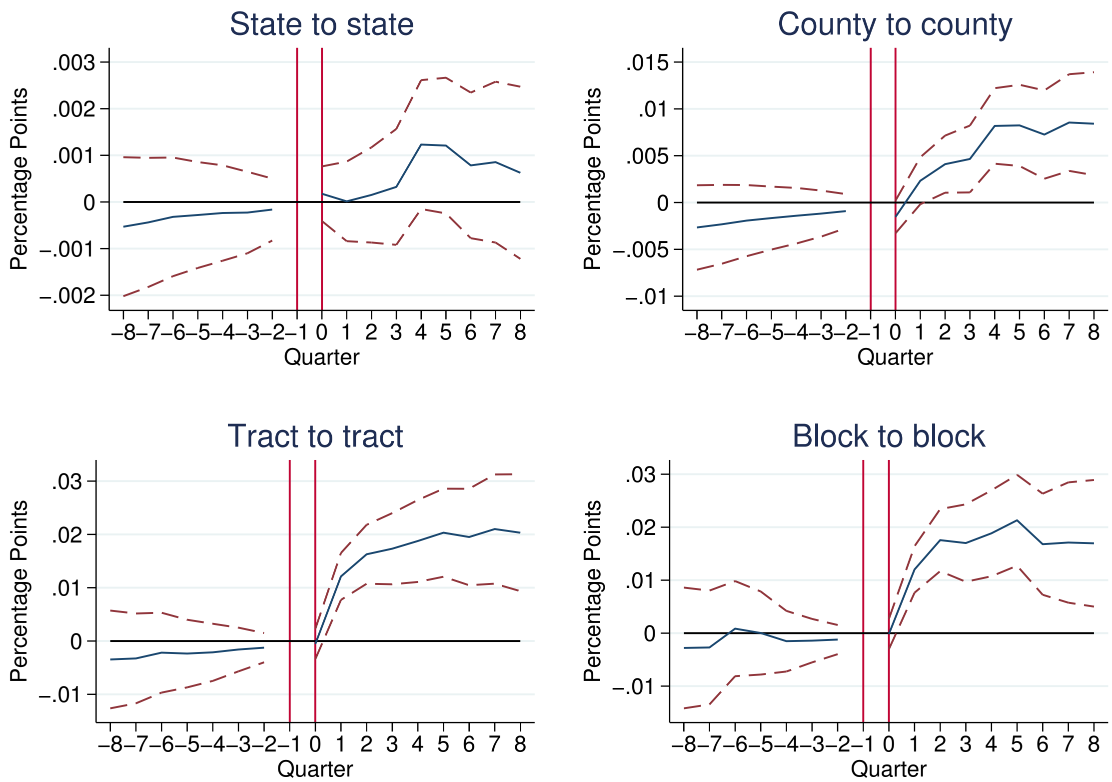

Figure 6: Migration outcomes, >575 structure fires. Propensity-score weighted effects of fires in burned and neighboring tracts. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel, St. Denis et al. (2020), and authors' calculations.

Among the other dramatic effects of the fires, we see, in Figure 7, that the share of people who have an outstanding mortgage dropped by approximately 1 percent immediately after the fire. For comparison, the mean share of treated individuals with a mortgage is .42 before the fire. The gap between the treated and untreated remains statistically significant two years after the fire. The average mortgage balances for the treated drift upward relative to the untreated, but the difference is not significant. Likewise, there are some movements in the differences in the share of delinquent mortgages and the mean delinquent dollar amounts.

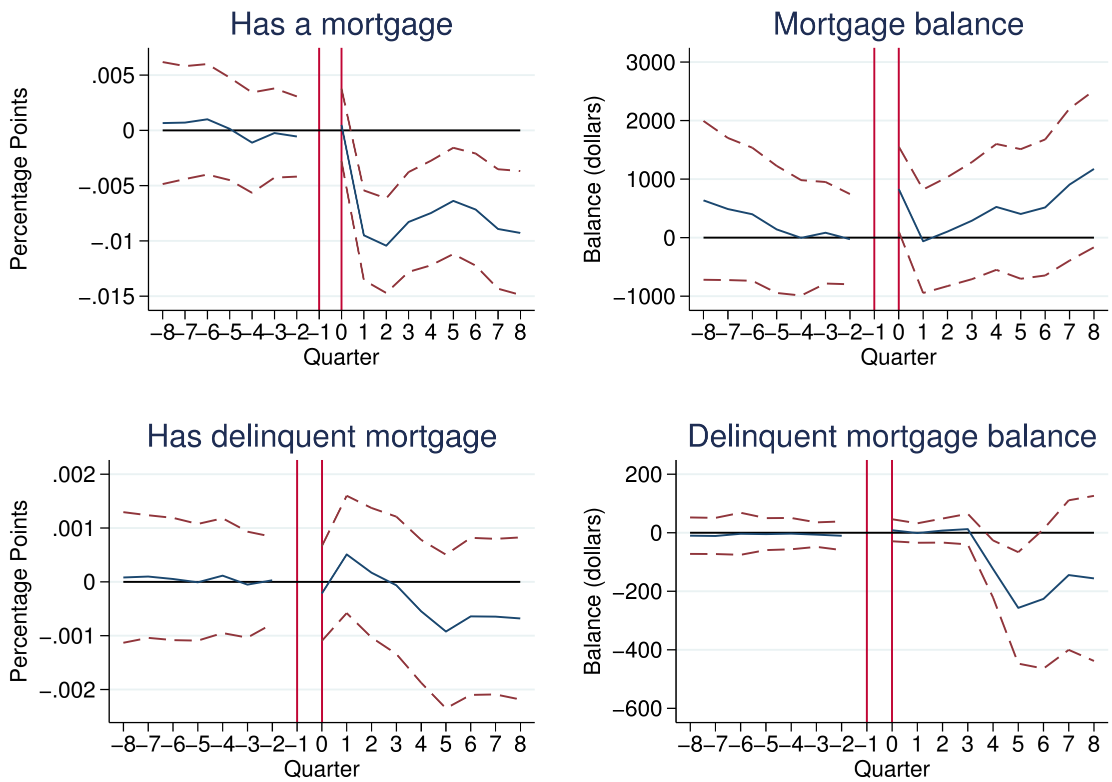

Figure 7: Mortgage outcomes, >575 structure fires. Propensity-score weighted effects of fires in burned tracts. Standard errors are clustered at the Census-block level. The mortgage balances include all home-secured debt, and the "has mortgage" variable indicates a positive value of this sum. Balances are delinquent if they are more than 90 days past due. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel, St. Denis et al. (2020).

Figure 8 displays the fire effects on four other measures of credit health. The first is the effect on the Equifax Risk Score. This score is similar to other credit scores as it is estimated to predict a similar outcome: the probability of the borrower's debt becoming seriously delinquent in the next 24 months. Equifax Risk Scores range from 350 to 850, with a mean of 711 and a standard deviation of 101 in the study population.[2] The gap in the credit scores between treated and control individuals climbs over the five quarters following the fire to reach 1.8 points. The difference is significant in all eight post-fire quarters. In another reflection of a shift in the distributions of credit scores, we see that the share of people whose score falls below the subprime cut-off of 640 declines among the treated relative to people who lived in the untreated tracts. Before the fire, approximately 22 percent of treated individuals had subprime scores. The gap reaches -.008 in the fifth post-fire quarter before narrowing slightly. The post-fire trends in the difference in the share of individuals who have a bankruptcy or foreclosure flag on their credit record within the last three years seem to

[2]The population mean is 700 and the population standard deviation is 100.

slightly favor the people who lived in the fire-treated tract. However, none of the differences are statistically significant.

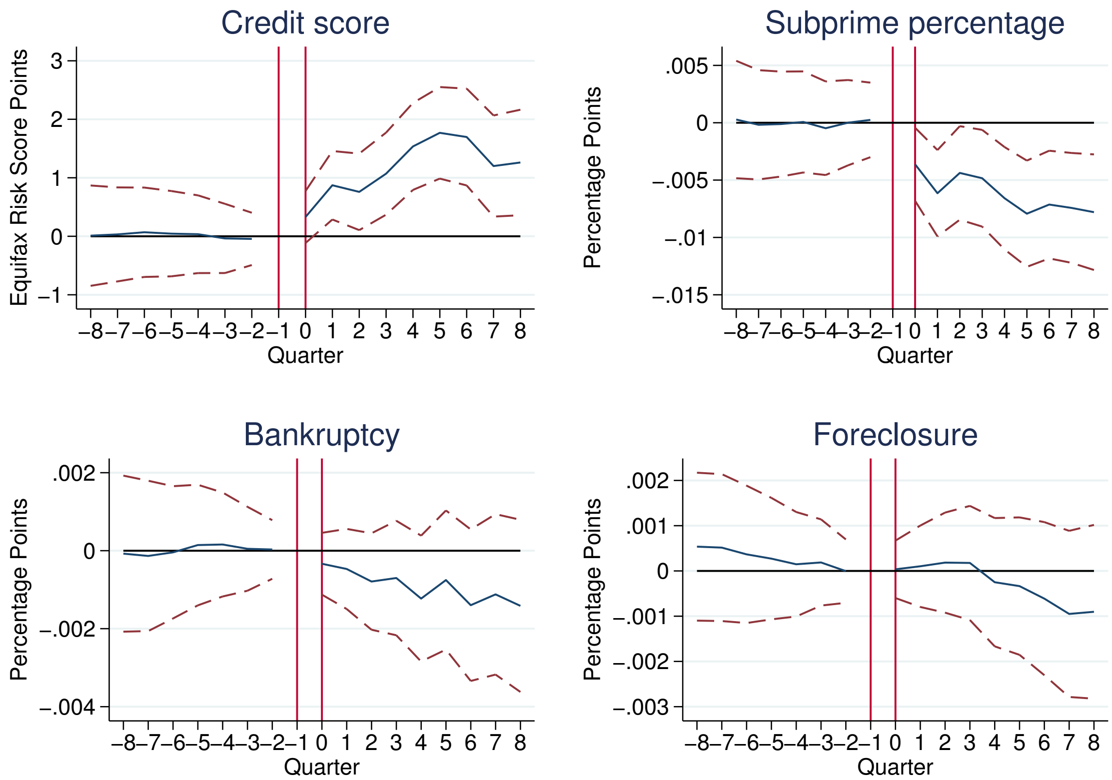

Figure 8: Credit outcomes, >575 structure fires. Propensity-score weighted effects of fires in burned tracts. Standard errors are clustered at the Census-block level. The credit score variables are based on the Equifax Risk Score. The subprime cut-off for this score is 640. The bankruptcy and foreclosure variables indicate filings within the last three years. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel, St. Denis et al. (2020).

Figures for the three smaller debt categories can be found in the Appendix (Figures A3, A4, and A5). Very few of the differences are statistically significant. An exception is delinquent auto balances. The mean of this measure for fire-treated individuals is $71 during the pre-fire quarters, and a gap opens up to -$16 in favor of the treated individuals.

To further our understanding of some of the significant differences between fire-treated and untreated individuals noted in the preceding paragraphs, we can disaggregate the samples using observable characteristics. Which individuals are most likely to move after a fire? Figures 9 and 10 show that it is the oldest individuals and the people with the highest pre-fire credit scores. Increased tract-to-tract migration is visible for people in each third of the Equifax Risk Score distribution, but the gaps are over twice as large for people with scores above 770 relative to groups with lower scores. The same is true if we contrast people over the age of 60, whose migration increases the most, relative to people between the ages of 40 and 60 or below 40. People older than 60 are also most likely to shift from homeownership to renting in the quarters following a wildfire as illustrated in figure 11.

