Catastrophic Fires, Human Displacement, and Real Estate Prices in California

February 29, 2024

Abstract

Millions of people are displaced by natural disasters each year, yet little is known about how evacuees affect host communities. We analyze the migratory effects of the most destructive fire in California history, the 2018 Camp Fire, which destroyed over 18,000 structures and displaced roughly 50,000 people. By merging geospatial information on the fire's footprint with Zillow's housing transaction data, we estimate both the spatial and temporal effects of the fire on real estate prices at a granular level. A number of important insights emerge. First, within the fire's footprint, home prices increased by 25 percent in the six-week aftermath of the fire. Effects decay with distance and are statistically insignificant beyond 100 miles. Second, effects are detected within two weeks of the fire, fully materialize within four weeks, and are persistent up to ten months (which exhausts our period of consideration). Results are consistent the observed migratory behavior of displaced people and are robust to a variety of specifications and modeling assumptions.

Keywords: Catastrophic Fires, Housing Prices, Hedonic Model, Demand Shocks, Climate Change

JEL Classification: Q54; Q56; R3; R11; R21; R23

1. Introduction

In 2020, thirty-million people worldwide were displaced from their homes due to fires, floods, and storms (IDMC, 2020). For reference, this is roughly three times the number of people displaced due to conflict worldwide (IDMC, 2020), and this trend is expected to continue (IPCC, 2014; Clement et al., 2021). While people living in the developing world are particularly vulnerable to the effects of climate change (Sokona and Denton, 2001; Ikeme, 2003) and host a disproportionate number of climate migrants (Drabo and Mbaye, 2015), those in the developed world are also at risk of displacement. In 2020, nearly two million Americans were displaced by disasters, 62 percent of whom were displaced by wildfires.[1,2]

Displacement resulting from fires is an acutely pressing issue as climate change, fuel accumulation, and population growth in the wildland-urban interface have made major destructive wildfires more frequent (Radeloff et al., 2018; Keeley and Syphard, 2021). This transition has uniquely impacted California. Of the twenty most destructive fires in California state history, sixteen occurred in the last ten years—and seven since 2020.[3] With tens of millions of people living in high-risk fire zones in the United States alone[4], understanding how the sudden displacement of fire evacuees impacts host communities is of clear importance to policymakers, homeowners, real estate investors, and future fire victims alike. And yet, little is known about how evacuees respond to such events and how their responses influence real estate markets in host communities.

This study examines the migratory behavior of evacuees of the 2018 Camp Fire, and the effect it had on regional housing prices in northern California. Being the most destructive fire in California state history, the Camp Fire serves as a natural case study and apparent precursor of things to come, in California and beyond.[5] The fire was ignited by electrical transmission lines near the town of Pulga in Northern California and spread quickly due to unusually dry vegetation and Red Flag conditions including strong winds and low humidity. Within just a couple hours of the ignition, the Camp Fire reached the town of Paradise. The resulting damage was catastrophic and rightfully garnered international attention.[6] The fire incinerated roughly 11,000 homes and displaced roughly 50,000 people (IDMC, 2020). Writing for the New York Times, Jon Moallem describes the event as something

[1]Authors calculations based on data collected from (IDMC, 2020)

[2]In a 2021 survey of U.S. residents, roughly half of the respondents who planned to relocate in the next year reported that climate threats factored into their decision-making process (Katz, 2021).

[3]https://wfca.com/wildfire-articles/history-of-california-wildfires/

[4]https://tinyurl.com/ynwt259u

[5]After the present study had been initiated, Hawaii experienced the most destructive fire in it's history in 2023.

[6]https://www.bbc.com/news/av/world-us-canada-47795403

beyond a mere disaster:

> *"Paradise had prepared for disasters. But it had prepared merely for disasters, and this was something else. In a matter of hours, the town's roads were swamped, its emergency plans outstripped. Nine of every ten homes were destroyed and at least 85 people were dead. Many were elderly, some were incinerated in their cars while trying to flee and others apparently never made it that far."*

The preceding passage highlights two distinct features of catastrophic wildfires. First, such events create trauma. Many people who evacuated from the Camp Fire - even those who did so early - experienced symptoms of post-traumatic stress disorder.[7] Trauma can cause people to become more risk averse, in this case making low-fire risk zones relatively more attractive to evacuees (Kim and Lee, 2014). Catastrophic events also garner significant media attention, which can influence the saliency of wildfire risk. Second, catastrophic fires are distinct in their destructiveness, typically resulting in a significant loss of infrastructure and housing. While the existing economics literature has long recognized the potential for wildfires to influence housing prices by altering risk perceptions (Loomis, 2004; Donovan et al., 2007; Venn et al., 2010; Holmes et al., 2012; McCoy and Walsh, 2018)[8], or degrading view sheds (Venn et al., 2010; McCoy and Walsh, 2018; Garnache, 2020), catastrophic fires create an additional "displacement" effect resulting from the sudden loss of housing.

Such fast-onset disasters create fast-onset effects, the identification of which requires temporally and spatially granulated data. To satisfy these requirements, we merged geospatial information on the fire's footprint with Zillow's geo-coded daily property transaction data. These data are sufficiently rich to allow us to map out the spatial and temporal ripple of the "displacement" effect created by the fire. Our empirical approach is a hedonic property model applied to a triple difference-in-differences framework designed to allow for regional seasonal variation in housing price. Identification relies on the assumption that the location and timing of the Camp Fire was random, conditional on spatial and temporal fixed effects.

In the six-week aftermath of the Camp Fire, we find that prices within the fire's footprint increased by roughly 25 percent. Effects decay as distance from the fire increases, existing up to 100 miles away. The demand effect was persistent, lasting up to ten months (which exhausts the posterior period of our sample). Outside of the fire's footprint, estimated price premiums are similar for properties located in low or medium wildfire-risk zones compared to properties located in high or very high wildfire-risk zones, though this at least partially

[7] https://www.washingtonpost.com/magazine/2021/10/27/camp-fire-ptsd/

[8] There is also a large related literature that examines how other types of natural disasters affect risk perceptions. See, for example, (Kousky, 2010; Hennighausen and Suter, 2020).

reflects the fact that, near the fire's footprint, housing supply is much greater in low-fire risk zones.

Our estimates of the "demand effect" on housing prices are corroborated by our analysis of the migratory behavior of displaced people, who had a clear preferences to remain close (within 150 miles of the fire's footprint). We also matched destination addresses of displaced people with census tract characteristics, allowing us to explore a rich set of factors associated with with peoples migration decisions. Whereas 65% of displaced people moved from very-high risk properties to low-risk ones, this is at least partially explained by the fact that, within 100 miles of the fires footprint, there are many more low-fire-risk homes in the Sacramento Valley compared to high-fire-risk ones in the Sierra Nevada and Coastal mountain ranges.

This work contributes to two main bodies of research. The first examines the drivers and effects of climate migration discussed by Mason (2017). While climate migration is most often talked about in non-U.S. contexts (see e.g., Gray and Mueller (2012); Millock (2015), more than a million Americans were at least temporarily displaced from their homes in 2020 due to wildfire evacuations.[9] Using annual county-migration data spanning 1990 to 2015, Winkler and Rouleau (2020) show that the occurrence of a wildfire and/or extreme temperatures led to a net reduction in the number of people living in the affected counties, either by increased out-migration or decreased in-migration. Other types of natural disasters have also been shown to cause sudden migration. For example, it is estimated that 100,000 to 150,000 people migrated to Houston, Texas in the aftermath of Hurricane Katrina in 2005. This sudden migratory shift is estimated to have decreased long run housing prices in Houston (Daepp et al., 2020), while contemporaneously adversely affecting native Houstonian wages and employment (McIntosh, 2008). Catastrophic fires are unique from flooding in two important dimensions. First, whereas structures may only be partially destroyed due to flooding, the destruction from a catastrophic fire is complete and may make permanent emigration more likely. Second, catastrophic fires are negatively serially correlated; if a location burns this year, it is less likely to burn in the immediate future due to reduced fuel availability. This is in contrast to flood probability, which is independently distributed across time (Hennighausen and Suter, 2020).

We also contribute to a body of research analyzing the effect of natural disasters on housing markets. McCoy and Walsh (2018), for example, finds that the price of homes in Colorado located inside high-wildfire-risk areas temporarily decreased after the occurrence of a wildfire, suggesting an immediate and short-lived increase in risk perceptions. Our work contributes to this literature by highlighting a distinct feature of catastrophic fires on real estate markets: disaster displacement from reduced housing stock. Our conclusion

[9] https://tinyurl.com/3bs78tef

that the fire altered the risk perceptions of evacuees echoes some of the findings of the aforementioned study of Colorado housing prices (McCoy and Walsh, 2018), as well as that of post-fire housing prices in Los Angeles county (Mueller et al., 2009) and Montana (Venn et al., 2010). Generally speaking, these studies conclude that the occurrence of a nearby wildfire temporarily increases the salience of the risk, leading to a reduction in the willingness-to-pay for properties subject to high wildfire risk.

2. Background: Paradise & the Camp Fire

Paradise is situated in northern California about ninety miles north of Sacramento in the foothills of the Sierra Nevada mountain range. While the origination of its name is debated, legend has it that a man named William Leonard was returning from the valley below after making a lumber delivery on a hot day. He sat in the shade of a large Ponderosa Pine tree and exclaimed to his crew, "boys, this is Paradise".

Drawn by those same large trees, in addition to panoramic views of the central California Valley and relatively cheap real estate prices, the population of Paradise swelled to 30,000 residents by 2018. Paradise is surrounded be dense forest, while also being in close proximity to other population centers. The town of Chico (2018 population 90,000) sits about ten miles to the west at the edge of the Sacramento Valley. Oroville (2018 population 20,000) is seventeen miles to the south. Many other smaller towns are scattered throughout the area. Butte County, home to Chico, Paradise, and Oroville, is home to roughly 220,000 people.

The Camp Fire ignited the morning of November 8th 2018, approximately ten miles northeast of the city of Paradise. While the official cause of the Camp Fire is a malfunctioning PG&E transmission tower, conditions for the fire to form were fueled by years-long drought, misguided fire-management policy, and dry Diablo winds with gusts topping 70 mph.[10] The fire grew in intensity and size quickly and surrounded the town of Paradise and neighboring communities with little warning. Within hours, the Camp Fire had destroyed 90 percent of the housing stock in the area, immediately displacing more than 50,000 people. While Paradise incurred the brunt of the destruction, it was not the only town directly impacted by the fire. Parts of Magalia, Concow, Centerville, Pulga, Butte Creek Canyon, Berry Creek, and Yankee Hill also burned and some experienced fatalities.