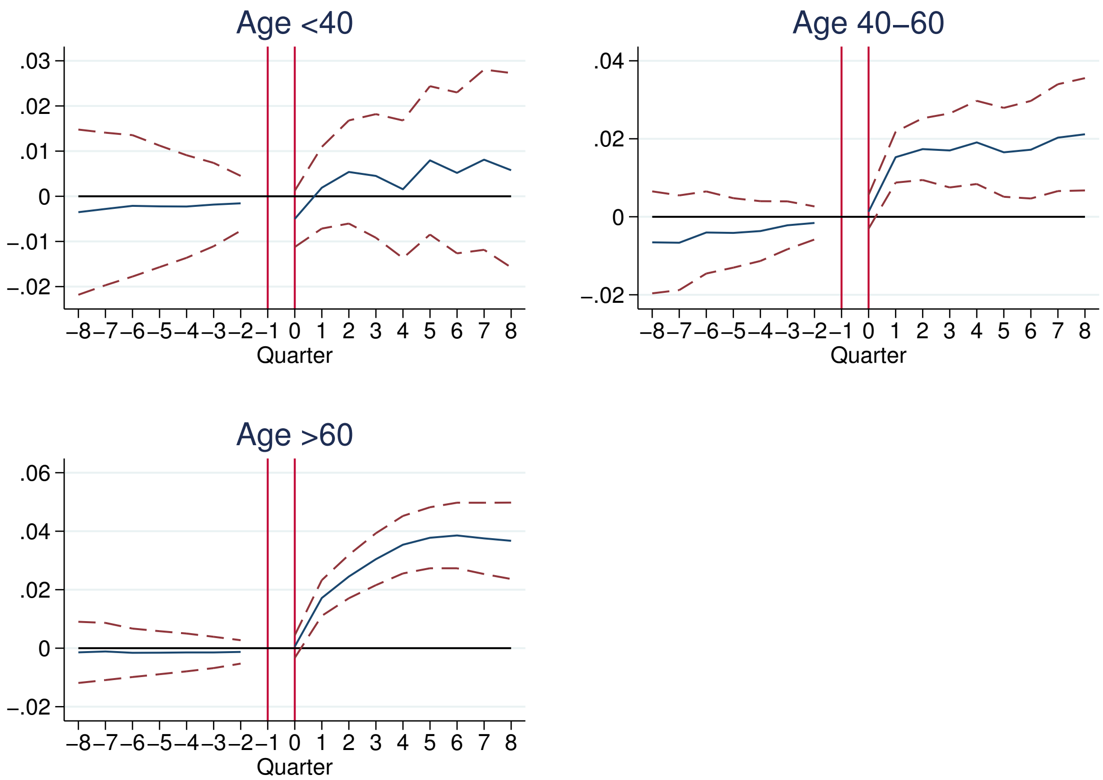

Figure 9: Migration outcomes, >575 structure fires. Propensity-score weighted effects of fires in burned tracts. Standard errors are clustered at the Census-block level. The migration measures are the share of individuals within the group that made the indicated relocation within the last three years. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel, St. Denis et al. (2020).

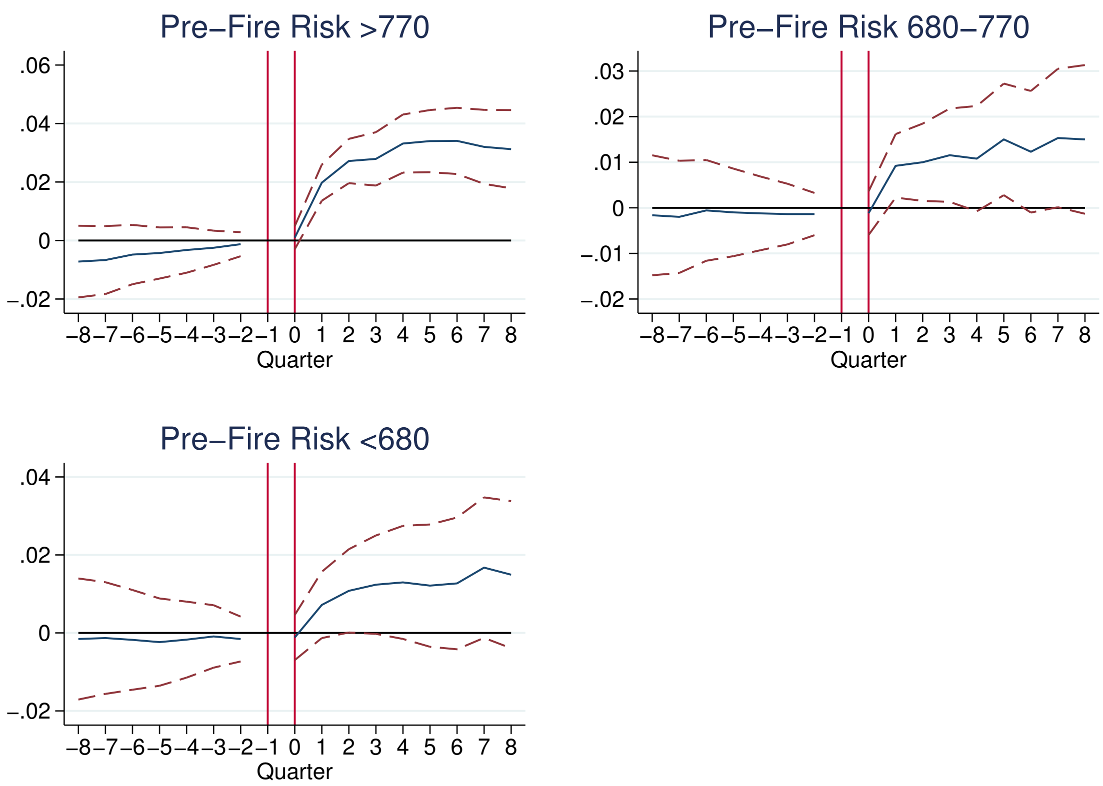

Figure 10: Migration outcomes, >575 structure fires. Propensity-score weighted effects of fires in burned tracts. Standard errors are clustered at the Census-block level. The migration measures are the share of individuals within the group that made the indicated relocation within the last three years. The credit score variables are based on the Equifax Risk Score. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel, St. Denis et al. (2020).

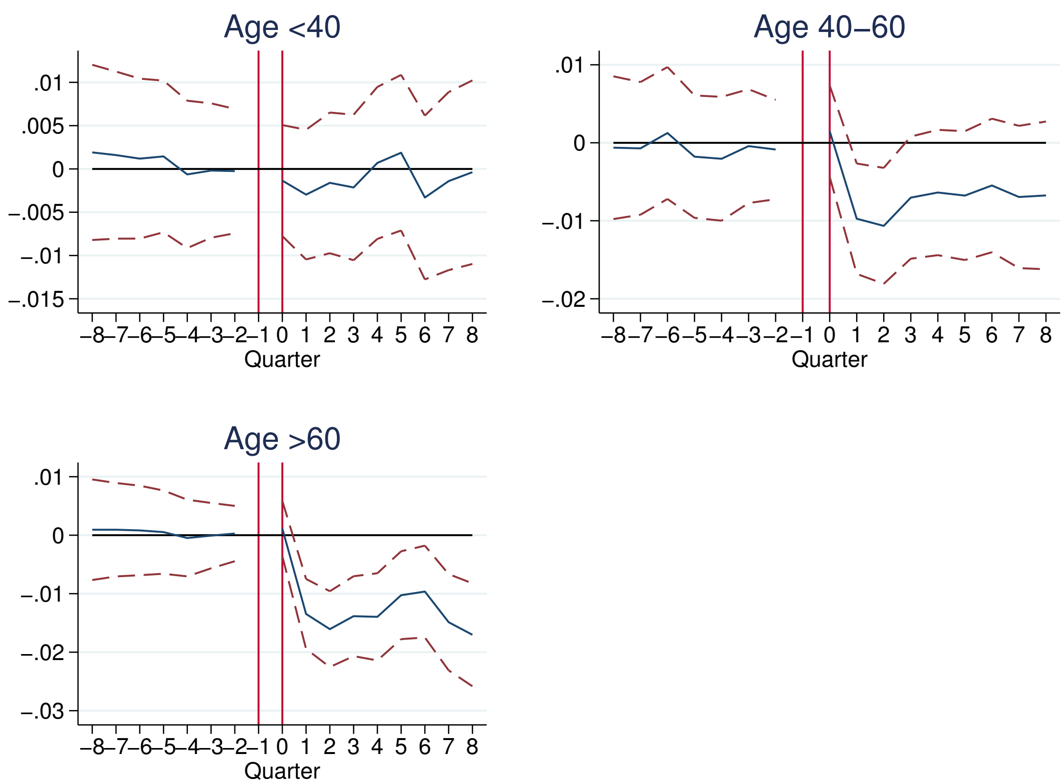

Figure 11: Has Mortgage, >575 structure fires. Propensity-score weighted effects of fires in burned tracts. Standard errors are clustered at the Census-block level. The mortgage balances include all home secured debt, and the "has mortgage" variable indicates a positive value of this sum. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel, St. Denis et al. (2020).

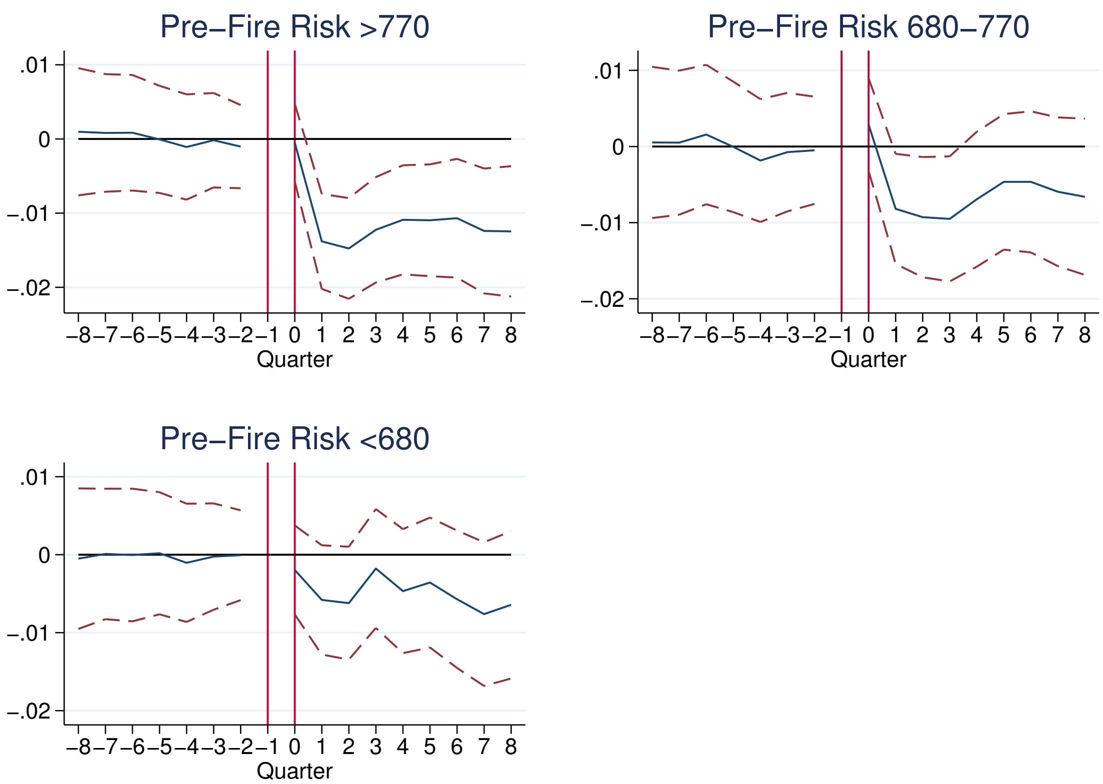

Figure 12: Has Mortgage, >575 structure fires. Propensity-score weighted effects of fires in burned tracts. Standard errors are clustered at the Census-block level. The credit score variables are based on the Equifax Risk Score. The mortgage balances include all home-secured debt, and the “has mortgage” variable indicates a positive value of this sum. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel, St. Denis et al. (2020).

We can use the presence of any home-secured debt (mortgage, home equity line of credit, etc.) as an indicator of the individual being a homeowner rather than a renter. We might hypothesize that the fire has destroyed insured homes, the insurance settlement has paid off the borrowers' mortgages, and those borrowers can more easily service their remaining debts; therefore their credit scores improve. If this is the cause of the observed gap between treated and control individuals, it should be concentrated among those who owned homes before the fire. For the estimates in Figure 13, we have pulled a subsample of only individuals who had $0 mortgage balances in all eight pre-fire quarters ("Renter" in the top left panel) and a subsample of only individuals who had a positive home-secured debt balance in all pre-fire quarters ("Homeowner" in the top right panel). The advantage in credit scores for treated individuals is visible in both groups, with the peak gap for renters reaching 2.8 points and the peak gap for homeowners reaching 2.1 points. This evidences suggests that the elimination of mortgages is not the most important channel relating the fire to improved credit scores.

An alternate explanation for the rise in credit scores among the treated is that when the fire forces some people to move, these individuals re-optimize by choosing a location that gives them a favorable combination of earnings opportunities and lower expenses. There is suggestive evidence for this in the estimates presented in the bottom two panels of Figure 13. On the left, the score gap is estimated for people who in quarter 8 are living in the same tract they were living in quarter -1. This includes people who temporarily left and returned. On the right are individuals who are living in a different tract in quarter 8. The credit scores of the fire-tract leavers are higher than those of the control-tract leavers by 3.5 points within one year after the fire. The score gap for stayers also favors the treated, but only by 2.3 points after six quarters.

Figure 14 reveals that the improvements in credit scores are observable in the middle and lower third of the score distribution, but are not significant among the highest third. Four quarters after the fire, the treat-vs-untreated score gap among people with scores below 680 reaches 4 points and the gap among people with mid-level scores reaches 2.9 points.

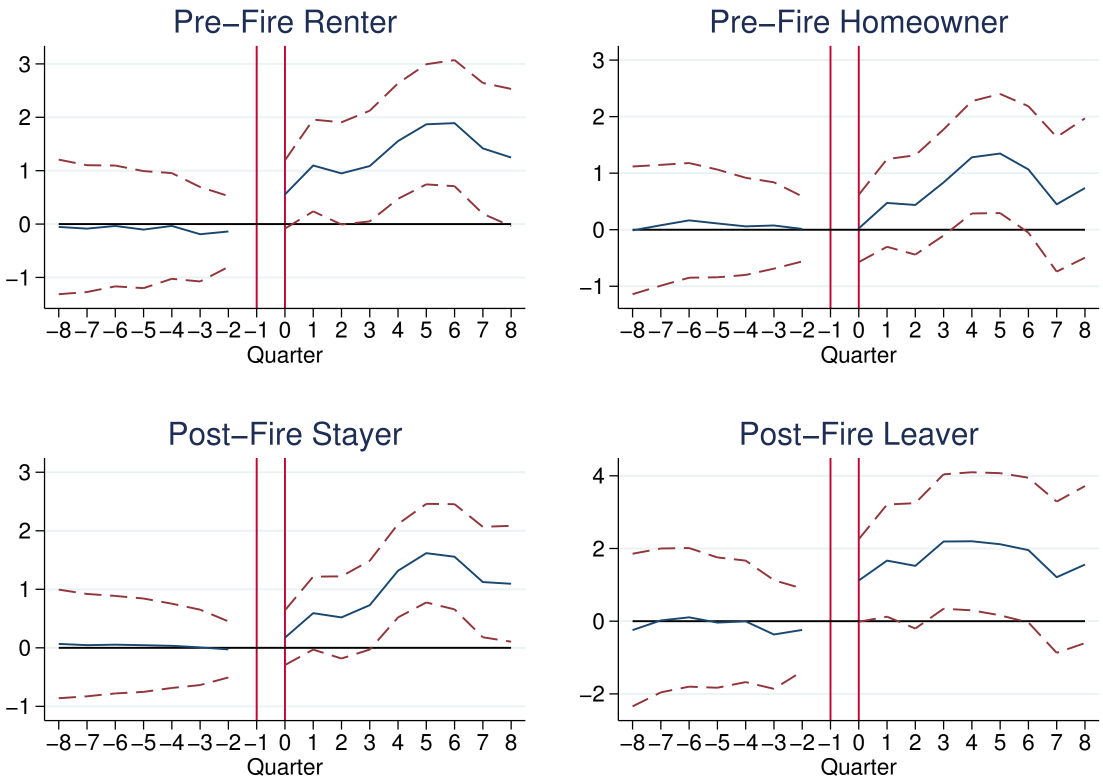

Figure 13: Credit score, >575 structure fires. Propensity-score weighted effects of fires in burned tracts. Standard errors are clustered at the Census-block level. The credit score variables are based on the Equifax Risk Score. The mortgage balances include all home secured debt. "Renters" had a zero mortgage balance in all pre-fire quarters. "Owners" had a positive mortgage balance in all pre-fire quarters. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel, St. Denis et al. (2020).

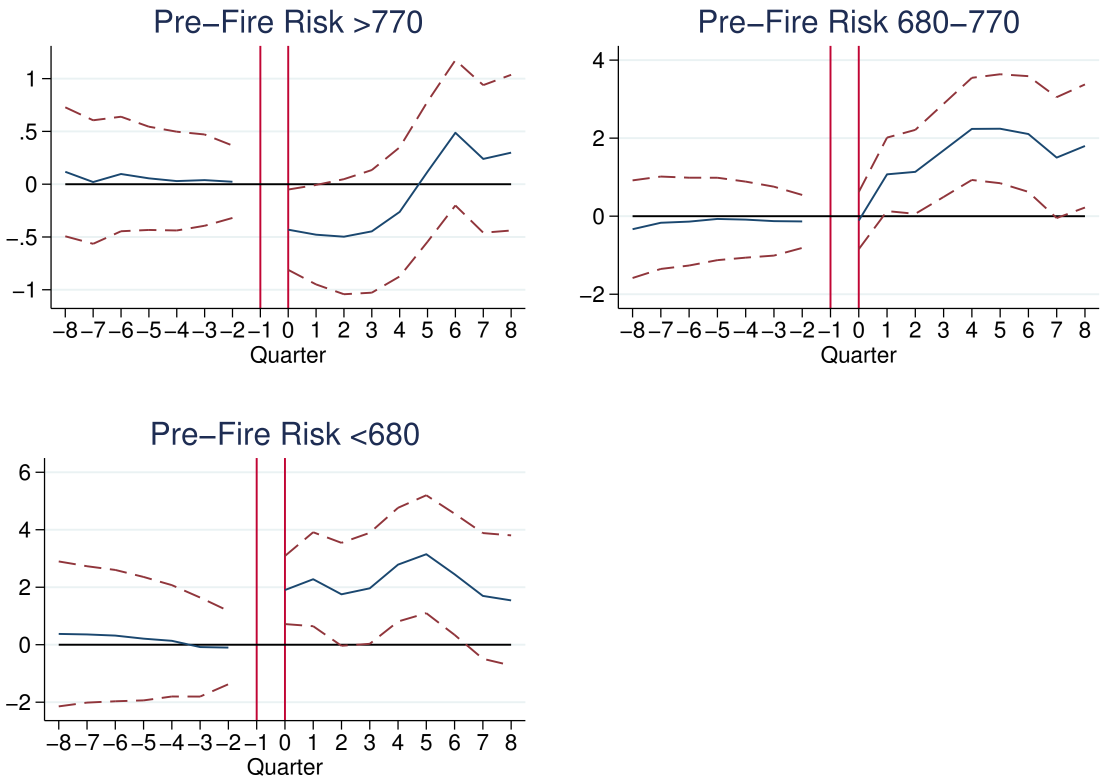

Figure 14: Credit score, >575 structure fires. Propensity-score weighted effects of fires in burned tracts. Standard errors are clustered at the Census-block level. The credit score variables are based on the Equifax Risk Score. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel, St. Denis et al. (2020).

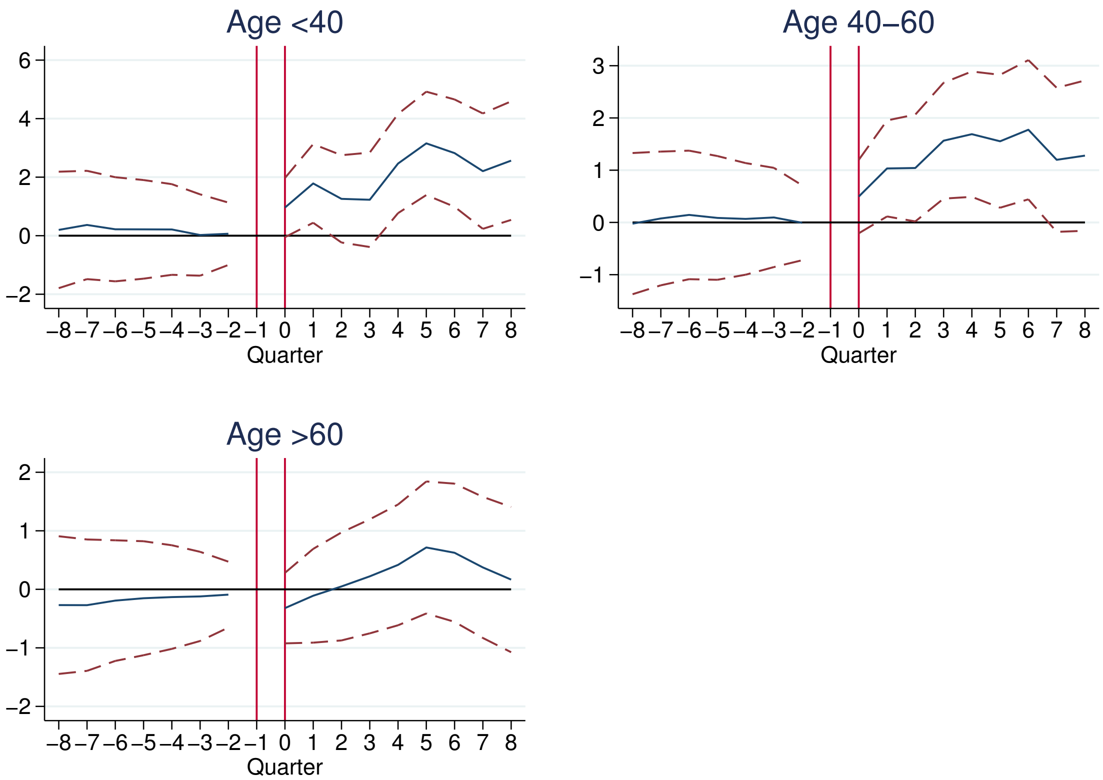

Figure 15: Credit score, >575 structure fires. Propensity-score weighted effects of fires in burned tracts. Standard errors are clustered at the Census-block level. The credit score variables are based on the Equifax Risk Score. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel, St. Denis et al. (2020).

To investigate whether the significant results reported in Section 4.5 are dependent on the specification, we repeated the analysis with the propensity score weighting removed. Without the weighting, the significant results for tract- and block-level migration remain, as does the decline in the share of people with mortgage debt. The increase in credit scores and the decline in subprime share both become insignificant if the weighting is removed. The pre-fire differences remain insignificant without the weighting, which re-emphasizes that our untreated individuals in the neighboring tracts had similar trends in the outcome variables before the fires.

We attempted to disaggregate our analysis by race and ethnicity as other studies have done. There is no measure of race in the CCP, so disaggregation has to be done by merging the estimates of population shares at the tract level from the Decennial Census and the American Community Survey. To have a reasonable assurance that one is observing the intended subpopulation, we would want to isolate tracts with high proportions of African American or Latino/a residents, for example. In our data, approximately 72 percent of tracts have mostly (>75 percent) non-Latino/a white residents. Only 2 percent of the tracts are mostly Latino/a, and only a fraction of 1 percent of the tracts have primarily Black residents. The remaining tracts have more integrated populations. For the time being, destructive wildfires have not impacted enough neighborhoods with predominantly residents of color to make it possible to identify any differential impacts with available data.

5 Discussion

Our results suggest that, on average, destructive wildfires caused a very slight increase in out-migration probability among affected tracts in the United States. These effects are stronger among the highest quintile of wildfires, which destroyed 17 buildings or more, and stronger still among the top 5 percent most destructive wildfires. Analysis of the single most destructive wildfire in our dataset, the 2018 Camp Fire, illustrates the sharpest increase in out-migration, with an average of 7 additional out-migrants per 100 residents per quarter in the two years following the event. These findings contrast with prior research on non-wildfire rapid-onset environmental hazards, which has generally found that such events have little effect on migration. Our conclusions instead affirm previous research on a smaller subset of FEMA disaster-declared wildfire disasters, which has suggested that such fires are associated with heightened out-migration (Winkler and Rouleau, 2020).