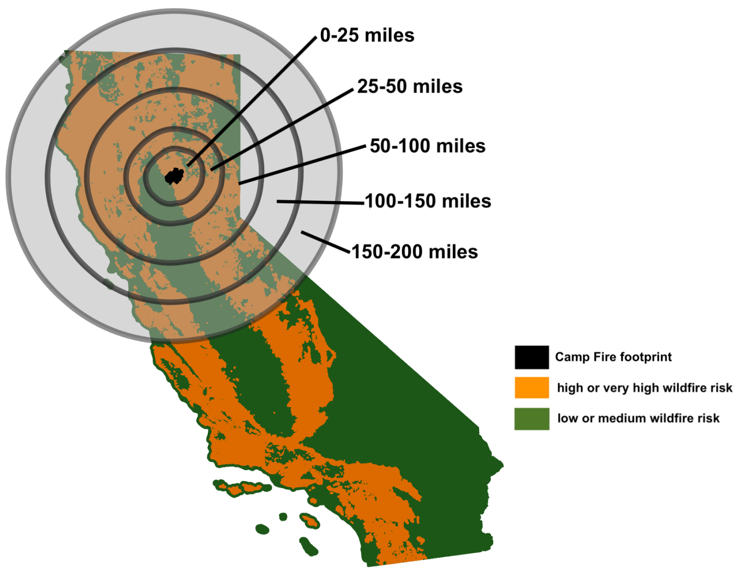
The Camp Fire is the most destructive and deadliest wildfire in California history, causing 85 fatalities and the destruction of over 19,000 buildings. It was also the costliest disaster

[10] https://www.buttecounty.net/Portals/30/CFReport/PGE-THE-CAMP-FIRE-PUBLIC-REPORT.pdf

in the world for insurers in 2018, with losses totaling $16.5 billion dollars.[11]

Figure 1 gives the relative location of the Camp Fire, with the fire's footprint overlaid on a map of California. Spatial information on the Camp Fire burn perimeter (footprint) is provided by the California Department of Forestry and Fire Protection (CAL FIRE).[12] Mutually exclusive spatial bands around the Camp Fire—which are used in our analysis—are also provided in the figure.

Figure 1: Study area & distance bins



Note: The area inside the first distance bin marks the footprint of the Camp Fire. Wildfire risk zones were generated using CAL FIRE's Fire Hazard Severity Zone data. For the analysis, bins continue in 50 mile increments until 500 miles from the Camp Fire.

We expect the Camp Fire to have had immediate effects on nearby housing prices as people reasonably started searching for alternative housing fairly quickly. While some evacuees would have faced liquidity constraints that may have otherwise made securing alternative housing difficult, many insurance companies made at least partial payments within a matter of days following the fire.[13] In fact, in many cases, insurance companies were able to assess client damages before clients could do so through the use of high-resolution aerial imagery made available by the National Insurance Crime Bureau.[14]

[11] `https://www.munichre.com/topics-online/en/climate-change-and-natural-disasters/natural-disasters/the-natural-disasters-of-2018-in-figures.html/`

[12] https://osfm.fire.ca.gov/divisions/community-wildfire-preparedness-and-mitigation/wildfire-preparedness/fire-hazard-severity-zones/fire-hazard-severity-zones-map/

[13] Based on anecdotal conversations with evacuees in the days following the Camp Fire.

[14] https://www.redding.com/story/news/2018/11/12/woosley-fire-update-homeowners-uncertainty-california-fires/1981226002/

3. Data

3.1 California Real Estate Transactions & Property Characteristics

Property transaction data come from Zillow's Transaction and Assessment Database (ZTRAX), which contains records on property characteristics and transactions. Our sample is composed of arms-length transactions of single-family residences located within California and 500 miles of the Camp Fire boundary.[15] Our sample includes transactions occurring between 2010 and 2019.

The ZTRAX data describe the sale date of each transaction and location (physical address in addition to latitude and longitude) of each property. The sale date corresponds to when escrow closed. In practice, there is typically a one month lag between when a buyer and seller agree upon a price, and when the sale is recorded. We also observe some key home characteristics including year built, structure size, lot size, number of bedrooms and number of bathrooms. To observe location of a property in a wildfire-risk zone, we link properties' latitude-longitude to CAL FIRE's Fire Hazard Severity Map.[16]

Transactions with prices less than the first percentile or greater than the 99th percentile of all prices within a given year and distance bin, properties with square footage less than the first percentile or greater than the 99th percentile, properties with lot sizes less than the first percentile or greater than the 99th percentile and properties built in 2018 or later were omitted from the sample.[17] Following guidance from Nolte et al. (2023), we also dropped properties that had multiple recorded transactions on a single day, properties that transacted more than five times between 2010 and 2019 as well as properties that transacted twice within the same calendar year for the same price. The final sample spans ten years and 41 California counties. Summary statistics for the entire sample are presented in Table A2.[18] The average sale price in the final analysis sample is $449,948. The majority (89%) of homes are in low or moderate wildfire-risk zones.

[15] Single-family homes are those with *RR101* as their land use code, properties with less than two units and properties fewer than two buildings.

[16] https://osfm.fire.ca.gov/what-we-do/community-wildfire-preparedness-and-mitigation/fire-hazard-severity-zones

[17] Our results are also robust to including the omitted properties, as shown in Table A1.

[18] Summary statistics by bin are presented in Table A3.

3.2 Wildfire-Risk Zones

Wildfire-risk zone information comes from the California Department of Forestry and Fire Protection (CAL FIRE).[19] CAL FIRE identifies Fire Hazard Severity Zones (FHSZ) — hereforth called wildfire-risk zones — based on a number of factors that influence fire likelihood and fire behavior. These factors include existing and potential fuel (vegetation), terrain, typical weather for the area and fire history. Nearly all of the housing stock in the Camp Fire footprint was in a high or very high wildfire-risk zone. Outside the Camp Fire footprint, and within 500 miles of the Camp Fire, 11 percent of the properties in our sample are located in a high or very high wildfire-risk zone, and 89 percent of properties are located in a low or medium wildfire-risk zone. Figure 1 shows the locations of the low or medium risk zones and the high or very high risk zones. Wildfire-risk zones are coarsely defined and based on aggregate geographic features of the landscape. This is convenient for our purposes because risk zones are largely exogenous to individual efforts to reduce fire risk (such as clearing vegetation away from homes) which could be correlated with other determinants of home price.

4. Identification Strategy

We identify the effect of the Camp Fire on regional housing markets using a series of difference-in-differences estimation equations. In all specifications, a home's distance to the footprint of the fire plays a key role. We assign each home to a distance bin, or "donut", based on its euclidean distance from the boundary of the Camp Fire. These distance bins are depicted in Figure 1.

Homes located between 450 and 500 miles from the fire's footprint serve as comparison units. This choice was guided by United States Postal Service change-of-address data, which shows that the vast majority of fire victims re-located to a property within 150 miles of the fire's boundary (Figure 4). By estimating negligent effects in bins between 150 and 450 miles of the fire, we are confident our control units do not receive treatment and that the SUTVA conditions are satisfied.[20]

Our main specification aims to capture the very short-run (up to 10 weeks and 10 months following the fire) impacts of the Camp Fire on regional housing prices. Anecdotal evidence shows that housing in Butte County may have been constrained following the fire, as 6.5% of

[19] https://osfm.fire.ca.gov/divisions/community-wildfire-preparedness-and-mitigation/wildfire-preparedness/fire-hazard-severity-zones/fire-hazard-severity-zones-map/

[20] Table A4 demonstrates that our conclusions are robust to the inclusion of properties beyond 500 miles in the control group.

the county's housing stock was destroyed.[21] Hypothetically this would increase the demand for housing in other areas as evacuees searched for a place to live, leading to an increase in house prices in areas not directly affected by the fire. For our main analysis, we restrict home sales to those that occurred between September 27 and November 7 (six weeks before the fire) and December 6 to January 17 (the six weeks following the one-month anniversary of the fire). We do not include the four weeks of transactions after the fire in our baseline specification because of concerns surrounding escrow periods.

4.1 Price seasonality specific to distance bins

One, seemingly straight-forward approach to estimating the effect of the Camp Fire on housing prices, is to implement a simple difference-in-differences estimation around November 8, 2018 (the date of the Camp Fire). This approach, however, produces biased estimates if there are bin-specific seasonal trends in housing prices (i.e. across the September - January period). We empirically test for this by first restricting the transaction data to the September 27 - Nov 7 and December 6 - January 17 period in each year. Note that, here, a "year" refers to the September 27-January 17 period that spans two calendar years. Using all pre-fire years (2010 to 2017) we then estimate the relative effect of being in the "post" period for each bin using the following equation:

$$\ln\left(\text{Price}_{it}\right) = \sum_{b=0}^{11} \gamma_{0,b} D_{bi} + \gamma_1 \text{Post}_t + \sum_{b=0}^{11} \gamma_{2,b} (\text{Post}_t \times D_{bi}) + \text{Year}_y \times \text{County}_i + \lambda \mathbf{X}_i + \epsilon_{it}, \tag{1}$$

where $b(\in 0, 25, 50, 100, 150...450)$ indexes distance bins or "donuts" around the Camp Fire. For example, $b = 0$ indicates a home is zero miles from the perimeter of the fire, i.e., it is within the fire's footprint, $b = 25$ indicates a home is less than 25 miles from the perimeter, but not within it, and so on. The indicator $D_{b,i}$ is unity for homes sold within bin b. The spatial bin 450 - 500 miles from the fire is the reference bin.

Post_t indicates that a transaction occurred between December 6 and January 17 in *any* year. Our coefficients of interest are those on the interaction terms. These coefficients capture normal seasonal price trends specific to each distance bin, independent of property characteristics ($\gamma \mathbf{X}_i$) and year-by-county fixed effects ($\text{Year}_y \times \text{County}_i$). The coefficient on Post_t captures price seasonality for the 450 - 500 mile distance bin, i.e. the reference bin.

[21] https://www.chicoer.com/2018/11/12/butte-county-lacks-housing-capacity-for-those-displaced-by-camp-fire/

Table A5 in the Appendix shows that, in the seven years prior to the fire, bins did indeed experience differential seasonal price trends. In particular, relative to homes in the reference bin, homes in the 50-100 mile bin experienced, on average, a .019 log point increase in housing prices in the post period. Homes in the 150-200 mile bin experienced an average relative decline of 0.04 log points. More problematic is that homes within the footprint of the Camp Fire experienced a 0.214 relative log point decline in home prices in the post period. Such bin-specific seasonal trends in housing prices will bias the estimated effect of the Camp Fire using a simple difference-in-differences estimation strategy, and warrants use of an alternative specification.[22]

4.2 Main specification

We account for bin-specific seasonal trends using a triple difference specification. To do this, we construct three sets of variables indicating i) the spatial bin in which a home is located, ii) the period a home is sold in (pre- or post-November 8), and iii) an indicator for whether the year coincides with the Camp Fire.[23]

Equation (2) formalizes our econometric approach:

$$\begin{aligned}
&\ln\left(\text{Price}_{it}\right) = \\
&\alpha_0 + \alpha_1 \text{Post}_t + \alpha_2 \text{CampFireYear}_y + \sum_{b=0}^{11} \alpha_{3b} D_{bi} + \\
\beta_1 \text{Post}_t \times \text{CampFireYear}_y + \sum_{b=0}^{11} \beta_{2b} (\text{CampFireYear}_y \times D_{bi}) + &\sum_{b=0}^{11} \beta_{3b} (\text{Post}_t \times D_{b,i}) + \\
&\sum_{b=0}^{11} \pi_b (\text{Post}_t \times \text{CampFireYear}_y \times D_{b,i}) + \\
&\text{Year}_y \times \text{County}_i + \gamma \mathbf{X}_i + \\
&\epsilon_{i,t}
\end{aligned} \tag{2}$$

where $b (\in 0, 25, 50, 100, 150, ..., 450)$, again, indexes distance bins around the Camp Fire. The indicator $D_{b,i}$ is unity for homes sold within bin b, and the 450 - 500 mile distance bin

[22]Table A6 provides point estimates from a simple difference-in-difference model, i.e. the sample only includes transactions between September 2018 and January 2018. Compared to the triple difference specification given by Equation 2, the difference-in-difference model underestimates the demand effect inside the Camp Fire footprint, and overestimates the demand effect 50 - 100 miles from the Camp Fire footprint.

[23]Tables A7 and A8 provide a snapshot of the triple difference structure, illustrating sale counts for each "year", distance bin and pre/post period combination.

serves as the reference bin.