While our all-wildfire model suggests a slight increase in in-migration among burned tracts, this trend does not emerge in any damage subsets of the data, including quintiles, the highest 5 percent most destructive wildfires, or our Camp Fire analysis. Therefore, we place little weight on this finding.

While there are modest out-migration effects among subsets of more destructive wildfires, it is also critical to note that the majority of wildfires do not destroy a large number of buildings and do not affect migration at the tract level. For fires ranging from 1 to 17 buildings destroyed, we instead observe relative immobility - no changes to in-migration or out-migration. This suggests that Winkler and Rouleau's hypothesized "disamenity shifts," wherein environmental characteristics previously considered by residents to be amenities instead come to be considered disamenities, are not occurring to any degree that has affected migration patterns among most residents living with wildfires (Winkler and Rouleau, 2020). This finding should temper any overstatements of mass migration away from fire-prone regions at present. However, given the rapid increase in annual counts of wildfire building destruction, residents' migratory behaviors and perceptions of environmental risk may change as well.

It is possible that our identification approach may have failed to detect migratory effects at the tract level among these less-destructive fires. Spatial spillovers from the burned tracts to their neighboring tracts may have been large enough to minimize the difference-in-differences coefficients. However, if this were the case, we would expect to observe a similar masking of migratory effects among large-scale fires, which we do not. Second, it is possible that wildfire destruction changed mobility patterns, but that affected households moved locally within the same tract, which our research design would not identify. This tendency would be in keeping with findings from a Colorado-based survey, in which residents in a fire-affected region who desired to move preferred nearby destinations (Nawrotzki et al., 2014). However, even if such within-tract residential mobility were taking place, it would still affirm our broader conclusion: residents by and large remained in fire-prone regions after less destructive events.

Future research may distinguish whether the observed migratory effects vary not just by damage level, but by the social or geographical context of a given wildfire. Analyses across demographic subpopulations, geographic regions, and a tract's level of urbanicity would all provide valuable qualifications to our population-level findings. Additionally, the time period examined for this work concludes at the beginning of what appears to be a radically changing fire regime, as the level of annual physical damage caused by wildfires has increased exponentially in recent years. Research on non-fire environmental changes has described non-linear relationships between climatic variables and migration trends (Bohra-Mishra, Oppenheimer, and Hsiang, 2014), suggesting that there may be tipping points at which environment-migration relationships begin to change or amplify. So, while our findings describe past wildfire effects on migration, further work is needed to monitor whether the nature of this relationship will change under intensifying wildfire seasons.

With regard to personal finance outcomes, even the largest wildfires do not appear to have the detrimental impacts observed in some studies of hurricanes. There are no pronounced increases in bankruptcy, foreclosure, or delinquent debts among people impacted by major wildfires. Credit scores display small but statistically significant increases among the fire treated. Experiencing a destructive fire in one's tract does lower home ownership, but the impact is concentrated among individuals over 60 and individuals with the highest credit scores. Credit scores are positively correlated with age; so these populations likely overlap. High-score individuals have the ability to return to home ownership if they desire, but the oldest among them may prefer renting over the borrowing and effort necessary to rebuild and then maintain a replacement house. Depending on the level of insurance coverage the borrower had relative to the remaining mortgage balance, the settlement could provide a cash-out opportunity that many retirees pursue via sales or reverse mortgages. Further research should be undertaken to confirm or refute this.

Appendix

Table A1: Camp Fire Migration Probability Summary Statistics

	Migration Probability
In-Migration, Camp Fire-Affected Tracts	0.046
In-Migration, Neighboring Tracts	0.046
Out-Migration, Camp Fire-Affected Tracts	0.067
Out-Migration, Neighboring Tracts	0.042

Sources: Federal Reserve Bank of New York/Equifax Consumer Credit Panel. St. Denis et al. (2020).

Table A2: 2018 Camp Fire

	Dependent Variables:	
	Arrivals	Departures
	(1)	(2)
(Intercept)	0.0315***	0.0449***
	(0.0024)	(0.0032)
Wildfire-Affected Tract	0.0043	−0.0253***
	(0.0027)	(0.0072)
Post-Fire Period	0.0024	−0.0150**
	(0.0031)	(0.0053)
Fire-Affected*Post-Fire	0.0078	0.0704***
	(0.0057)	(0.0139)
Observations	84600	84600

Note: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

All models include tract and quarter fixed effects. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel. St. Denis et al. (2020).

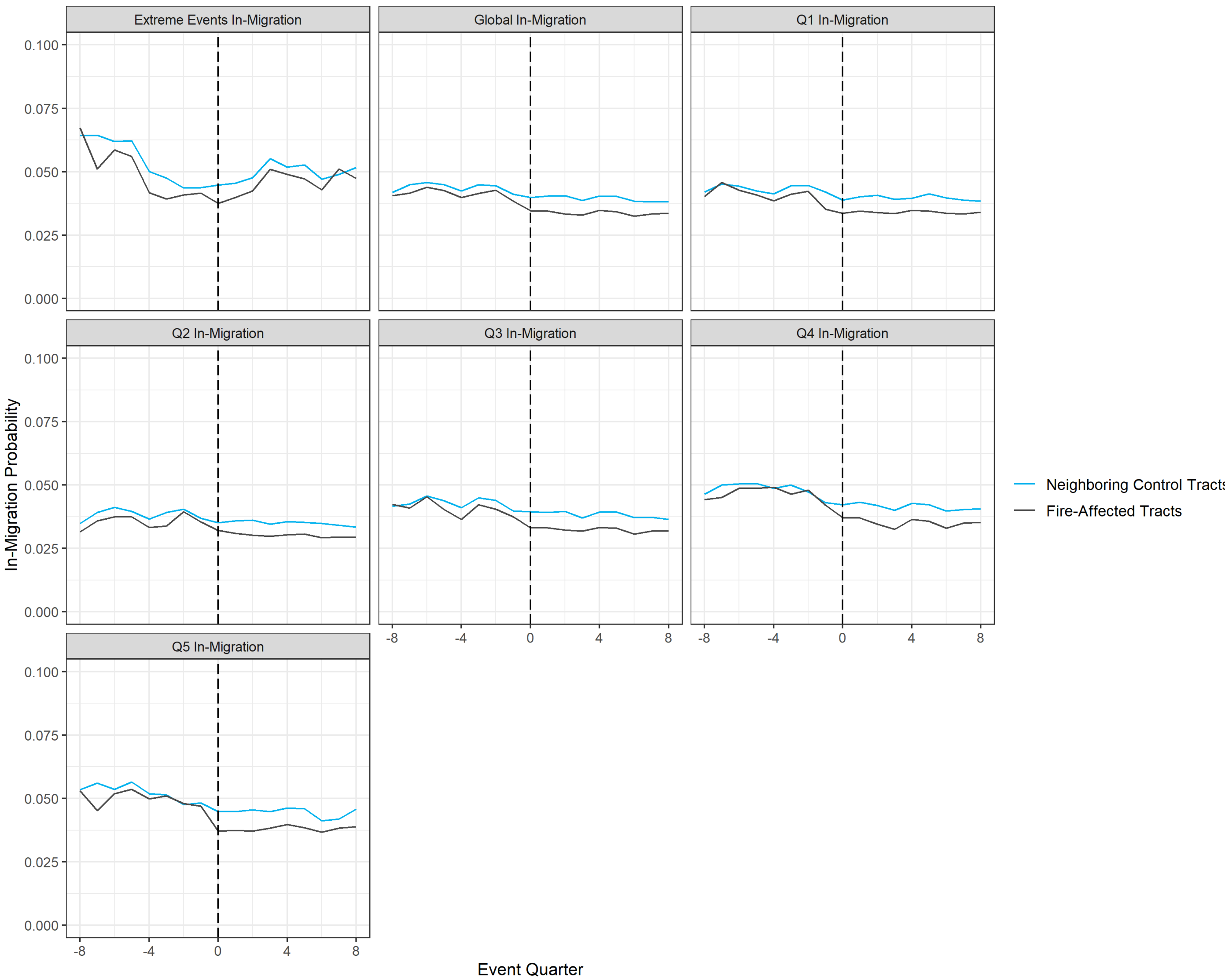

Figure A1: Parallel trend plots for in-migration probability. The values are means of the individual tract estimates. Unlike the regression coefficients, they are not weighted by observation counts and do not account for tract fixed effects. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel. St. Denis et al. (2020).

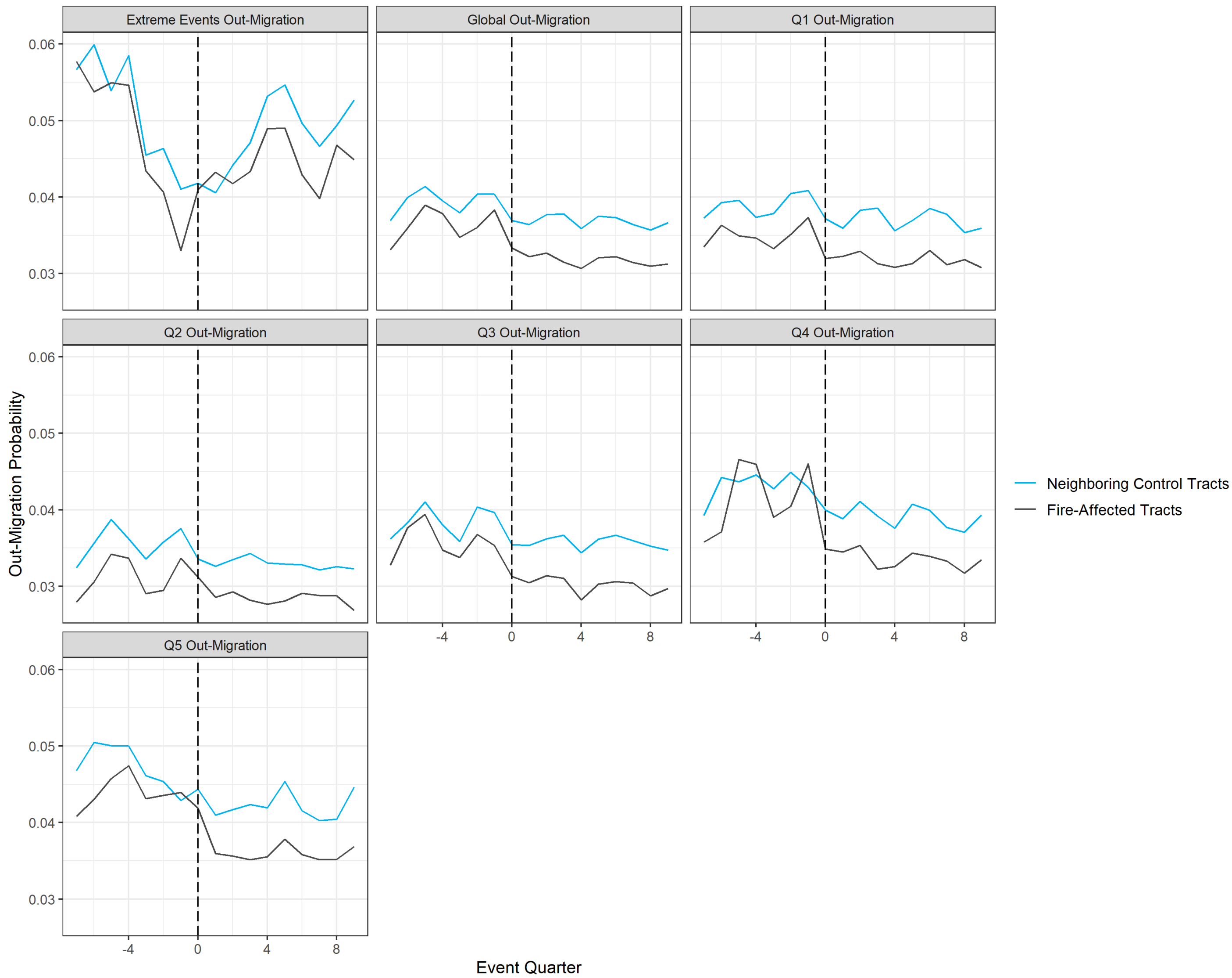

Figure A2: Parallel trend plots for out-migration probability. The values are means of the individual tract estimates. Unlike the regression coefficients, they are not weighted by observation counts and do not account for tract fixed effects.. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel. St. Denis et al. (2020).

Table A3: All-Wildfire Model In-Migration

	Dependent Variables:
	In-Migration Probability
	(1)
Burned Tract	0.0004
	(0.0004)
Event Quarter	0.0012***
	(0.0002)
1 Quarter Post	0.0007***
	(0.0002)
2 Quarters Post	0.0008***
	(0.0002)
3 Quarters Post	0.0005*
	(0.0002)
4 Quarters Post	0.0009***
	(0.0002)
5 Quarters Post	0.0006**
	(0.0002)
6 Quarters Post	0.0006**
	(0.0002)
7 Quarters Post	0.0006**
	(0.0002)
8 Quarters Post	0.0004
	(0.0002)
Burned*Event Quarter	0.0006
	(0.0004)
Burned*1 Quarter Post	0.0009*
	(0.0004)
Burned*2 Quarters Post	0.0004
	(0.0004)
Burned*3 Quarters Post	0.0011**
	(0.0004)
Burned*4 Quarters Post	0.0007
	(0.0004)
Burned*5 Quarters Post	0.0007
	(0.0004)
Burned*6 Quarters Post	0.0008
	(0.0004)
Burned*7 Quarters Post	0.0012**
	(0.0004)
Burned*8 Quarters Post	0.0011*
	(0.0005)
Observations	304704

Note: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

All models include tract and quarter fixed effects. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel. St. Denis et al. (2020).

Table A4: All-Wildfire Model Out-Migration

	Dependent Variables:
	Out-Migration Probability
	(1)
Burned Tract	0.0002
	(0.0003)
Event Quarter	−0.0003
	(0.0002)
1 Quarter Post	0.0006***
	(0.0002)
2 Quarters Post	0.0008***
	(0.0002)
3 Quarters Post	0.0007***
	(0.0002)
4 Quarters Post	0.0002
	(0.0002)
5 Quarters Post	0.0009***
	(0.0002)
6 Quarters Post	0.0005**
	(0.0002)
7 Quarters Post	0.0005**
	(0.0002)
8 Quarters Post	0.0002
	(0.0002)
Burned*Event Quarter	0.0000
	(0.0005)
Burned*1 Quarter Post	0.0012***
	(0.0003)
Burned*2 Quarters Post	0.0013***
	(0.0003)
Burned*3 Quarters Post	0.0007*
	(0.0003)
Burned*4 Quarters Post	0.0010**
	(0.0003)
Burned*5 Quarters Post	0.0004
	(0.0004)
Burned*6 Quarters Post	0.0010**
	(0.0004)
Burned*7 Quarters Post	0.0014***
	(0.0004)
Burned*8 Quarters Post	0.0012**
	(0.0004)
Observations	304704

Note: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$
All models include tract and quarter fixed effects. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel. St. Denis et al. (2020).

Table A5: In-Migration by Destruction Quintile

	Dependent variable:				
	In-Migration Probability				
	(Q1)	(Q2)	(Q3)	(Q4)	(Q5)
Burned Tract	0.0005	0.0003	0.0016	−0.0004	0.0004
	(0.0009)	(0.0007)	(0.0009)	(0.0011)	(0.0015)
Event Quarter	0.0007	0.0010**	0.0011**	0.0007	0.0008
	(0.0004)	(0.0003)	(0.0004)	(0.0004)	(0.0006)
1 Quarter Post	−0.0004	0.0008*	0.0002	0.0011*	0.0013*
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0006)
2 Quarters Post	−0.0000	0.0010**	−0.0001	0.0013**	0.0017*
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0007)
3 Quarters Post	0.0000	0.0004	−0.0003	0.0006	0.0009
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0007)
4 Quarters Post	0.0003	0.0014***	0.0002	0.0008	0.0000
	(0.0005)	(0.0004)	(0.0004)	(0.0005)	(0.0007)
5 Quarters Post	−0.0002	0.0008	−0.0001	−0.0000	0.0019**
	(0.0005)	(0.0004)	(0.0005)	(0.0005)	(0.0007)
6 Quarters Post	−0.0004	0.0010*	−0.0000	0.0006	0.0008
	(0.0005)	(0.0004)	(0.0004)	(0.0006)	(0.0007)
7 Quarters Post	−0.0003	0.0007	0.0000	0.0008	0.0007
	(0.0005)	(0.0004)	(0.0005)	(0.0006)	(0.0007)
8 Quarters Post	−0.0000	0.0005	−0.0005	0.0006	−0.0002
	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0007)
Burned*Event Quarter	0.0007	0.0005	−0.0005	0.0008	−0.0004
	(0.0009)	(0.0006)	(0.0008)	(0.0009)	(0.0012)
Burned*1 Quarter Post	0.0018*	0.0003	−0.0003	0.0004	0.0007
	(0.0009)	(0.0007)	(0.0008)	(0.0009)	(0.0012)
Burned*2 Quarters Post	0.0005	−0.0005	−0.0002	0.0003	0.0003
	(0.0009)	(0.0007)	(0.0009)	(0.0009)	(0.0013)
Burned*3 Quarters Post	0.0014	0.0008	0.0006	0.0005	0.0008
	(0.0009)	(0.0007)	(0.0009)	(0.0010)	(0.0013)
Burned*4 Quarters Post	0.0017	−0.0005	−0.0003	0.0012	0.0002
	(0.0010)	(0.0007)	(0.0009)	(0.0010)	(0.0013)
Burned*5 Quarters Post	0.0013	0.0001	0.0004	0.0008	−0.0011
	(0.0010)	(0.0008)	(0.0009)	(0.0010)	(0.0014)
Burned*6 Quarters Post	0.0019	−0.0003	0.0001	0.0004	0.0005
	(0.0010)	(0.0008)	(0.0009)	(0.0010)	(0.0013)
Burned*7 Quarters Post	0.0019	0.0004	0.0001	0.0017	0.0007
	(0.0010)	(0.0008)	(0.0009)	(0.0011)	(0.0014)
Burned*8 Quarters Post	0.0017	0.0005	0.0012	0.0014	−0.0005
	(0.0011)	(0.0008)	(0.0010)	(0.0011)	(0.0014)
Observations	67331	71624	68095	57040	34422

Note: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

All models include tract and quarter fixed effects. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel. St. Denis et al. (2020).

Table A6: Out-Migration by Destruction Quintile

	Dependent variable:				
	Out-Migration Probability				
	(Q1)	(Q2)	(Q3)	(Q4)	(Q5)
Burned Tract	0.0004	−0.0003	−0.0001	−0.0005	−0.0019
	(0.0007)	(0.0006)	(0.0007)	(0.0009)	(0.0012)
Event Quarter	−0.0002	−0.0004	−0.0004	−0.0008	0.0005
	(0.0005)	(0.0004)	(0.0005)	(0.0006)	(0.0008)
1 Quarter Post	0.0006	0.0001	0.0006	−0.0001	0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0005)
2 Quarters Post	0.0005	0.0004	0.0008*	0.0004	0.0008
	(0.0004)	(0.0003)	(0.0004)	(0.0004)	(0.0006)
3 Quarters Post	0.0009*	0.0005	0.0004	0.0003	0.0004
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0006)
4 Quarters Post	0.0000	0.0000	0.0001	−0.0008	0.0005
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0006)
5 Quarters Post	0.0007	0.0005	0.0007	0.0005	0.0010
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0007)
6 Quarters Post	0.0001	0.0005	0.0009*	−0.0007	0.0005
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0006)
7 Quarters Post	0.0010*	−0.0005	0.0009*	0.0003	−0.0007
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0006)
8 Quarters Post	−0.0003	0.0004	0.0004	−0.0007	−0.0005
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0006)
Burned*Event Quarter	0.0004	0.0020*	0.0006	−0.0046***	−0.0002
	(0.0011)	(0.0009)	(0.0013)	(0.0013)	(0.0016)
Burned*1 Quarter Post	0.0012	0.0007	0.0006	0.0004	0.0030*
	(0.0007)	(0.0006)	(0.0007)	(0.0008)	(0.0012)
Burned*2 Quarters Post	0.0015*	0.0014*	0.0001	0.0003	0.0037**
	(0.0007)	(0.0006)	(0.0007)	(0.0008)	(0.0012)
Burned*3 Quarters Post	−0.0004	0.0004	0.0008	−0.0004	0.0032**
	(0.0007)	(0.0006)	(0.0007)	(0.0008)	(0.0012)
Burned*4 Quarters Post	0.0007	0.0010	−0.0002	0.0011	0.0025*
	(0.0007)	(0.0006)	(0.0007)	(0.0009)	(0.0011)
Burned*5 Quarters Post	0.0003	0.0008	−0.0002	−0.0002	0.0012
	(0.0008)	(0.0006)	(0.0007)	(0.0009)	(0.0012)
Burned*6 Quarters Post	0.0013	0.0010	0.0000	0.0012	0.0016
	(0.0008)	(0.0007)	(0.0007)	(0.0009)	(0.0011)
Burned*7 Quarters Post	−0.0000	0.0023**	0.0007	0.0015	0.0038**
	(0.0007)	(0.0007)	(0.0007)	(0.0009)	(0.0012)
Burned*8 Quarters Post	0.0023**	0.0012	−0.0002	0.0003	0.0030*
	(0.0008)	(0.0008)	(0.0007)	(0.0010)	(0.0012)
Observations	67331	71624	68095	57040	34422

Note: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

All models include tract and quarter fixed effects. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel. St. Denis et al. (2020).

Table A7: Extreme Events In-Migration

	Dependent Variables:
	In-Migration Probability
	(1)
Burned Tract	−0.0032
	(0.0032)
Event Quarter	0.0029
	(0.0017)
1 Quarter Post	0.0050**
	(0.0018)
2 Quarters Post	0.0031
	(0.0020)
3 Quarters Post	0.0007
	(0.0021)
4 Quarters Post	−0.0001
	(0.0023)
5 Quarters Post	0.0023
	(0.0023)
6 Quarters Post	0.0028
	(0.0024)
7 Quarters Post	0.0022
	(0.0026)
8 Quarters Post	0.0004
	(0.0028)
Burned*Event Quarter	−0.0027
	(0.0023)
Burned*1 Quarter Post	0.0017
	(0.0024)
Burned*2 Quarters Post	−0.0004
	(0.0026)
Burned*3 Quarters Post	0.0047
	(0.0029)
Burned*4 Quarters Post	0.0024
	(0.0029)
Burned*5 Quarters Post	0.0022
	(0.0031)
Burned*6 Quarters Post	0.0011
	(0.0031)
Burned*7 Quarters Post	0.0039
	(0.0036)
Burned*8 Quarters Post	0.0003
	(0.0032)
Observations	5436

Note: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

All models include tract and quarter fixed effects. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel. St. Denis et al. (2020).

Table A8: Extreme Events Out-Migration

	Dependent Variables:
	Out-Migration Probability
	(1)
Burned Tract	−0.0036
	(0.0028)
Event Quarter	0.0004
	(0.0022)
1 Quarter Post	0.0017
	(0.0016)
2 Quarters Post	0.0032
	(0.0020)
3 Quarters Post	0.0039*
	(0.0017)
4 Quarters Post	0.0015
	(0.0019)
5 Quarters Post	0.0012
	(0.0018)
6 Quarters Post	0.0009
	(0.0019)
7 Quarters Post	0.0003
	(0.0021)
8 Quarters Post	−0.0004
	(0.0019)
Burned*Event Quarter	0.0014
	(0.0026)
Burned*1 Quarter Post	0.0113**
	(0.0042)
Burned*2 Quarters Post	0.0100**
	(0.0037)
Burned*3 Quarters Post	0.0057
	(0.0031)
Burned*4 Quarters Post	0.0072*
	(0.0033)
Burned*5 Quarters Post	0.0068*
	(0.0028)
Burned*6 Quarters Post	0.0064*
	(0.0029)
Burned*7 Quarters Post	0.0042
	(0.0031)
Burned*8 Quarters Post	0.0080*
	(0.0031)
Observations	5436

Note: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$
All models include tract and quarter fixed effects. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel. St. Denis et al. (2020).