Recalling that the Camp Fire occurred on November 8 2018, we restrict home sales to those that occurred between September 27 and November 7 (six weeks before the fire) and December 6 to January 17 (the six weeks following the one-month anniversary of the fire) in each September to January period ("year") from 2010 to 2019. Transactions occurring the four weeks after November 8 are excluded from the analysis to account for what is typically a one month escrow period. We observe nine of these years.

CampFireYear_y is equal to unity for homes sold in the year coinciding with the Camp Fire (September 27 - November 7, 2018 and December 6, 2018 - January 17, 2019) and zero otherwise. Post_t is equal to unity for homes sold between December 6 and January 17 in any year and zero otherwise. The reference period is therefore September27 - November 7 — the six weeks prior to the Camp Fire.[24]

Modeled this way, $\text{Post}_t \times D_{b,i}$ captures the bin-specific effect of a home being sold in the winter rather than fall and Post_t captures seasonal effects in the reference bin (the 450-500 mile bin). CampFireYear_y captures the effect of a home being sold in the 2018/2019 period (year) and D_{bi} captures the effect of a home being located in distance bin b relative to the reference bin. The interaction of Post_t and CampFireYear_y accounts for price seasonality that varies by year and is common to all distance bins. The interaction of CampFireYear_y and D_{bi} accounts for the effect of a home being sold in the 2018/2019 period (year) specific to each distance bin, but common to both the pre- and post-period. Our primary coefficient of interest is on the interaction term $Post_t \times CampFireYear_y \times D_{bi}$, which is the "additional" effect of a sale occurring in the post-period, within a designated distance bin that is unique to the the year of the Camp Fire.

A reasonable concern is that the fire altered the composition of housing being purchased. If evacuees favored higher quality homes after the fire, prices may reflect variation in the quality of housing rather than a pure demand effect that we aim to measure. And in fact, we see some evidence of this. For example, Figures A1 - A4 describe average home characteristics (property price, structure age, structure size, and lot size) by year and distance bin. For homes in the footprint of the fire, and those within 25 miles, we see a clear spike in housing

[24]While other destructive fires did occur in northern California around the timing of the Camp Fire, they arguably did not destruct a sufficient share of homes to cause meaningful bias in our estimates. The Camp Fire is, by far, the most destructive fire in California history with 18,804 structures destroyed. Of the top 10 most destructive wildfires in California, three (other than the Camp Fire) occurred during our 2010-2019 study period: (1) the Tubbs Fire in October 2017 destroyed 5,643 structures, (2) the Woolsey Fire in November 2018 destroyed 1,643 structures and (3) the Carr Fire in July 2018 destroyed 1,614 structures. Table A9 demonstrates that our conclusions are robust to removing properties located in counties affected by the Tubbs, Woolsey and Carr fires (Napa, Sonoma, Lake, Los Angeles, Ventura, Shasta and Trinity Counties) from the analysis.

prices following the fire. However, we also document a clear decrease in structure age and an increase in structure size—both of which should increase sale prices. To address bias resulting from compositional changes, we condition effects on home size, lot size, home age, home age-squared, number of bedrooms and number of bathrooms. Finally, we condition on year-by-county fixed effects to account for annual, county-specific variation in home prices.

5. Results

5.1 Average Treatment Effects

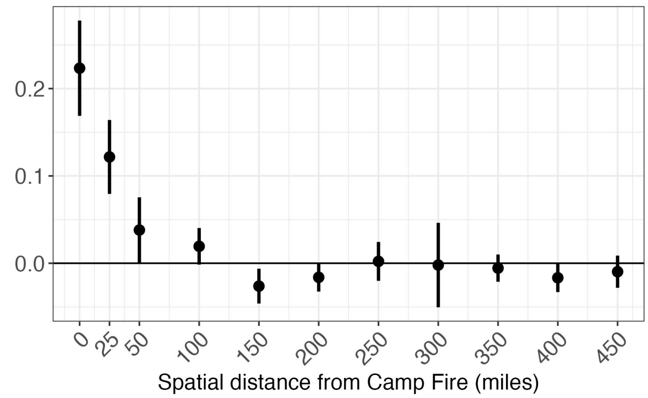
The results from the estimation of the spatial model Equation (2) are provided in panel (a) of Figure 2. Specific point estimates are provided in Table A10. In the four to ten weeks after fire (so, six weeks excluding the four week escrow period), home prices within the footprint increased by 25 percent.[25] To put this result into proper context, the average home price within the fire's footprint prior to the fire was \$303,591. The fire therefore induced a price premium of approximately \$75,000 within its footprint. We document a 13% (p=0.000) increases in home prices within 25 miles (but outside the fire's footprint), which amounts to a $0.13\times\$299,221$ = \$38,899 price premium. Between 25 and 50 miles, the estimated treatment effects falls to 4% (p=0.019), implying a price premium of 0.04×\$309,434=\$12,377.

Having established the spatial dimensions of the average six-week treatment effect of the fire, we turn our attention to dynamic effects. Specifically, we estimate variants of Equation (2) in which we interact distance bins (indicators for being between 0 and 25 miles and between 25 and 100 miles of the Camp Fire) with two-week temporal indicators beginning immediately following the fire (so, here we include the escrow period that was dropped in our spatial model). This allows us to map out the ten-week effect of the fire in two-week intervals. To reveal any bin-specific pre-trends, we also estimate effects up to six weeks prior to the fire (also in two week intervals). Informed by our spatial estimates, the reference group are homes sold between 100 and 500 miles from the fire in the two week period immediately preceding the fire.

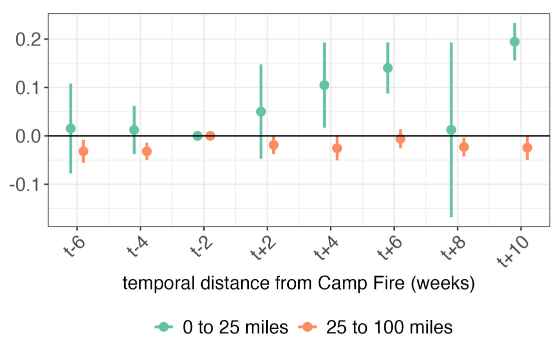
These bi-weekly results are provided in panel (b) of Figure 2. Within 25 miles of the fire, it took up to four weeks for the demand effect to reach statistically significant levels; four weeks after the fire, home prices within 25 miles of the fire had risen 11 percent. Assuming a four week escrow window, these results are consistent with fairly sudden effects on home prices. Among homes further away (between 25 and 100 miles from the fire), we document no meaningful average effects of the fire on home prices in the ten weeks following the fire.

[25] A coefficient estimate of 0.223 implies a $e^{0.22} - 1 = 25$ percent increase in price.

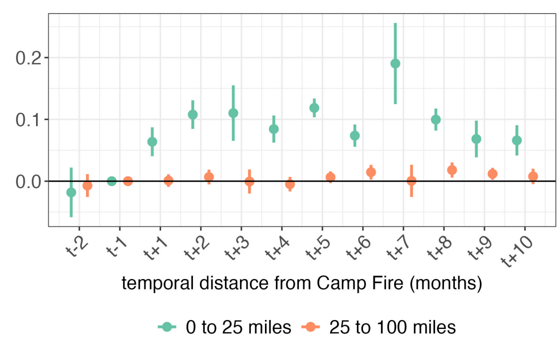
Figure 2: Pooled effects



(a) Pooled



(b) up to 10 weeks post fire



(c) up to 10 months post fire

Note: Points indicate estimates and vertical lines indicate 95 percent confidence intervals. Panel (a) reports one estimate for the 6 weeks after the Camp Fire by distance bin. The comparison group is properties located greater than 450 miles and less than 500 miles from the fire. Panel (b) reports estimates for each two-week period up to 10 weeks after the Camp Fire, comparing properties located within 50 miles of the fire to those 50 - 500 miles from the fire. Panel (c) reports estimates for each month period up to 10 months after the Camp Fire, comparing properties located within 50 miles of the fire to those 50 - 500 miles from the fire.

Specific point estimates are provided in Table A11.

We consider longer-run effects by replacing the bi-weekly indicators in the specification outlined above with monthly indicators. The reference group in this specification are homes sold between 100 and 500 miles away from the fire in the month immediately preceding the Camp Fire. We include the two months prior to the fire to test for pre trends.[26] In the ten months after the fire, treatment effects are persistent among homes within 25 miles of

[26] Our triple-difference specification does not allow for us to test for pre-trends beyond two months because three months prior to the fire coincides with ten months after the fire.

the footprint of the fire (panel (c) of Figure 2). It is interesting to note that these effects are relatively stable; the treatment effect is between 6 and 19 percent across all ten months. We again see minimal average effects on prices of homes further away, at least in the first five months after the fire. We do however document positive effects in the sixth and eighth month following the fire. The average coefficient among these periods is small (the average treatment effect is roughly 1.7%) but statistically significant at traditional levels. Specific point estimates are provided in Table A12. One speculative interpretation is that some of the evacuees of the fire purchased nearby homes relatively quickly. Eventually, others purchased homes further away, but did so perhaps after giving up on finding an affordable property closer to the footprint of the fire.

5.2 Heterogeneous Treatment Effects

Existing literature suggests that natural disasters cause people to update their risk perceptions (McCoy and Walsh, 2018; Mueller et al., 2009; Venn et al., 2010). We explore whether the demand effect was greater for properties with low-fire risk by estimating heterogeneous effects based on fire risk. Specifically, we partition our distance bins from Equation (2) into three mutually-exclusive areas as defined by CAL FIRE: (1) very high (2) high and (2) moderate or low-wildfire risk. See Section 3.2 for information about how risk zones are calculated and defined by CAL FIRE.

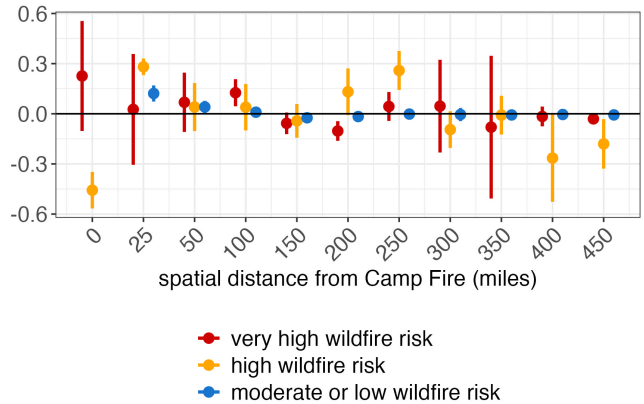
Panel (a) in Figure 3 provides results from estimating Equation 2 for up to 10 weeks post-fire. Panel (b) provides results from estimating Equation 2 for up to 10 months post-fire. Note that all of the properties sold after the fire and within the fire's footprint either have high or very high wildfire risk. Precise coefficient estimates are given in Table A13 for the 10 week estimates and Table A14 for the 10 month estimates.