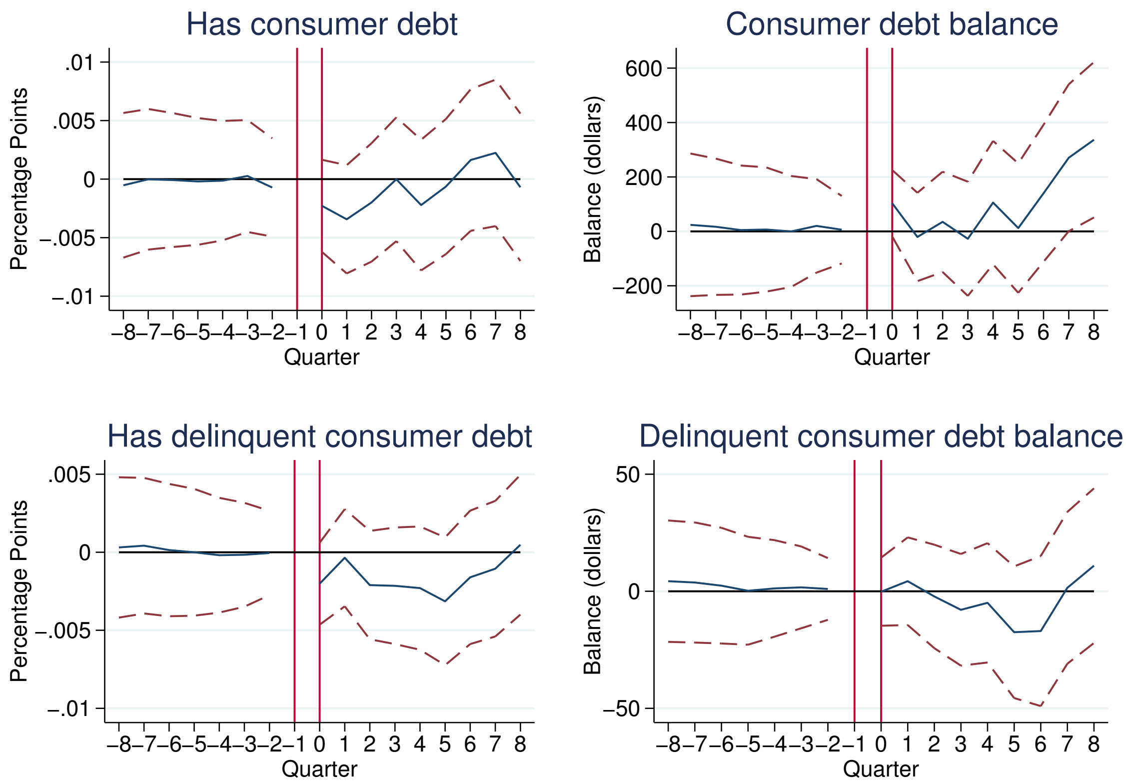

Figure A3: Consumer credit outcomes, >575 structure fires. Propensity-score weighted effects of fires in burned tracts. Standard errors are clustered at the Census-block level. Consumer balances include all credit cards, retail cards, and all other debt not secured by a home or automobile. Balances are delinquent if they are more than 90 days past due. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel, St. Denis et al. (2020).

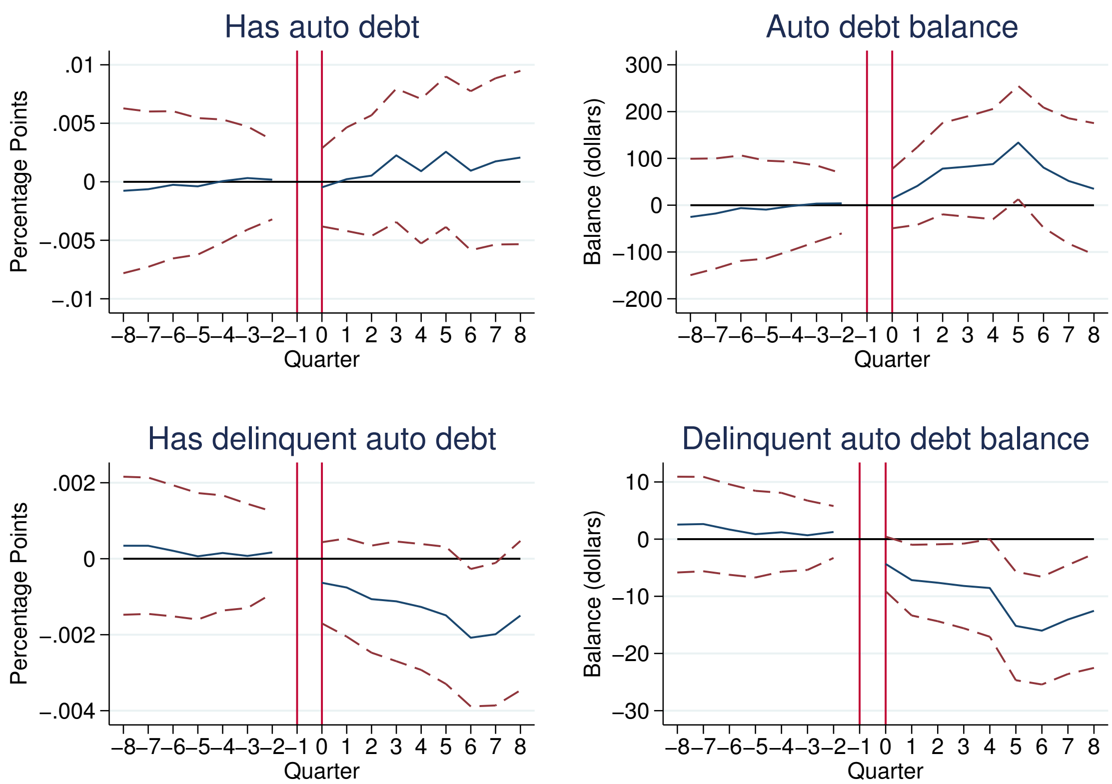

Figure A4: Auto credit outcomes, >575 structure fires. Propensity-score weighted effects of fires in burned tracts. Standard errors are clustered at the Census-block level. Balances are delinquent if they are more than 90 day past due. The bankruptcy and foreclosure variables indicate filings within the last three years. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel, St. Denis et al. (2020).

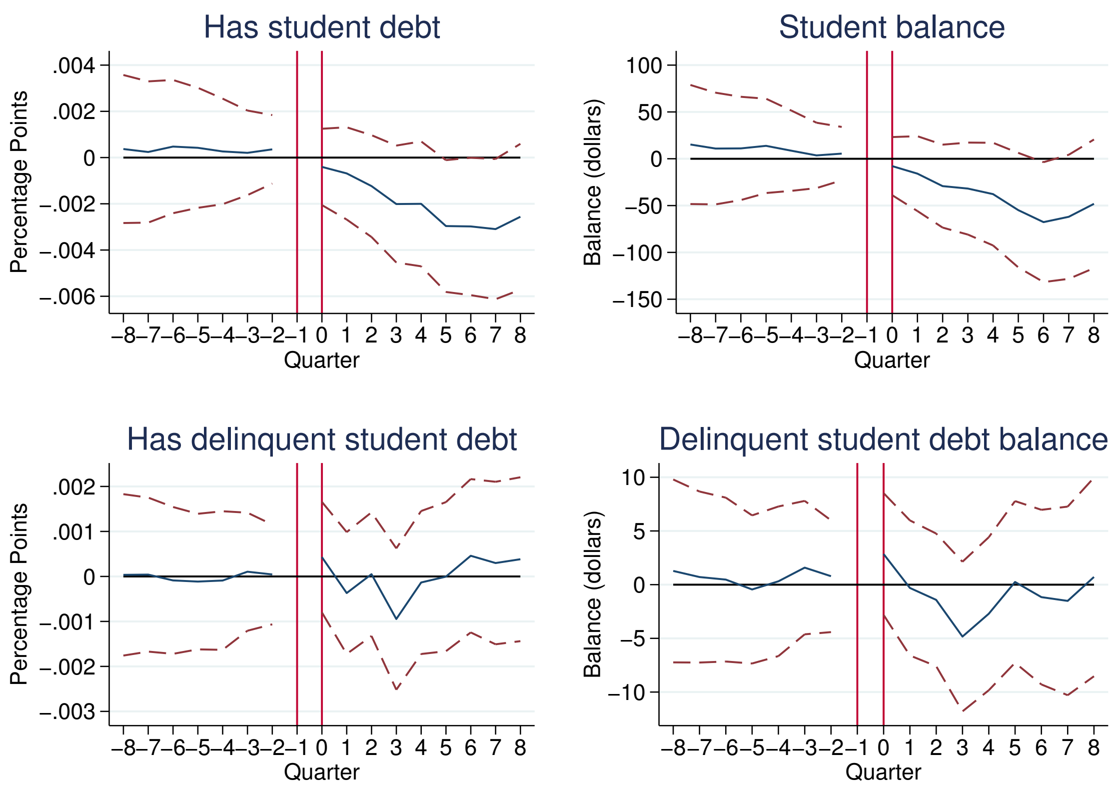

Figure A5: Student debt outcomes, >575 structure fires. Propensity-score weighted effects of fires in burned tracts. Standard errors are clustered at the Census-block level. Balances are delinquent if they are more than 90 day past due. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel, St. Denis et al. (2020).

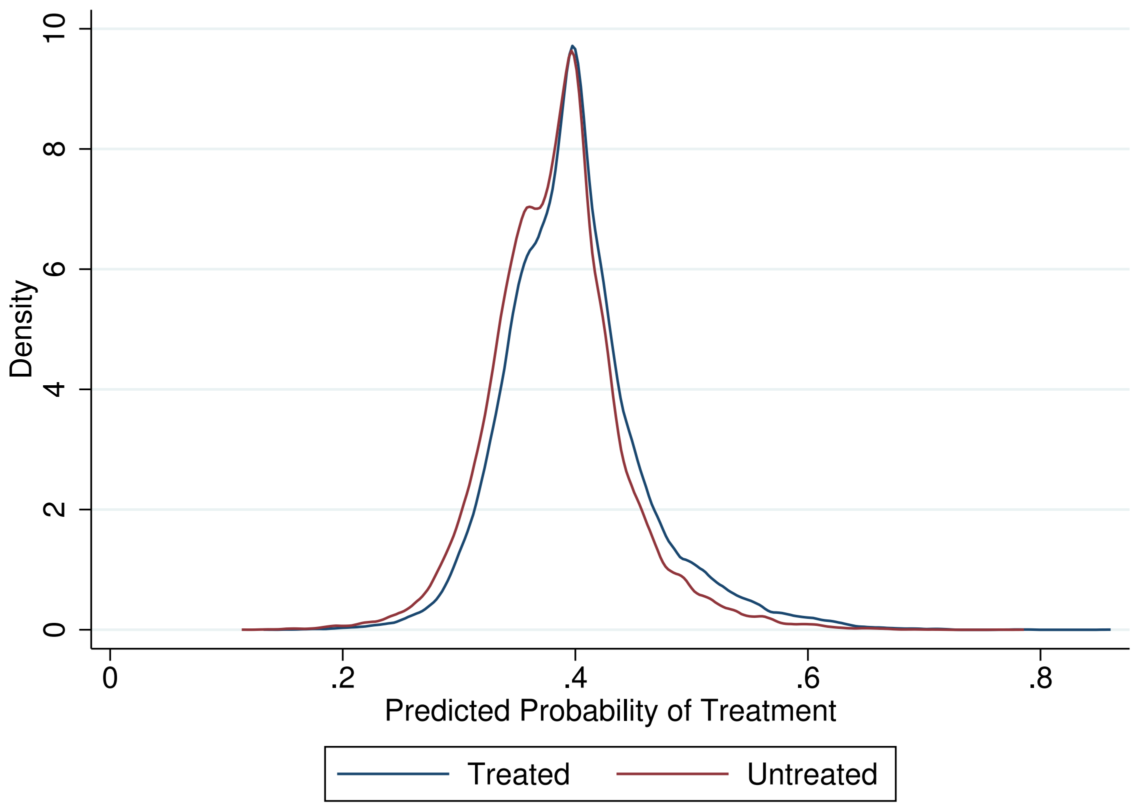

Figure A6: Propensity score kdensity plots for burned and neighboring tracts. *Sources:* Federal Reserve Bank of New York/Equifax Consumer Credit Panel, St. Denis et al. (2020).

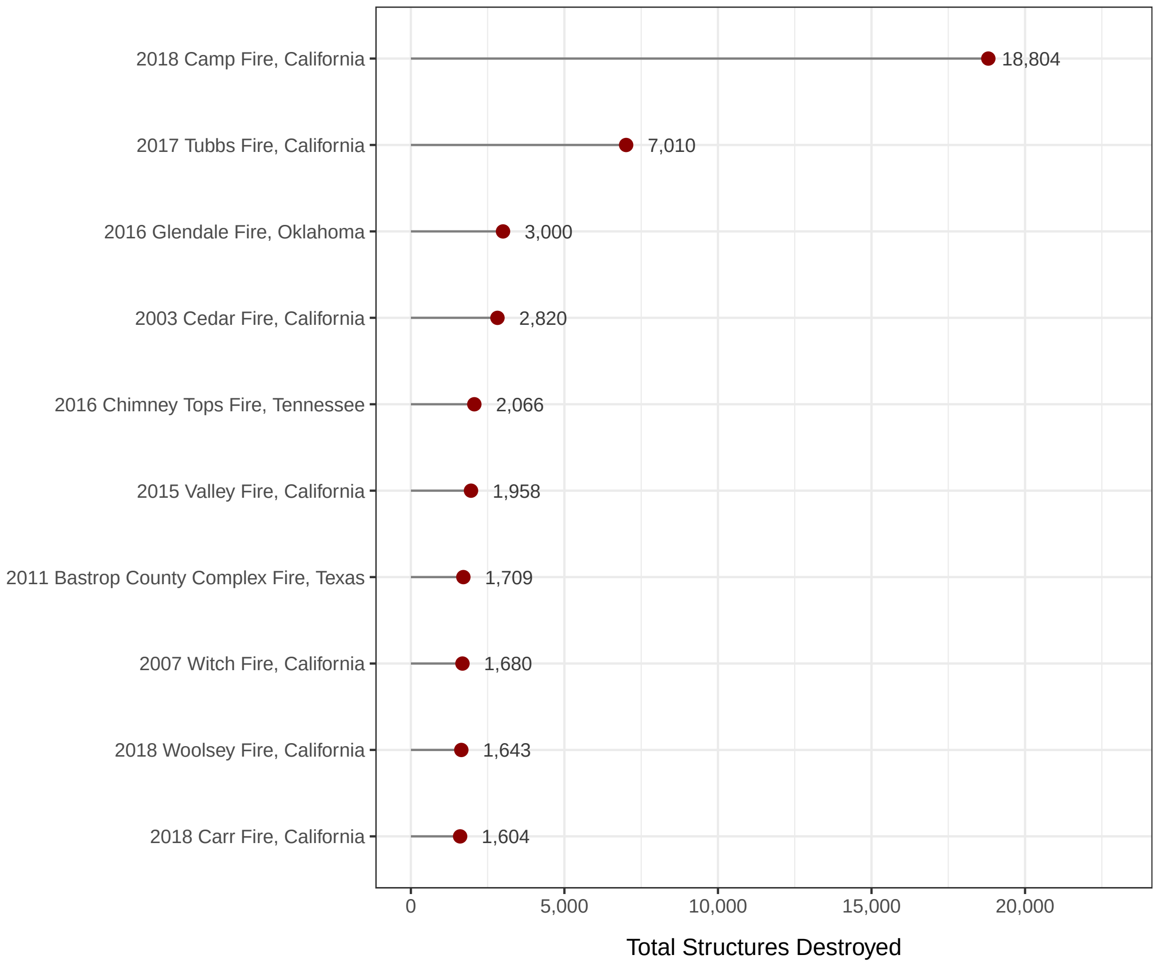

Figure A7: Wildfires which destroyed the largest number of buildings between 1999 and 2018. *Source:* St. Denis et al. (2020).

References

Abadie, Alberto (2005). “Semiparametric difference-in-differences estimators.” *The Review of Economic Studies*, 72(1), pp. 1–19. doi:10.1111/0034-6527.00321. URL https://doi.org/10.1111/0034-6527.00321.

Abatzoglou, John T. and A. Park Williams (2016). “Impact of anthropogenic climate change on wildfire across western US forests.” *Proceedings of the National Academy of Sciences*, 113(42), pp. 11,770–11,775. doi:10.1073/pnas.1607171113. URL http://www.pnas.org/lookup/doi/10.1073/pnas.1607171113.

Adams, Helen (2016). “Why populations persist: mobility, place attachment and climate change.” *Population and Environment*, 37(4), pp. 429–448. doi:10.1007/s11111-015-0246-3. URL https://doi.org/10.1007/s11111-015-0246-3.

Adger, W. Neil, Jon Barnett, Katrina Brown, Nadine Marshall, and Karen O’Brien (2013). “Cultural dimensions of climate change impacts and adaptation.” *Nature Climate Change*, 3(2), pp. 112–117. doi:10.1038/nclimate1666. URL https://www.nature.com/articles/nclimate1666.

Balch, Jennifer K., Bethany A. Bradley, John T. Abatzoglou, R. Chelsea Nagy, Emily J. Fusco, and Adam L. Mahood (2017). “Human-started wildfires expand the fire niche across the United States.” *Proceedings of the National Academy of Sciences*, 114(11), pp. 2946–2951. doi:10.1073/pnas.1617394114. URL https://www.pnas.org/content/114/11/2946.

Barbero, R., J. T. Abatzoglou, N. K. Larkin, C. A. Kolden, and B. Stocks (2015). “Climate change presents increased potential for very large fires in the contiguous United States.” *International Journal of Wildland Fire*, 24(7), pp. 892–899. doi:10.1071/WF15083. URL http://www.publish.csiro.au/WF/WF15083.

Bardsley, Douglas K. and Graeme J. Hugo (2010). “Migration and climate change: examining thresholds of change to guide effective adaptation decision-making.” *Population and Environment*, 32(2), pp. 238–262. doi:10.1007/s11111-010-0126-9. URL https://doi.org/10.1007/s11111-010-0126-9.

Baylis, Patrick and Judson Boomhower (2019). “Moral hazard, wildfires, and the economic incidence of natural disasters.” Technical report, National Bureau of Economic Research. doi:10.3386/w26550.

Billings, Stephen B., Emily Gallagher, and Lowell Ricketts (Forthcoming). “Let the rich be flooded: The distribution of financial aid and distress after hurricane Harvey.” *Journal of Financial Economics*. doi:10.2139/ssrn.3396611.

Black, Richard, Nigel W. Arnell, W. Neil Adger, David Thomas, and Andrew Geddes (2013). “Migration, immobility and displacement outcomes following extreme events.” *Environmental Science & Policy*, 27, pp. S32–S43. doi:10.1016/j.envsci.2012.09.001. URL http://www.sciencedirect.com/science/article/pii/S1462901112001475.

Bleemer, Zachary and Wilbert van der Klaauw (2019). "Long-run net distributionary effects of federal disaster insurance: The case of hurricane Katrina." *Journal of Urban Economics*, 110, pp. 70–88. doi:10.1016/j.jue.2019.01.005.

Bohra-Mishra, Pratikshya, Michael Oppenheimer, and Solomon M. Hsiang (2014). "Nonlinear permanent migration response to climatic variations but minimal response to disasters." *Proceedings of the National Academy of Sciences*, 111(27), pp. 9780–9785. doi:10.1073/pnas.1317166111. URL https://www.pnas.org/content/111/27/9780.

Boustan, Leah Platt, Matthew E. Kahn, and Paul W. Rhode (2012). "Moving to higher ground: Migration response to natural disasters in the early twentieth century." *American Economic Review*, 102(3), pp. 238–244. doi:10.1257/aer.102.3.238.

Boyd, Eugene and Oscar R. Gonzales (2012). *Community Development Block Grant funds in disaster relief and recovery*. Congressional Research Service Washington, DC. URL https://crsreports.congress.gov/product/pdf/RL/RL33330.

Brevoort, Kenneth P., Philipp Grimm, and Michelle Kambara (2016). "Credit invisibles and the unscored." *Cityscape*, 18(2), pp. 9–34. URL http://www.huduser.gov/portal/periodicals/cityscpe/vol18num2/ch1.pdf.

Busby, Gwenlyn, Gregory S. Amacher, and Robert G. Haight (2013). "The social costs of homeowner decisions in fire-prone communities: Information, insurance, and amenities." *Ecological Economics*, 92, pp. 104–113. doi:10.1016/j.ecolecon.2013.02.019.

Champ, Patricia A., James R. Meldrum, Hannah Brenkert-Smith, Travis W. Warziniack, Christopher M. Barth, Lilia C. Falk, and Jamie B. Gomez (2020). "Do actions speak louder than words? Comparing the effect of risk aversion on objective and self-reported mitigation measures." *Journal of Economic Behavior & Organization*, 169, pp. 301–313. doi:10.1016/j.jebo.2019.11.019.

Deryugina, Tatyana, Laura Kawano, and Steven Levitt (2018). "The economic impact of hurricane Katrina on its victims: Evidence from individual tax returns." *American Economic Journal: Applied Economics*, 10(2), pp. 202–233. doi:10.1257/app.20160307.

DeWaard, Jack, Janna E. Johnson, and Stephan D. Whitaker (2019). "Internal Migration in the United States: A comprehensive comparative assessment of the Consumer Credit Panel." Working Paper 18-04R, Federal Reserve Bank of Cleveland. doi:10.26509/frbc-wp-201804r.

Do Yun, Seong and Brigitte S. Waldorf (2016). "The day after the disaster: forced migration and income loss after hurricanes Katrina and Rita." *Journal of Regional Science*, 56(3), pp. 420–441. doi:10.1111/jors.12250.

Donovan, Geoffrey H., Patricia A. Champ, and David T. Butry (2007). "Wildfire risk and housing prices: a case study from Colorado Springs." *Land Economics*, 83(2), pp. 217–233. doi:10.3368/le.83.2.217.

Eidenshink, Jeff, Brian Schwind, Ken Brewer, Zhi-Liang Zhu, Brad Quayle, and Stephen Howard (2007). "A project for monitoring trends in burn severity." *Fire Ecology*, 3(1), pp. 3–21. doi:10.4996/fireecology.0301003. URL https://fireecology.springeropen.com/articles/10.4996/fireecology.0301003, number: 1 Publisher: SpringerOpen.

FEMA (2013). *Louisiana recovery: eight years after Hurricanes Katrina and Rita*, volume DR-1603/07 - 994. Federal Emergency Management Agency (FEMA). URL https://www.fema.gov/news-release/2013/08/28/louisiana-recovery-eight-years-after-hurricanes-katrina-and-rita.

Gallagher, Justin and Daniel Hartley (2017). "Household finance after a natural disaster: The case of hurricane Katrina." *American Economic Journal: Economic Policy*, 9(3), pp. 199–228. doi:10.1257/pol.20140273.

Hauer, Mathew E. (2017). "Migration induced by sea-level rise could reshape the US population landscape." *Nature Climate Change*, 7(5), p. 321. doi:10.1038/nclimate3271. URL https://www.nature.com/articles/nclimate3271.

Hoffmann, Roman, Anna Dimitrova, Raya Muttarak, Jesus Crespo Cuaresma, and Jonas Peisker (2020). "A meta-analysis of country-level studies on environmental change and migration." *Nature Climate Change*, 10(10). doi:10.1038/s41558-020-0898-6. URL https://www.nature.com/articles/s41558-020-0898-6.