In both the short- and medium-run analyses, we do not see any consistent heterogeneous patterns emerge from the data.[27] While somewhat surprising, there are a couple potential explanations for this. First, it is possible that the Camp Fire did not alter people's risk preferences. This seems unlikely, however, given the trauma evacuees experienced and the effects on risk perceptions documented in the aforementioned literature. Second, it is possible that preferences for low-fire-risk properties were offset by preferences to live in in rural forested areas, similar to the terrain within the footprint of the Camp Fire. Third, housing density across high and low-risk areas is not symmetrical. Indeed, the vast majority of

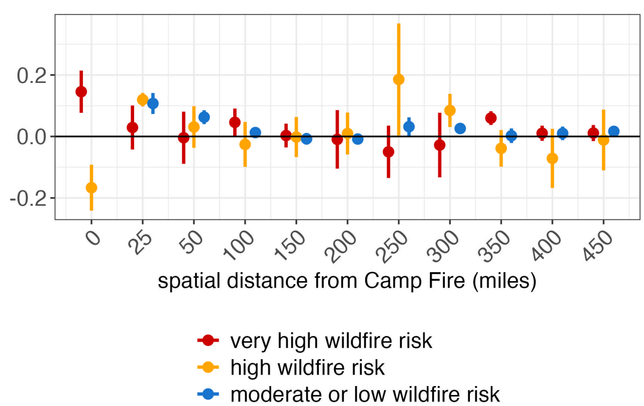
[27] We do see a statistically significant pattern within the Camp Fire boundary. However, given the small number of transactions that occurred within each risk zone inside the Camp Fire boundary in the 2018-2019 period, we are hesitant to give a strong interpretation to these results. See Table A2 in the Appendix for summary statistics of the properties that transacted in the 2018-2019 period inside the Camp Fire boundary.

housing surrounding the Camp Fire is located in the (low-fire risk) Sacramento Valley. This makes it difficult to identify people's relative preferences based on variation on home prices, and motivates an analysis of actual migration behavior which is carried out in the next section.

Figure 3: Effects by risk group



(a) up to 10 weeks post-fire



(b) up to 10 months post-fire

Note: Points indicate estimates and vertical lines indicate 95 percent confidence intervals. Panel (a) reports one estimate for each risk group and distance band for up to 10 weeks after the Camp Fire. Panel (b) reports one estimate for each risk group and distance band for up to 10 months after the Camp Fire. In both analyses, the comparison group is all properties located 450 to 500 miles from the fire.

5.3 Migration

We supplement our analysis of real-estate prices with one of the migration behavior of Camp Fire evacuees. Doing so paints a more complete picture of the migration decisions of the displaced population and lends credibility to our assumption that the 450-500 mile buffer serves an appropriate counterfactual unit (i.e., that it was not effectively treated).

Variation in housing prices reflects migration decisions, but are also influenced by the distribution of housing around the Camp Fire. Supposing a fixed housing supply (a reasonable short run assumption), a percent change in home price is a linear function of the percent change in demand for housing:

$$\%\Delta Price = \frac{\%\Delta Demand}{\epsilon_D}, \tag{3}$$

where ϵ_D is the price elasticity of demand for housing. This implies that larger markets (like Sacramento, which is disproportionately low-fire risk), are able to absorb more evacuees without experiencing a meaningful appreciation in home values. Observing actual migration behavior avoids this thorny issue, and allows us to estimate the effect of distance—and a host of other factors—on the relocation decisions of evacuees.

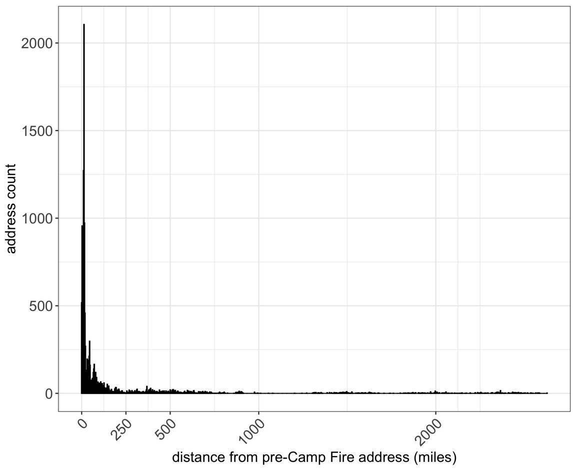
Migration data were graciously shared with us by Peter Hansen at California State University, Chico, who collected the data from the United States Post Service Change of Address file for Butte County. Data were collected in several waves: once in April of 2019 (roughly five months after the Camp Fire), in September of 2019 (roughly ten months after the Camp Fire) and in September 2021 (nearly three years after the Camp Fire). Residents of Butte county who moved from a location outside of the footprint of the fire were dropped from the dataset, and only permanent address changes are included. Unfortunately, the data do not reflect the universe of people displaced by the Camp Fire. By April 2019, only a third (roughly 11,000 people) of the displaced population had registered a permanent change of address. By September of 2019, this number had increased to 35%. The data also do not reflect a random sample. For example, by September of 2019, 45% of homeowners had submitted a permanent change of address, whereas just 17% of renters had done so.[28] Our results should therefore be viewed with some caution as our sample is non-random.

Figure 4 describe the distribution of migration following the fire. Panel (a) provides a histogram of the number of migrants according to distance from the fire's footprint. Panel (b) restricts the observations to migrants that moved within 500 miles of the Camp Fire's boundary, and panel (c) provides a geographic description of migrants' relocation decisions within California. As can be seen, the large majority of evacuees remained within 150 miles of the footprint of the fire. It's also worth mentioning that a number of evacuees were displaced out of the state of California, but are not included in our analysis. For example, whereas 11,986 evacuees in our sample remained in California, 235 moved to Arizona, 206

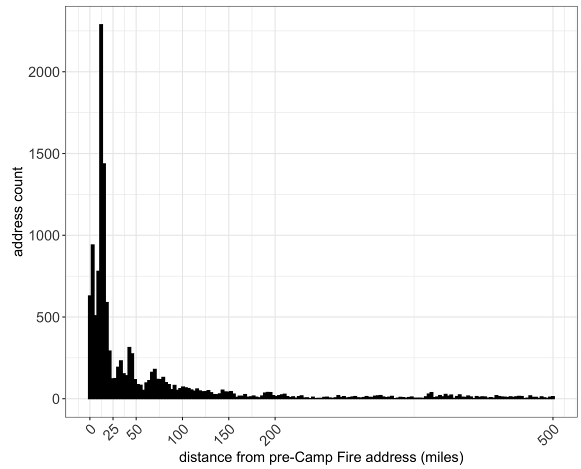
[28]A more complete description of how these data were generated is given in Chase and Hansen (2021).

to Idaho, 243 to Nevada, 540 to Oregon, 6 to Alaska, and 17 to Wyoming.[29]

Figure 4: Histogram of Migratory Behavior



(a) All Addresses



(b) Addresses within 500 miles

(c) Destination address within California

Note: Panels (a) and (b) provide the spatial distribution of the distance that people moved from the footprint of the Camp Fire, comparing pre-fire addresses to post-fire addresses. Data were originally collected from the United States Postal Service Change-of-Address database. Panel (c) graphically describes the distribution of migration within the sate of California. Zip codes that did not house at least one evacuee are indicated in black.

Using an Ordinary Least Squares regression, we estimate the relationship between the (log) number of migrants that relocate to a specific census tract and a rich set of census tract characteristics. In doing so, we are able to disentangle the role of distance from, for example,

[29]See Table A17 for the number of evacuees who moved to each state.

the cost of housing, employment opportunities, and the risk of wildfire in determining where people chose to relocate.

Using the USPS change-of-address information, we first count the number of migrants that moved to each census tract within California from the Camp Fire footprint, dropping any census tracts that didn't see migration.[30,31] We normalize these data by taking logs. Then, for each destination census tract, we calculate the average distance (in miles) between the migrants' origin latitude-longitude and their destination latitude-longitude. We call this "distance to origin". To understand the socio-economic characteristics of destination census tracts, we rely on information from the 2017 American Community Survey (1-year). We record information about census tract population density, median income, median house value, and the local unemployment rate. Finally, we collect information about destination census tract wildfire risk in two ways. First, combining CAL FIRE's wildfire-risk zone information with property location information from ZTRAX, we calculate the proportion of "wildfire-risky" properties (high or very high wildfire risk) within each census tract. This yields an estimate of the percent of homes within a tract exposed to major wildfire risk. Second, we collect census tract-specific wildfire risk information from FEMA's National Risk Index.[32]. Specifically, we collect information about each census tract's expected annual frequency of wildfire (here called "annualized frequency of wildfire"), as well as each tract's relative wildfire risk rating (referred to as "WRR"), which is a combination of wildfire hazard and potential losses in each census tract. Summary statistics are provided in Table A15.

We estimate the relationship between the various census tract characteristics discussed above and the number of (log) migrants that a census tract receives using the following estimation equation:

$$\ln(\text{Count migrated}_i) = \alpha_0 + \gamma' X_i + \epsilon_i, \tag{4}$$

where the outcome variable is the log number of migrants that re-located to census tract i, X_i is a matrix of location characteristics(distance to origin, population density, median income, median house value, unemployment rate, and wildfire risk) belonging to census tract i, α_0 is the constant term, and ϵ_i is the error term. We estimate Equation 4 using robust standard errors.

The results are provided in Table 1. For added robustness and detail, we estimate six variants of Equation 4. Columns 1-5 include log distance as a covariate. Column 6 reports the results controlling for distance using a series of distance bins.

[30] 84% of evacuees stayed in California. See Table A17 for details.

[31] Where possible, we rely on addresses given by the September 2019 data collection. Where addresses aren't available in September 2019, we rely on data from the September 2021 collection.

[32] https://hazards.fema.gov/nri/https://hazards.fema.gov/nri/

Starting with column 1, we see that evacuees had a clear preference to remain near the fire's footprint. The coefficient on ln(Dist to Origin) is 0.947, implying that a 1% increase in distance is associated with a 0.947 log point (1.58%) reduction in the number of migrants who move there. The effect of distance is fairly stable across model specifications 1-5.

Across models 1-5, we also find that census tracts with higher median household income or unemployment received fewer migrants. Specifically, a 1% increase in income is associated with roughly a 0.45% decline in migration, and a 1% increase in the unemployment rate is associated with roughly a 0.16% decline in migration. Note that, after dropping median income as a control (column 2), the effect of median home price becomes negative and statistically significant due to the fact that income and home price are positively correlated.

Somewhat surprisingly, increasing the share of properties that are exposed to high or very high fire risk (% Risky (CAL FIRE)), is associated with more migrants. These results are corroborated in columns 4 and 5 which include controls for FEMA assessed measures of fire risk; census tracts with more fire risk appear to have been preferred to those with less risk.[33] This result is especially surprising because the vast majority of evacuees moved to low-fire-risk properties (see Table A16). However, these two results are not altogether inconsistent. In fact, considered jointly, they suggest that people had a preference to live in census tracts that had some fire risk (e.g., tracts near the perimeter of the Camp Fire, that had some vegetation, and were more likely to be rural), but preferred their new home not be in the high-risk part of that census tract.

Finally, in column 6, we see that the relationship between distance and migration is not linear. Relative to census tracts in excess of 500 miles from the fire's footprint, those within 0-25, 25-50, 50-100, and 100-150 miles of the fire received 4.2, 2.1, 0.73, and 0.28 more (log point) migrants. Conditional on these distance bins, we continue to see that census tracts with lower unemployment rates received more migrants, as did tracts at more risk of fire damage.

6. Robustness

We carry out a series of robustness checks to gauge the sensitivity of our results to various modeling assumptions and decisions. We also explore a broader set of outcomes to paint a clearer picture of the migratory effects of the Camp Fire.

While we control for home attributes—structure size, age, and lot size—one may still be

[33] While somewhat surprising, this result is consistent with existing literature. For example, (Eyer et al., 2018) finds that evacuees of hurricane Katrina were more likely to move to nearby counties which were more populous, had low unemployment rates, higher income, and more prone to natural disaster.

Table 1: Relocation & Destination Characteristics

	Dependent variable: ln(Count Migrants)					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Dist to Origin)	−0.947***	−0.950***	−0.932***	−0.979***	−0.925***	
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	
0 - 25 mile bin						4.218***
						(0.174)
25 - 50 mile bin						2.096***
						(0.169)
50 - 100 mile bin						0.728***
						(0.140)
100 - 150 mile bin						0.285**
						(0.142)
150 - 200 mile bin						0.203
						(0.153)
200 - 250 mile bin						0.271
						(0.185)
250 - 300 mile bin						0.141
						(0.325)
300 - 350 mile bin						0.167
						(0.220)
350 - 400 mile bin						−0.212
						(0.349)
400 - 450 mile bin						0.095
						(0.187)
450 - 500 mile bin						−0.006
						(0.164)
ln(SFH)	0.022	−0.009	0.012	0.008	0.022	0.021
	(0.038)	(0.037)	(0.038)	(0.038)	(0.038)	(0.032)
ln(Pop Dens)	0.090	0.074	0.156*	0.165*	0.125	0.064
	(0.087)	(0.088)	(0.089)	(0.086)	(0.087)	(0.074)
ln(Med Income)	−0.373***		−0.372***	−0.439***	−0.415***	−0.156
	(0.129)		(0.128)	(0.126)	(0.127)	(0.108)
ln(Med Value)	−0.009	−0.195***	−0.009	0.068	0.026	−0.058
	(0.090)	(0.063)	(0.089)	(0.089)	(0.088)	(0.077)
Unemp. Rate	−0.015*	−0.008	−0.016*	−0.016*	−0.015*	−0.017**
	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)	(0.007)
% "risky" (Cal Fire)			0.328***			
			(0.105)			
Fire Freq.				35.742***		
				(5.911)		
No Rating					0.027	−0.133*
					(0.093)	(0.079)
WRR R. Low Risk					0.223*	0.061
					(0.114)	(0.096)
WRR R. Mod. Risk					0.273**	0.198**
					(0.112)	(0.095)
WRR R. High Risk					0.355***	0.192**
					(0.108)	(0.091)
WRR V. High Risk					0.599***	0.340***
					(0.136)	(0.116)
Constant	8.978***	7.525***	8.367***	8.268***	8.430***	2.215**
	(1.115)	(1.000)	(1.126)	(1.098)	(1.114)	(1.022)
Observations	840	840	840	840	840	840
R^2	0.519	0.514	0.524	0.539	0.539	0.677

Note: ln(Dist to Origin) is the log of the distance from an evacuees updated permanent address and their original one within the Camp Fire. ln(Pop Dens), ln(Med Income), ln(Med Price), and ln(SFH) are the log of population density, median income, median home value, and the count of single family homes of destination census tracts. % Risky is the percent of homes within a census tract that are in high or very high risk zones. Fire Frequency is FEMA's annualized predicted frequency of wildfire. R. (relatively) Low, R. Mod. (moderate), R. High and V High (very high) risk correspond to FEMA's wildfire risk rating which incorporate information regarding both hazard and expected damages. The omitted category is Very Low Risk. No Rating implies no risk of wildfire. *p<0.1; **p<0.05; ***p<0.01

concerned that our estimated demand effects are contaminated by unobserved compositional changes in the housing stock being purchased. For example, if fire evacuees purchased homes that are relatively expensive for some unobserved reason (such as view sheds, lot size, or proximity to particular amenities), our estimates of the pure demand effect would be upward biased.

To further address this concern, we estimate the impact of the Camp Fire on sales volume. To do so, we first count the number of home sales within each census tract by distance bin, year-period, pre- and post-November 8th. The sales count variable — transformed with hyperbolic sine — serves as the dependent variable in the estimation.[34] The explanatory variables are identical to that of Equation (2), meaning we include indicator variables and their interactions for each distance bin, the post-November 8th variable and the 2018 - 2019 treatment-year period. Contrary to Equation (2), we spatially aggregate to the 0 - 25 mile bin (including transactions inside the Camp Fire footprint) and the 25 - 100 mile bin, and temporally aggregate to three-month quarters to assure sufficient sample size in each spatial-temporal bin. The estimation also includes year, quarter, and tract-distance bin fixed effects, the latter of which ensures that estimation of the sales volume effect is derived from within-tract-distance bin variation in sales count.

Graphical results are provided in Figure A5 and precise coefficient estimates in Table A18. The Camp Fire increased the volume of home sales within 25 miles of the fire. In the first quarter, sales volume increased by nearly 70 percent. In the second quarter, the effect is halved, though still statistically significant at the one-percent level. For properties 25 to 100 miles from the Camp Fire, we do not observe a change in sales volume in the first two quarters, though we do observe a relatively smaller bump in sales in the third quarter. These findings reinforce the idea that the estimated effects on home prices reflect a demand shock from an increase in the number of people looking to purchase homes, rather than merely a compositional change in the characteristics of the housing stock purchased.

Recall that our primary analysis leverages homes sold between 450 and 500 miles away from the Camp Fire perimeter as the reference group. This choice is admittedly arbitrary. While our results suggest this is a reasonable reference bin (we document insignificant effects of the fire beyond 100 miles of the Camp Fire), we use a series of alternative reference bins and re-estimate our baseline results for added robustness. Not surprisingly, our baseline estimates are not sensitive to the choice of reference bin. For brevity, these results are available upon request.

[34] We use hyperbolic sine transformation on the sales count variable to account for groupings with zero sales in the balanced panel.

7. Discussion & Conclusion

Wildfires are becoming more prevalent and destructive due to a combination of natural and human factors, including climate change, population growth in the wildland-urban interface, and historical fire suppression policies. California has been uniquely impacted by this transition. Compared to other states, California has the highest number of wildfires and the most significant damages due to the state's large size, diverse topography, and climate conditions that contribute to extreme fire behavior. Of the 20 most destructive fires in California's history, thirteen have occurred in the last five years.[35]

This study leverages the most destructive fire in California history—the Camp Fire—to better understand the spillover effects of disaster-induced migration on nearby housing markets. Occurring on November 8, 2018, the Camp Fire destroyed the town of Paradise in northern California, killing 85 people, destroying thousands of homes, and displacing roughly 50,000 people. We find that the fire had large effects on nearby real estate markets, causing prices to rise within 100 miles of the fire's footprint. The "demand effect" on housing prices was greatest near the perimeter of the fire; within 25 miles, prices rose 25% in six weeks following the fire. Prices remained elevated for at least ten months after the fire. We observe similar price effects in high and low fire-risk zones, though, the large majority of evacuees moved to low-fire-risk properties.

Our results highlight a less salient feature of catastrophic fires and climate-driven natural disasters more generally: resulting general equilibrium effects are hard to hide from. In the case of the Camp Fire, even people living in low fire-risk areas outside of the fire's footprint were indirectly affected as thousands of evacuees moved into their communities.

In addition to causing crime, homelessness, and traffic congestion in neighboring communities (Marandi and Main, 2021), our results suggest that the fire also caused a large transfer of wealth from fire evacuees to homeowners in surrounding areas. In fact, in the ten months after the fire, we estimate that 71 million dollars was transferred to homeowners within 50 miles of the Camp Fire—solely as a result of rising home prices due to the "demand effect" of the Camp Fire.[36]

While rising housing prices provides some benefits to homeowners in host communities,

[35]https://www.fire.ca.gov/media/t1rdhizr/top20$_d$*estruction.pdf*

[36]This number should not be confused with the total value of homes purchased by fire evacuees. Rather, it is only the estimated additional money spent on housing that resulting from rising prices. To calculate this number, we first estimated the average effect of the fire on housing prices in the ten months after the fire for $b = 0$, $b = 25$, and $b = 50$ (referring to Equation (2)). These numbers are 21.3 percent, 7.5 percent, and 3.4 percent, respectively. We then multiply these percent changes by the average sale price within each distance bin in the six weeks prior to the fire ($229,722, $307,909, and $299,704, respectively). Finally, we multiply the resulting values within each distance bin by the respective number of home sales in the ten months following the fire (which were 166, 1,830, and 1,988, respectively).

it also creates some challenges. For example, following the Camp Fire, rental rates soared in the neighboring town of Chico, contributing to homelessness and labor shortages (Marandi and Main, 2021). Policy makers interested in dampening rising real estate prices have levers to pull. For example, taxes and restrictions on crowd-sourced rental housing via Airbnb and Vrbo could be temporarily removed or relaxed. Cities could also create policies that encourage temporary, unconventional housing arrangements such as tent and trailer camping on private property.[37] While these unconventional housing arrangements will undoubtedly create pressures on public infrastructure such as sewer utilities and public safety, they could be taxed to accommodate for the additional provision of public goods. In the longer run, the building and permitting process for new housing units could be streamlined. For example, cities could have pre-approved freely available plans for Accessory Dwelling Units (ADUs) available to the public (such is the case in Chico, California).

As with any case study, the external validity of our results should be considered. Because each fire is unique, and will occur within a distinct housing market, we caution against using our estimates to forecast the effects of future catastrophic fires which will depend upon the density and distribution of housing specific to those areas.

[37] Similar to Airbnb and Vrbo, https://www.boondockerswelcome.com is an online property-sharing service where property owners list their driveways or other parts of their property as places where others can boondock, usually for a fee. Currently most cities and counties in California make it illegal to camp on private property.

References

Chase, J. and Hansen, P. (2021). Displacement after the camp fire: Where are the most vulnerable? *Society & Natural Resources*, 34(12):1566–1583.

Clement, V., Rigaud, K. K., de Sherbinin, A., Jones, B., Adamo, S., Schewe, J., Sadiq, N., and Shabahat, E. (2021). *Groundswell Part 2: Acting on Internal Climate Migration.* World Bank.

Daepp, M. et al. (2020). Disaster-induced displacement: Effects on destination housing prices.

Donovan, G. H., Champ, P. A., and Butry, D. T. (2007). Wildfire risk and housing prices: a case study from colorado springs. *Land Economics*, 83(2):217–233.

Drabo, A. and Mbaye, L. M. (2015). Natural disasters, migration and education: an empirical analysis in developing countries. *Environment and Development Economics*, 20(6):767–796.

Eyer, J., Dinterman, R., Miller, N., and Rose, A. (2018). The effect of disasters on migration destinations: evidence from hurricane katrina. *Economics of disasters and climate change*, 2:91–106.

Garnache, C. (2020). Does the salience of risk affect large, risky asset prices? *Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract*$_i$*d* = 3398404.

Gray, C. L. and Mueller, V. (2012). Natural disasters and population mobility in bangladesh. *Proceedings of the National Academy of Sciences*, 109(16):6000–6005.

Hennighausen, H. and Suter, J. F. (2020). Flood risk perception in the housing market and the impact of a major flood event. *Land Economics*, 96(3):366–383.

Holmes, T. P., González-Cabán, A., Loomis, J., and Sánchez, J. (2012). The effects of personal experience on choice-based preferences for wildfire protection programs. *International journal of wildland fire*, 22(2):234–245.

IDMC (2020). Global interanl displacement database. https://www.internal-displacement.org/database/displacement-data. Accessed May 9, 2021.

Ikeme, J. (2003). Climate change daaptational deficiencies in developing countries: the case of sub-saharan africa. *Mitigation and Adaptation Strategies for Global Change*, 8(1):29–52.

IPCC (2014). *Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.* [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland.

Katz, L. (2021). Nearly half of americans who plan to move say natural disasters, extreme temperatures factored into their decision to relocate: Survey. https://www.redfin.com/news/climate-change-migration-survey/.

Keeley, J. E. and Syphard, A. D. (2021). Large california wildfires: 2020 fires in historical context. *Fire Ecology*, 17(22).

Kim, Y.-I. and Lee, J. (2014). The long-run impact of a traumatic experience on risk aversion. *Journal of Economic Behavior and Organizaion*, 108:174–186.