Hornbeck, Richard and Suresh Naidu (2014). "When the levee breaks: black migration and economic development in the American south." *American Economic Review*, 104(3), pp. 963–990. doi:10.1257/aer.104.3.963.

Howell, Junia and James R. Elliott (2018). "Damages done: The longitudinal impacts of natural hazards on wealth inequality in the United States." *Social Problems*, 66(3), pp. 448–467. doi:10.1093/socpro/spy016. URL https://academic.oup.com/socpro/advance-article/doi/10.1093/socpro/spy016/5074453.

Hunter, Lori M., Jessie K. Luna, and Rachel M. Norton (2015). "Environmental dimensions of migration." *Annual Review of Sociology*, 41(1), pp. 377–397. doi:10.1146/annurev-soc-073014-112223. URL https://doi.org/10.1146/annurev-soc-073014-112223.

Internal Revenue Service (IRS) (2006). *Information for taxpayers affected by Hurricanes Katrina, Rita, and Wilma*. Government Printing Office. URL https://www.irs.gov/publications/p4492.

Jia, Shenyue, Seung Hee Kim, Son V. Nghiem, Paul Doherty, and Menas C. Kafatos (2020). "Patterns of population displacement during mega-fires in California detected using Facebook disaster maps." *Environmental Research Letters*, 15(7), p. 074,029. doi:10.1088/1748-9326/ab8847. URL https://doi.org/10.1088/1748-9326/ab8847, publisher: IOP Publishing.

Kaczan, David J. and Jennifer Orgill-Meyer (2020). "The impact of climate change on migration: a synthesis of recent empirical insights." *Climatic Change*, 158(3), pp. 281–300. doi:10.1007/s10584-019-02560-0. URL https://doi.org/10.1007/s10584-019-02560-0.

Keenan, Jesse M., Thomas Hill, and Anurag Gumber (2018). "Climate gentrification: from theory to empiricism in Miami-Dade County, Florida." *Environmental Research Letters*, 13(5), p. 054,001. doi:10.1088/1748-9326/aabb32. URL http://stacks.iop.org/1748-9326/13/i=5/a=054001.

Lee, Donghoon and Wilbert van der Klaauw (2010). "An Introduction to the New York Fed Consumer Credit Panel." Staff Report 479, Federal Reserve Bank of New York. URL https://www.newyorkfed.org/research/staff_reports/sr479.html.

Lu, Xin, David J. Wrathall, Pål Roe Sundsøy, Md. Nadiruzzaman, Erik Wetter, Asif Iqbal, Taimur Qureshi, Andrew Tatem, Geoffrey Canright, Kenth Engø-Monsen, and Linus Bengtsson (2016). "Unveiling hidden migration and mobility patterns in climate stressed regions: A longitudinal study of six million anonymous mobile phone users in Bangladesh." *Global Environmental Change*, 38, pp. 1–7. doi:10.1016/j.gloenvcha.2016.02.002. URL http://www.sciencedirect.com/science/article/pii/S0959378016300140.

Lustgarten, Abrahm (2020). "The great climate migration has begun." *The New York Times*. URL https://www.nytimes.com/interactive/2020/07/23/magazine/climate-migration.html.

Mason, Larry, Germaine White, Gary Morishima, Ernesto Alvarado, Louise Andrew, Fred Clark, Mike Durglo, Jim Durglo, John Eneas, Jim Erickson, Margaret Friedlander, Kathy Hamel, Colin Hardy, Tony Harwood, Faline Haven, Everett Isaac, Laurel James, Robert Kenning, Adrian Leighton, Pat Pierre, Carol Raish, Bodie Shaw, Steven Smallsalmon, Vernon Stearns, Howard Teasley, Matt Weingart, and Spus Wilder (2012). "Listening and learning from traditional knowledge and western science: A dialogue on contemporary challenges of forest health and wildfire." *Journal of Forestry*, 110(4), pp. 187–193. doi:10.5849/jof.11-006. URL https://academic.oup.com/jof/article/110/4/187/4599525, publisher: Oxford Academic.

McCoy, Shawn J. and Randall P. Walsh (2018). "Wildfire risk, salience & housing demand." *Journal of Environmental Economics and Management*, 91, pp. 203–228. doi:10.1016/j.jeem.2018.07.005.

Millock, Katrin (2015). "Migration and environment." *Annual Review of Resource Economics*, 7(1), pp. 35–60. doi:10.1146/annurev-resource-100814-125031. URL https://doi.org/10.1146/annurev-resource-100814-125031.

Mockrin, Miranda H., Hillary K. Fishler, and Susan I. Stewart (2018). "Does wildfire open a policy window? Local government and community adaptation after fire in the United States." *Environmental Management*, 62(2), pp. 210–228. doi:10.1007/s00267-018-1030-9. URL https://doi.org/10.1007/s00267-018-1030-9.

Mueller, Julie, John Loomis, and Armando González-Cabán (2009). "Do repeated wildfires change homebuyers' demand for homes in high–risk areas? A hedonic analysis of the short and long–term effects of repeated wildfires on house prices in southern California." *Journal of Real Estate Finance Economics*, 38(2), pp. 155–172. doi:10.1007/s11146-007-9083-1.

Mueller, V., C. Gray, and K. Kosec (2014). "Heat stress increases long-term human migration in rural Pakistan." *Nature Climate Change*, 4(3), pp. 182–185. doi:10.1038/nclimate2103. URL https://www.nature.com/articles/nclimate2103, number: 3 Publisher: Nature Publishing Group.

Nawrotzki, Raphael J., Hannah Brenkert-Smith, Lori M. Hunter, and Patricia A. Champ (2014). "Wildfire-Migration Dynamics: Lessons from Colorado's Fourmile Canyon Fire." *Society & Natural Resources*, 27(2), pp. 215–225. doi:10.1080/08941920.2013.842275. URL https://doi.org/10.1080/08941920.2013.842275.

Pausas, Juli G. and Jon E. Keeley (2019). "Wildfires as an ecosystem service." *Frontiers in Ecology and the Environment*, 17(5), pp. 289–295. doi:10.1002/fee.2044. URL https://esajournals.onlinelibrary.wiley.com/doi/abs/10.1002/fee.2044, _eprint: https://esajournals.onlinelibrary.wiley.com/doi/pdf/10.1002/fee.2044.

Piguet, Etienne, Raoul Kaenzig, and Jérémie Guélat (2018). "The uneven geography of research on "environmental migration"." *Population and Environment*, 39(4), pp. 357–383. doi:10.1007/s11111-018-0296-4. URL https://doi.org/10.1007/s11111-018-0296-4.

Plane, D. A., C. J. Henrie, and M. J. Perry (2005). "Migration up and down the urban hierarchy and across the life course." *Proceedings of the National Academy of Sciences*, 102(43), pp. 15,313–15,318. doi:10.1073/pnas.0507312102. URL https://www.pnas.org/content/102/43/15313, publisher: National Academy of Sciences Section: Social Sciences.

Radeloff, Volker C., David P. Helmers, H. Anu Kramer, Miranda H. Mockrin, Patricia M. Alexandre, Avi Bar-Massada, Van Butsic, Todd J. Hawbaker, Sebastián Martinuzzi, Alexandra D. Syphard, and Susan I. Stewart (2018). "Rapid growth of the US wildland-urban interface raises wildfire risk." *Proceedings of the National Academy of Sciences*, 115(13), pp. 3314–3319. doi:10.1073/pnas.1718850115. URL http://www.pnas.org/lookup/doi/10.1073/pnas.1718850115.

Rigaud, Kanta K., Alex de Sherbinin, Bryan R. Jones, Jonas Sebastian Bergmann, Viviane Wei Chen Clement, Kayly Jennifer Ober, Jacob Schewe, Susana Adamo, Brent McCusker, Silke Heuser, and Amelia Midgley (2018). "Groundswell: preparing for internal climate migration." Technical Report 124719, The World Bank. URL http://documents.worldbank.org/curated/en/846391522306665751/Main-report.

Robalino, Juan, José Jimenez, and Adriana Chacón (2015). "The effect of hydro-meteorological emergencies on internal migration." *World Development*, 67, pp. 438–448. doi:10.1016/j.worlddev.2014.10.031. URL https://www.sciencedirect.com/science/article/pii/S0305750X14003465.

Schewel, Kerilyn (2020). “Understanding immobility: Moving beyond the mobility bias in migration studies.” *International Migration Review*, 54(2), pp. 328–355. doi:10.1177/0197918319831952. URL https://doi.org/10.1177/0197918319831952, publisher: SAGE Publications Inc.

Schoennagel, Tania, Jennifer K. Balch, Hannah Brenkert-Smith, Philip E. Dennison, Brian J. Harvey, Meg A. Krawchuk, Nathan Mietkiewicz, Penelope Morgan, Max A. Moritz, Ray Rasker, Monica G. Turner, and Cathy Whitlock (2017). “Adapt to more wildfire in western North American forests as climate changes.” *Proceedings of the National Academy of Sciences*, 114(18), pp. 4582–4590. doi:10.1073/pnas.1617464114. URL https://www.pnas.org/content/114/18/4582.

Schumann, Ronald L., Miranda Mockrin, Alexandra D. Syphard, Joshua Whittaker, Owen Price, Cassandra Johnson Gaither, Christopher T. Emrich, and Van Butsic (2020). “Wildfire recovery as a “hot moment” for creating fire-adapted communities.” *International Journal of Disaster Risk Reduction*, 42, p. 101,354. doi:10.1016/j.ijdrr.2019.101354. URL http://www.sciencedirect.com/science/article/pii/S2212420919303346.

Shafran, Aric P. (2008). “Risk externalities and the problem of wildfire risk.” *Journal of Urban Economics*, 64(2), pp. 488–495. doi:10.1016/j.jue.2008.05.001.

Sharygin, Ethan (2021). “Estimating migration impacts of wildfire: California’s 2017 North Bay fires.” In Dávid Karácsonyi, Andrew Taylor, and Deanne Bird, editors, *The Demography of Disasters: Impacts for Population and Place*, pp. 49–70. Springer International Publishing, Cham. doi:10.1007/978-3-030-49920-4_3. URL https://doi.org/10.1007/978-3-030-49920-4_3.

St. Denis, Lise A., Nathan P. Mietkiewicz, Karen C. Short, Mollie Buckland, and Jennifer K. Balch (2020). “All-hazards dataset mined from the US National Incident Management System 1999–2014.” *Scientific Data*, 7(1), pp. 1–18. doi:10.1038/s41597-020-0403-0. URL https://www.nature.com/articles/s41597-020-0403-0.

Syphard, Alexandra D., Jon E. Keeley, Avi Bar Massada, Teresa J. Brennan, and Volker C. Radeloff (2012). “Housing arrangement and location determine the likelihood of housing loss due to wildfire.” *PLOS ONE*, 7(3), p. e33,954. doi:10.1371/journal.pone.0033954. URL https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0033954.

Syphard, Alexandra D., Heather Rustigian-Romsos, Michael Mann, Erin Conlisk, Max A. Moritz, and David Ackerly (2019). “The relative influence of climate and housing development on current and projected future fire patterns and structure loss across three California landscapes.” *Global Environmental Change*, 56, pp. 41–55. doi:10.1016/j.gloenvcha.2019.03.007. URL http://www.sciencedirect.com/science/article/pii/S0959378018313293.

Whitaker, Stephan D. (2018). “Big Data versus a survey.” *The Quarterly Review of Economics and Finance*, 67, pp. 285–296. doi:10.1016/j.qref.2017.07.011. URL http://www.sciencedirect.com/science/article/pii/S1062976917300170.

Wibbenmeyer, Matthew, Sarah E. Anderson, and Andrew J. Plantinga (2019). “Salience and the government provision of public goods.” *Economic Inquiry*, 57(3), pp. 1547–1567. doi:10.1111/ecin.12781.

Winkler, Richelle L. and Mark D. Rouleau (2020). “Amenities or disamenities? Estimating the impacts of extreme heat and wildfire on domestic US migration.” *Population and Environment*. doi:10.1007/s11111-020-00364-4. URL https://doi.org/10.1007/s11111-020-00364-4.