Kousky, C. (2010). Learning from extreme events: Risk perceptions after the flood. *Land Economics*, 86(3):395–422.

Loomis, J. (2004). Do nearby forest fires cause a reduction in residential property values? *Journal of Forest Economics*, 10(3):149–157.

Marandi, A. and Main, K. L. (2021). Vulnerable city, recipient city, or climate destination? towards a typology of domestic climate migration impacts in us cities. *Journal of environmental studies and sciences*, 11:465–480.

Mason, C. F. (2017). Climate change and migration: A dynamic model. *CESifo Economic Studies*, 63(4):421–444.

McCoy, S. J. and Walsh, R. P. (2018). Wildfire risk, salience housing demand. *Journal of Environmental Economics and Management*, 91:203–228.

McIntosh, M. F. (2008). Measuring the labor market impacts of hurricane katrina migration: Evidence from houston, texas. *American Economic Review*, 98(2):54–57.

Millock, K. (2015). Migration and environment. *Annu. Rev. Resour. Econ.*, 7(1):35–60.

Mueller, J., Loomis, J., and Gonzalez-Caban, A. (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. *The Journal of Real Estate Finance and Economics*, 38:155–172.

Nolte, C., Boyle, K. J., Chaudhry, A., Clapp, C., Guignet, D., Hennighausen, H., Kushner, I., Liao, Y., Mamun, S., Pollack, A., et al. (2023). Data practices for studying the impacts of environmental amenities and hazards with nationwide property data. *Land Economics*.

Radeloff, V. C., Helmers, D. P., Kramers, H. A., Mockrin, M. H., Alexandre, P. M., Bar-Massada, A., Butsic, V., Hawbaker, T. J., Martinuzzi, S., Syphard, A. D., and Stewart, S. I. (2018). Rapid growth of the us wildland-urban interface raises wildfire risk. *Proceedings of the National Academy of Sciences*, 115(13):3314–3319.

Sokona, Y. and Denton, F. (2001). Climate change impacts: can africa cope with the challenges? *Climate Policy*, 1(1):117–123.

Venn, T., Stetler, K. M., and Calkin, D. E. (2010). The effects of wildfire and environmental amenities on property values in northwest montana, usa. *Ecological Economics*, 69(11):2233–2243.

Winkler, R. L. and Rouleau, M. D. (2020). Amenities or disamenities? estimating the impacts of extreme heat and wildfire on domestic us migration. *Population and Environment*, 42:622–648.

8. Appendix

Appendix Tables

Table A1: Robustness with omitted transactions

	Dependent variable:			
	log(price):			
inside campfire x post x campfire year	0.223***	0.200***	0.161***	0.113***
	(0.028)	(0.030)	(0.033)	(0.032)
0 - 25 mile bin x post x campfire year	0.122***	0.131***	0.137***	0.140***
	(0.022)	(0.021)	(0.020)	(0.021)
25 - 50 mile bin x post x campfire year	0.038*	0.085**	0.080**	0.078***
	(0.019)	(0.032)	(0.032)	(0.028)
50 - 100 mile bin x post x campfire year	0.019*	0.029*	0.022	0.024
	(0.011)	(0.016)	(0.015)	(0.015)
100 - 150 mile bin x post x campfire year	−0.026**	−0.030**	−0.028**	−0.029**
	(0.010)	(0.014)	(0.013)	(0.013)
150 - 200 mile bin x post x campfire year	−0.016*	−0.023*	−0.023*	−0.027*
	(0.008)	(0.012)	(0.013)	(0.016)
200 - 250 mile bin x post x campfire year	0.002	0.017	0.009	0.007
	(0.011)	(0.018)	(0.018)	(0.016)
250 - 300 mile bin x post x campfire year	−0.002	0.008	0.012	0.018
	(0.025)	(0.029)	(0.029)	(0.027)
300 - 350 mile bin x post x campfire year	−0.006	0.022***	0.024***	0.020***
	(0.008)	(0.008)	(0.008)	(0.007)
350 - 400 mile bin x post x campfire year	−0.017*	−0.004	−0.011	−0.012
	(0.008)	(0.023)	(0.020)	(0.020)
400 - 450 mile bin x post x campfire year	−0.010	−0.012	−0.018	−0.020*
	(0.009)	(0.010)	(0.011)	(0.010)
price restriction	Yes	No	No	No
square footage restriction	Yes	Yes	No	No
acreage restriction	Yes	Yes	Yes	No
Observations	477,785	487,463	497,325	507,285
R^2	0.742	0.686	0.698	0.694
Adjusted R^2	0.741	0.686	0.697	0.694

Note: Results of the estimation of equation 2. Price restriction refers to the omission of transactions with prices less than the first percentile or greater than the 99th percentile of all prices within a given year and distance bin. Square footage restriction refers to the omission of properties with less than the first percentile of square footage. Acreage restriction refers to the omission of properties with a lot size greater than one acre. Treatment effects are conditioned on home age, age squared, log square feet, log acreage, number of bedrooms, number of bathrooms and county-by-year fixed effects. The control group is transactions occurring on properties located 450-500 miles from the Camp Fire. For brevity, only the coefficients on the triple interactions are reported. *p<0.1; **p<0.05; ***p<0.01.

Table A2: Summary Statistics

Statistic	Mean	St. Dev.	Min	Max
Sales price	\$449,948	\$376,078	\$18,500	\$4,496,000
Property inside Camp Fire footprint	0.0003	0.02	0	1
Property inside 0 - 25 mile distance bin	0.008	0.09	0	1
Property inside 25 - 50 mile distance bin	0.02	0.12	0	1
Property inside 50 - 100 mile distance bin	0.15	0.36	0	1
Property inside 100 - 150 mile distance bin	0.36	0.48	0	1
Property inside 150 - 200 mile distance bin	0.07	0.26	0	1
Property inside 200 - 250 mile distance bin	0.05	0.22	0	1
Property inside 250 - 300 mile distance bin	0.02	0.15	0	1
Property inside 300 - 350 mile distance bin	0.04	0.20	0	1
Property inside 350 - 400 mile distance bin	0.04	0.19	0	1
Property inside 400 - 450 mile distance bin	0.26	0.44	0	1
Property inside 450 - 500 mile distance bin	0.15	0.36	0	1
Sale occurred after November 8 in any year	0.43	0.50	0	1
Sale occurred between 9/27/2010 and 01/16/2011	0.11	0.31	0	1
Sale occurred between 9/27/2011 and 01/16/2012	0.12	0.32	0	1
Sale occurred between 9/27/2012 and 01/16/2013	0.12	0.33	0	1
Sale occurred between 9/27/2013 and 01/16/2014	0.11	0.31	0	1
Sale occurred between 9/27/2014 and 01/16/2015	0.10	0.31	0	1
Sale occurred between 9/27/2015 and 01/16/2016	0.11	0.32	0	1
Sale occurred between 9/27/2016 and 01/16/2017	0.12	0.32	0	1
Sale occurred between 9/27/2017 and 01/16/2018	0.11	0.32	0	1
Sale occurred between 9/27/2018 and 01/16/2019	0.09	0.29	0	1
Property inside high or very high wildfire risk zone	0.11	0.300	0	1
Property inside low or moderate wildfire risk zone	0.89	0.300	0	1
Lot size (acres)	0.04	0.3	0.04	4.8
House size (square feet)	1,842	718	703	4,843
Age of house (years)	38	26	1	241
Bedrooms	3	1	0	33
Bathrooms	2	1	0	20

N = 477,785

Table A3: Summary statistics by bin

Distance bin	No. of trans.	mean(price)	mean(age)	mean(sq. footage)	mean(lot size)	mean(bedrooms)	mean(baths)
inside campfire	174	$269,085	31.07	1,894.23	1.82	2.82	2.12
0 - 25 mile bin	4,414	$247,161	37.16	1,666.78	0.88	3.05	1.88
25 - 50 mile bin	8,206	$263,494	34.37	1,792.75	1.30	3.06	1.97
50 - 100 mile bin	76,506	$345,043	31.25	1,842.75	0.36	3.31	2.10
100 - 150 mile bin	94,305	$563,755	45.31	1,823.12	0.24	3.28	2.07
150 - 200 mile bin	35,634	$801,422	40.57	1,874.89	0.37	3.42	2.14
200 - 250 mile bin	25,248	$294,999	32.80	1,806.20	1.21	3.26	1.78
250 - 300 mile bin	11,346	$267,849	30.43	2,560.91	0.76	3.04	1.97
300 - 350 mile bin	21,242	$256,343	31.00	1,769.54	0.41	3.26	1.99
350 - 400 mile bin	18,114	$432,147	30.00	1,988.62	0.43	3.47	0.55
400 - 450 mile bin	134,019	$598,527	50.21	1,846.82	0.59	3.30	0.84
450 - 500 mile bin	78,077	$496,772	27.08	2,127.45	2.13	3.40	2.31

N = 477,785

Table A4: Pooled effects, including properties 500+ miles from the Camp Fire

	Dependent variable:
	log(price)
inside campfire x post x campfire year	0.223***
	(0.025)
0 - 25 mile bin x post x campfire year	0.132***
	(0.020)
25 - 50 mile bin x post x campfire year	0.038**
	(0.019)
50 - 100 mile bin x post x campfire year	0.020*
	(0.011)
100 - 150 mile bin x post x campfire year	−0.015
	(0.011)
150 - 200 mile bin x post x campfire year	−0.005
	(0.009)
200 - 250 mile bin x post x campfire year	0.013
	(0.013)
250 - 300 mile bin x post x campfire year	0.009
	(0.025)
300 - 350 mile bin x post x campfire year	0.006
	(0.009)
350 - 400 mile bin x post x campfire year	−0.007
	(0.010)
400 - 450 mile bin x post x campfire year	0.002
	(0.011)
Observations	518,512
R^2	0.739
Adjusted R^2	0.738
Residual Std. Error	0.372 (df = 517877)

Note: Results of the estimation of Equation 2. The control group is transactions for properties located 400-568 miles from the Camp Fire footprint. Treatment effects are conditioned on home age, age squared, log square feet, log acreage, number of bedrooms, county-by-year fixed effects. For brevity, only the coefficients on the triple interactions are reported. *p<0.1; **p<0.05; ***p<0.01.

Table A5: Testing for Bin-Specific Seasonal Effects

	Dependent variable:
	log(Price)
Inside Camp Fire boundary	−0.166***
	(0.037)
0 - 25 mile distance bin	−0.374***
	(0.130)
25 - 50 mile distance bin	−0.343***
	(0.105)
50 - 100 mile distance bin	0.006
	(0.039)
100 - 150 mile distance bin	−0.845***
	(0.306)
150 - 200 mile distance bin	−0.828**
	(0.313)
200 - 250 mile distance bin	−0.818**
	(0.332)
250 - 300 mile distance bin	−1.105***
	(0.363)
300 - 350 mile distance bin	−1.082***
	(0.375)
350 - 400 mile distance bin	−0.815***
	(0.092)
400 - 450 mile distance bin	0.005
	(0.083)
Post	−0.004
	(0.006)
Inside Camp Fire Boundary x Post	−0.124***
	(0.013)
0 - 25 mile distance bin x Post	−0.010
	(0.013)
25 - 50 mile distance bin x Post	0.004
	(0.010)
50 - 100 mile distance bin x Post	0.019**
	(0.009)
100 - 150 mile distance bin x Post	−0.024**
	(0.009)
150 - 200 mile distance bin x Post	−0.041***
	(0.013)
200 - 250 mile distance bin x Post	−0.0003
	(0.010)
250 - 300 mile distance bin x Post	−0.003
	(0.007)
300 - 350 mile distance bin x Post	−0.004
	(0.007)
350 - 400 mile distance bin x Post	−0.018*
	(0.010)
400 - 450 mile distance bin x Post	−0.007
	(0.006)
Property Characteristics	Yes
Year-by-County FEs	Yes
Observations	432,683
R^2	0.739
Adjusted R^2	0.739

Note: These are the results of estimating equation 1. Property characteristics include home age, age^2, log square footage, log lot size (acres), and the number of bedrooms and bathrooms. The 450-500 mile distance bin in the "pre" period (Sep 27-Nov 7) is the reference group of homes. The post period is defined as Nov 8-Jan 17, excluding the first month after November 8. Only pre-fire years (2010-2017) are included.*p<0.1; **p<0.05; ***p<0.01

Table A6: Pooled effects, simple difference-in-difference specification

	Dependent variable:
	log(price)
inside campfire x post x campfire year	0.150***
	(0.030)
0 - 25 mile bin x post x campfire year	0.124***
	(0.028)
25 - 50 mile bin x post x campfire year	0.056**
	(0.021)
50 - 100 mile bin x post x campfire year	0.040***
	(0.014)
100 - 150 mile bin x post x campfire year	−0.052***
	(0.015)
150 - 200 mile bin x post x campfire year	−0.059***
	(0.021)
200 - 250 mile bin x post x campfire year	0.004
	(0.013)
250 - 300 mile bin x post x campfire year	−0.008
	(0.022)
300 - 350 mile bin x post x campfire year	−0.014
	(0.011)
350 - 400 mile bin x post x campfire year	−0.032***
	(0.010)
400 - 450 mile bin x post x campfire year	−0.018
	(0.014)
Observations	45,108
R^2	0.722
Adjusted R^2	0.721
Residual Std. Error	0.350 (df = 45012)

Note: Results of a simple difference-in-difference estimation utilizing data from September 2018 - January 2019. The control group is transactions for properties located 400-500 miles from the Camp Fire footprint. Treatment effects are conditioned on home age, age squared, log square feet, log acreage, number of bedrooms, county-by-year fixed effects. For brevity, only the coefficients on the triple interactions are reported. *p<0.1; **p<0.05; ***p<0.01.

Table A7: Transaction count by year, bin and pre-post period, 2010-2015

year	bin	pre-November 8	post-November 8
09/2010 - 01/2011	inside campfire	1	
	0 - 25 mile bin	68	136
	25 - 50 mile bin	239	339
	50 - 100 mile bin	2214	3540
	100 - 150 mile bin	2794	4405
	150 - 200 mile bin	1041	1622
	200 - 250 mile bin	711	1062
	250 - 300 mile bin	303	522
	300 - 350 mile bin	801	1219
	350 - 400 mile bin	586	961
	400 - 450 mile bin	3074	4542
	450 - 500 mile bin	2720	3761
09/2011 - 01/2012	inside campfire	3	2
	0 - 25 mile bin	121	177
	25 - 50 mile bin	264	367
	50 - 100 mile bin	2830	4090
	100 - 150 mile bin	3087	4481
	150 - 200 mile bin	976	1514
	200 - 250 mile bin	888	1243
	250 - 300 mile bin	419	545
	300 - 350 mile bin	893	1280
	350 - 400 mile bin	699	972
	400 - 450 mile bin	3397	4771
	450 - 500 mile bin	2666	3975
09/2012 - 01/2013	inside campfire	1	3
	0 - 25 mile bin	94	163
	25 - 50 mile bin	276	400
	50 - 100 mile bin	2956	4239
	100 - 150 mile bin	3083	4564
	150 - 200 mile bin	1178	1603
	200 - 250 mile bin	855	1139
	250 - 300 mile bin	387	510
	300 - 350 mile bin	820	1184
	350 - 400 mile bin	699	1035
	400 - 450 mile bin	3901	5359
	450 - 500 mile bin	3075	4470
09/2013 - 01/2014	inside campfire	3	
	0 - 25 mile bin	106	163
	25 - 50 mile bin	255	359
	50 - 100 mile bin	2478	3420
	100 - 150 mile bin	2673	3623
	150 - 200 mile bin	957	1203
	200 - 250 mile bin	713	961
	250 - 300 mile bin	322	453
	300 - 350 mile bin	766	1087
	350 - 400 mile bin	564	768
	400 - 450 mile bin	3241	4196
	450 - 500 mile bin	2748	3524
09/2014 - 01/2015	inside campfire		2
	0 - 25 mile bin	131	182
	25 - 50 mile bin	287	411
	50 - 100 mile bin	2382	3453
	100 - 150 mile bin	2605	3419
	150 - 200 mile bin	925	1164
	200 - 250 mile bin	793	1075
	250 - 300 mile bin	397	549
	300 - 350 mile bin	822	1050
	350 - 400 mile bin	573	802
	400 - 450 mile bin	2855	3774
	450 - 500 mile bin	2585	3515

Table A8: Transaction count by year, bin and pre-post period, 2015-2019

year	bin	pre-November 8	post-November 8
09/2015 - 01/2016	inside campfire	2	3
	0 - 25 mile bin	131	187
	25 - 50 mile bin	322	427
	50 - 100 mile bin	2980	4423
	100 - 150 mile bin	2914	4172
	150 - 200 mile bin	893	1303
	200 - 250 mile bin	925	1237
	250 - 300 mile bin	395	575
	300 - 350 mile bin	924	1158
	350 - 400 mile bin	705	908
	400 - 450 mile bin	3430	4286
	450 - 500 mile bin	2919	4004
09/2016 - 01/2017	inside campfire	5	1
	0 - 25 mile bin	114	146
	25 - 50 mile bin	319	418
	50 - 100 mile bin	3552	4571
	100 - 150 mile bin	3188	4100
	150 - 200 mile bin	1071	1348
	200 - 250 mile bin	996	1398
	250 - 300 mile bin	476	593
	300 - 350 mile bin	936	1165
	350 - 400 mile bin	739	856
	400 - 450 mile bin	3494	4284
	450 - 500 mile bin	3254	3987
09/2017 - 01/2018	inside campfire	1	4
	0 - 25 mile bin	146	223
	25 - 50 mile bin	374	473
	50 - 100 mile bin	3364	4818
	100 - 150 mile bin	3248	4208
	150 - 200 mile bin	1111	1332
	200 - 250 mile bin	1197	1385
	250 - 300 mile bin	448	605
	300 - 350 mile bin	879	1106
	350 - 400 mile bin	654	806
	400 - 450 mile bin	3363	4347
	450 - 500 mile bin	3088	4142
09/2018 - 01/2019	inside campfire	4	
	0 - 25 mile bin	175	328
	25 - 50 mile bin	332	490
	50 - 100 mile bin	2633	3540
	100 - 150 mile bin	2447	3256
	150 - 200 mile bin	899	1140
	200 - 250 mile bin	928	1160
	250 - 300 mile bin	333	416
	300 - 350 mile bin	846	961
	350 - 400 mile bin	597	731
	400 - 450 mile bin	2749	3442
	450 - 500 mile bin	2689	3585

Table A9: Pooled effects, excluding counties affected by other fires

	Dependent variable:
	log(price)
inside campfire x post x campfire year	0.230***
	(0.027)
0 - 25 mile bin x post x campfire year	0.126***
	(0.022)
25 - 50 mile bin x post x campfire year	0.035*
	(0.019)
50 - 100 mile bin x post x campfire year	0.020*
	(0.012)
100 - 150 mile bin x post x campfire year	−0.024**
	(0.010)
150 - 200 mile bin x post x campfire year	−0.016*
	(0.009)
200 - 250 mile bin x post x campfire year	0.002
	(0.012)
250 - 300 mile bin x post x campfire year	−0.004
	(0.027)
300 - 350 mile bin x post x campfire year	−0.011
	(0.010)
350 - 400 mile bin x post x campfire year	−0.015
	(0.029)
400 - 450 mile bin x post x campfire year	0.008
	(0.007)
Observations	375,927
R^2	0.758
Adjusted R^2	0.758
Residual Std. Error	0.365 (df = 375361)

Note: Results of the estimation of Equation 2. The sample excludes properties located in counties that experienced destructive wildfires during the 2010 - 2019 study period. The destructive fires were the Tubbs, Woolsey and Carr fires, affecting Napa, Sonoma, Lake, Los Angeles, Ventura, Shasta and Trinity Counties. The control group is transactions for properties located 400-568 miles from the Camp Fire footprint. Treatment effects are conditioned on home age, age squared, log square feet, log acreage, number of bedrooms, county-by-year fixed effects. For brevity, only the coefficients on the triple interactions are reported. *p<0.1; **p<0.05; ***p<0.01.

Table A10: Pooled effects

	Dependent variable:
	log(price)
inside campfire x post x campfire year	0.223***
	(0.028)
0 - 25 mile bin x post x campfire year	0.122***
	(0.022)
25 - 50 mile bin x post x campfire year	0.038*
	(0.019)
50 - 100 mile bin x post x campfire year	0.019*
	(0.011)
100 - 150 mile bin x post x campfire year	−0.026**
	(0.010)
150 - 200 mile bin x post x campfire year	−0.016*
	(0.008)
200 - 250 mile bin x post x campfire year	0.002
	(0.011)
250 - 300 mile bin x post x campfire year	−0.002
	(0.025)
300 - 350 mile bin x post x campfire year	−0.006
	(0.008)
350 - 400 mile bin x post x campfire year	−0.017*
	(0.008)
400 - 450 mile bin x post x campfire year	−0.010
	(0.009)
Observations	477,785
R^2	0.742
Adjusted R^2	0.741
Residual Std. Error	0.374 (df = 477150)

Note: Results of the estimation of Equation 2. Estimates correspond to those presented in Figure 2. Treatment effects are conditioned on home age, age squared, log square feet, log acreage, number of bedrooms, and county-by-year fixed effects. For brevity, only the coefficients on the triple interactions are reported. *p<0.1; **p<0.05; ***p<0.01.

Table A11: Pooled Bi-Weekly Effects

	Dependent variable:
	log(price)
inside campfire - 25 mile bin x 4-6 weeks before fire x campfire year	0.015
	(0.047)
inside campfire - 25 mile bin x 2-4 weeks before fire x campfire year	0.012
	(0.025)
inside campfire - 25 mile bin x 0 - 2 weeks after fire x campfire year	0.050
	(0.050)
inside campfire - 25 mile bin x 2 - 4 weeks after fire x campfire year	0.105**
	(0.045)
inside campfire - 25 mile bin x 4 - 6 weeks after fire x campfire year	0.140***
	(0.027)
inside campfire - 25 mile bin x 6 - 8 weeks after fire x campfire year	0.012
	(0.092)
inside campfire - 25 mile bin x 8 - 10 weeks after fire x campfire year	0.195***
	(0.020)
25 - 100 mile bin x 4 - 6 weeks before fire x campfire year	−0.032**
	(0.012)
25 - 100 mile bin x 2 - 4 weeks before fire x campfire year	−0.032***
	(0.009)
25 - 100 mile bin x 0 - 2 weeks after fire x campfire year	−0.019*
	(0.009)
25 - 100 mile bin x 2 - 4 weeks after fire x campfire year	−0.025*
	(0.013)
25 - 100 mile bin x 4 - 6 weeks after fire x campfire year	−0.006
	(0.010)
25 - 100 mile bin x 6 - 8 weeks after fire x campfire year	−0.023**
	(0.010)
25 - 100 mile bin x 8 - 10 weeks after fire x campfire year	−0.024*
	(0.013)
Observations	638,821
R^2	0.714
Adjusted R^2	0.713
Residual Std. Error	0.394 (df = 638186)

Note: Estimates correspond to those presented in Figure 2, panel (b). The reference group of homes are those sold zero to two weeks before the Camp Fire, located between 100 and 500 miles from the footprint of the Camp Fire. Treatment effects are conditioned on home age, age squared, log square feet, log acreage, number of bedrooms, county-by-year fixed effects. For brevity, only the coefficients on the triple interactions are reported. *p<0.1; **p<0.05; ***p<0.01.

Table A12: Pooled Monthly Effects

	Dependent variable:
	log(price)
inside campfire - 50 mile bin x 2 months before fire x campfire year	−0.018
	(0.020)
inside campfire - 50 mile bin x 1 months after fire x campfire year	0.064***
	(0.012)
inside campfire - 50 mile bin x 2 months after fire x campfire year	0.108***
	(0.012)
inside campfire - 50 mile bin x 3 months after fire x campfire year	0.110***
	(0.023)
inside campfire - 50 mile bin x 4 months after fire x campfire year	0.084***
	(0.011)
inside campfire - 50 mile bin x 5 months after fire x campfire year	0.119***
	(0.008)
inside campfire - 50 mile bin x 6 months after fire x campfire year	0.074***
	(0.009)
inside campfire - 50 mile bin x 7 months after fire x campfire year	0.190***
	(0.033)
inside campfire - 50 mile bin x 8 months after fire x campfire year	0.100***
	(0.009)
inside campfire - 50 mile bin x 9 months after fire x campfire year	0.068***
	(0.015)
inside campfire - 50 mile bin x 10 months after fire x campfire year	0.066***
	(0.013)
50 - 100 mile bin x 2 months before fire x campfire year	−0.007
	(0.009)
50 - 100 mile bin x 1 months after fire x campfire year	0.001
	(0.005)
50 - 100 mile bin x 2 months after fire x campfire year	0.007
	(0.006)
50 - 100 mile bin x 3 months after fire x campfire year	−0.001
	(0.010)
50 - 100 mile bin x 4 months after fire x campfire year	−0.005
	(0.006)
50 - 100 mile bin x 5 months after fire x campfire year	0.006
	(0.005)
50 - 100 mile bin x 6 months after fire x campfire year	0.015**
	(0.006)
50 - 100 mile bin x 7 months after fire x campfire year	0.001
	(0.013)
50 - 100 mile bin x 8 months after fire x campfire year	0.018***
	(0.006)
50 - 100 mile bin x 9 months after fire x campfire year	0.012**
	(0.005)
50 - 100 mile bin x 10 months after fire x campfire year	0.008
	(0.006)
Observations	2,367,399
R^2	0.717
Adjusted R^2	0.717
Residual Std. Error	0.393 (df = 2366731)

Note: Estimates correspond to those presented in Figure 2, panel (c). The reference group of homes are those sold the month before the Camp Fire, located between 100 and 500 miles from the footprint of the Camp Fire. Treatment effects are conditioned on home age, age squared, log square feet, log acreage, number of bedrooms, county-by-year fixed effects. For brevity, only the coefficients on the triple interactions are reported. *p<0.1; **p<0.05; ***p<0.01.

Table A13: Effects by Risk Group, up to 10 weeks post-fire

	Dep. variable: log(price)
Very High Risk Properties	
Inside campfire x post x campfire year	0.226***
	(0.168)
0 - 25 mile bin x post x campfire year	0.026
	(0.169)
25 - 50 mile bin x post x campfire year	0.069
	(0.091)
50 - 100 mile bin x post x campfire year	0.126***
	(0.041)
100 - 150 mile bin x post x campfire year	−0.057*
	(0.033)
150 - 200 mile bin x post x campfire year	−0.103***
	(0.030)
200 - 250 mile bin x post x campfire year	0.044
	(0.044)
250 - 300 mile bin x post x campfire year	0.046
	(0.142)
300 - 350 mile bin x post x campfire year	−0.080
	(0.218)
350 - 400 mile bin x post x campfire year	−0.016
	(0.030)
400 - 450 mile bin x post x campfire year	−0.030***
	(0.010)
High Risk Properties	
Inside campfire x post x campfire year	−0.457***
	(0.056)
0 - 25 mile bin x post x campfire year	0.281***
	(0.025)
25 - 50 mile bin x post x campfire year	0.040
	(0.073)
50 - 100 mile bin x post x campfire year	0.039
	(0.071)
100 - 150 mile bin x post x campfire year	−0.043
	(0.051)
150 - 200 mile bin x post x campfire year	0.132*
	(0.071)
200 - 250 mile bin x post x campfire year	0.259***
	(0.059)
250 - 300 mile bin x post x campfire year	−0.095*
	(0.056)
300 - 350 mile bin x post x campfire year	−0.008
	(0.059)
350 - 400 mile bin x post x campfire year	−0.265*
	(0.133)
400 - 450 mile bin x post x campfire year	−0.180**
	(0.075)
Moderate or Low Risk Properties	
0 - 25 mile bin x post x campfire year	0.121***
	(0.025)
25 - 50 mile bin x post x campfire year	0.041**
	(0.019)
50 - 100 mile bin x post x campfire year	0.009
	(0.009)
100 - 150 mile bin x post x campfire year	−0.024**
	(0.009)
150 - 200 mile bin x post x campfire year	−0.017**
	(0.008)
200 - 250 mile bin x post x campfire year	−0.002
	(0.011)
250 - 300 mile bin x post x campfire year	−0.005
	(0.020)
300 - 350 mile bin x post x campfire year	−0.007
	(0.010)
350 - 400 mile bin x post x campfire year	−0.004
	(0.013)
400 - 450 mile bin x post x campfire year	−0.007
	(0.011)
Observations	477,785
R^2	0.748
Adjusted R^2	0.747
Residual Std. Error	0.370 (df = 477066)

Note: Results of the estimation of Equation 2 by fire risk group. Estimates correspond to those presented in panel (a) of Figure 3. Treatment effects are conditioned on home age, age squared, log square feet, log acreage, number of bedrooms, county-by-year fixed effects. For brevity, only the coefficients on the triple interactions are reported. *p<0.1; **p<0.05; ***p<0.01.

Table A14: Effects by Risk Group, up to 10 months post-fire

	Dep. variable: log(price)
<u>Very High Risk Properties</u>	
Inside campfire x post x campfire year	0.146***
	(0.035)
0 - 25 mile bin x post x campfire year	0.029
	(0.037)
25 - 50 mile bin x post x campfire year	−0.004
	(0.043)
	(0.091)
50 - 100 mile bin x post x campfire year	0.046**
	(0.023)
100 - 150 mile bin x post x campfire year	0.003
	(0.020)
150 - 200 mile bin x post x campfire year	−0.009
	(0.049)
200 - 250 mile bin x post x campfire year	−0.050
	(0.043)
250 - 300 mile bin x post x campfire year	−0.028
	(0.054)
300 - 350 mile bin x post x campfire year	0.060***
	(0.011)
350 - 400 mile bin x post x campfire year	0.010
	(0.013)
400 - 450 mile bin x post x campfire year	0.011
	(0.013)
<u>High Risk Properties</u>	
Inside campfire x post x campfire year	−0.167***
	(0.038)
0 - 25 mile bin x post x campfire year	0.120***
	(0.011)
25 - 50 mile bin x post x campfire year	0.031
	(0.035)
50 - 100 mile bin x post x campfire year	−0.026
	(0.037)
100 - 150 mile bin x post x campfire year	−0.002
	(0.033)
150 - 200 mile bin x post x campfire year	0.010
	(0.035)
200 - 250 mile bin x post x campfire year	0.185*
	(0.093)
250 - 300 mile bin x post x campfire year	0.085***
	(0.028)
300 - 350 mile bin x post x campfire year	−0.039
	(0.030)
350 - 400 mile bin x post x campfire year	−0.071
	(0.049)
400 - 450 mile bin x post x campfire year	−0.011
	(0.050)
<u>Moderate or Low Risk Properties</u>	
0 - 25 mile bin x post x campfire year	0.107***
	(0.017)
25 - 50 mile bin x post x campfire year	0.063***
	(0.012)
50 - 100 mile bin x post x campfire year	0.013
	(0.008)
100 - 150 mile bin x post x campfire year	−0.008
	(0.010)
150 - 200 mile bin x post x campfire year	−0.008
	(0.008)
200 - 250 mile bin x post x campfire year	0.032**
	(0.016)
250 - 300 mile bin x post x campfire year	0.026***
	(0.008)
300 - 350 mile bin x post x campfire year	0.002
	(0.012)
350 - 400 mile bin x post x campfire year	0.010
	(0.011)
400 - 450 mile bin x post x campfire year	0.017***
	(0.005)
Observations	2,206,483
R^2	0.751
Adjusted R^2	0.751
Residual Std. Error	0.368 (df = 2205757)

Note: Results of the estimation of Equation 2 by fire risk group. Estimates correspond to those presented in panel (b) of Figure 3. Treatment effects are conditioned on home age, age squared, log square feet, log acreage, number of bedrooms, county-by-year fixed effects. For brevity, only the coefficients on the triple interactions are reported. *p<0.1; **p<0.05; ***p<0.01.

Table A15: Summary Statistics for Migration Estimation

Statistic	Mean	St. Dev.	Min	Max
Count migrants	11	46	1	830
Distance to origin	161	137	1	561
SFH count	1017	585	0	1
Population density	4,578	1,513	322	12,904
Median income	$64,730	$31,422	$17,235	$233,750
Median home value	$414,167	$259,603	$19,800	$2,000,000
Unemployment rate	8%	4%	0%	26%
% "risky" (CAL FIRE)	14%	30%	0%	100%
Fire Freq.	0.003%	0.005%	0%	5%
No Rating	0.33	0.47	0	1
WRR Very Low Risk	0.13	0.34	0	1
WRR Relatively Low Risk	0.13	0.33	0	1
WRR Relatively Moderate Risk	0.15	0.35	0	1
WRR Relatively High	0.19	0.39	0	1
WRR Very High Risk	0.26	0.71	0	1

N = 1,133

Table A16: Origin & Destination Risk Zones

	Destination Risk Zone				
Origin Risk Zone	Very High	High	Moderate	Low	Total
Very High	2,345	607	500	7,381	10,833
High	17	18	8	214	257
Moderate	3	1	1	11	257
Low	31	5	3	66	105
Total	2,396	631	512	7,672	11,211

Note: Tables provides the number of evacuees who moved from one risk zone to another. For example, 2,345 evacuees moved from a very high-risk property to a very high-risk property, whereas 7,381 moved from a very high-risk property to a low-risk property.

Table A17: Number of migrants and percentage for each U.S. state

State	fips	Number of Camp Fire Migrants	Total	Percentage
Alabama	01	12	14249	0.08
Alaska	02	6	14249	0.04
Arizona	04	235	14249	1.65
Arkansas	05	21	14249	0.15
California	06	11986	14249	84.12
Colorado	08	67	14249	0.47
Connecticut	09	7	14249	0.05
Delaware	10	1	14249	0.01
Florida	12	76	14249	0.53
Georgia	13	16	14249	0.11
Hawaii	15	16	14249	0.11
Idaho	16	206	14249	1.45
Illinois	17	7	14249	0.05
Indiana	18	10	14249	0.07
Iowa	19	11	14249	0.08
Kansas	20	7	14249	0.05
Kentucky	21	17	14249	0.12
Louisiana	22	10	14249	0.07
Massachusetts	25	2	14249	0.01
Michigan	26	13	14249	0.09
Minnesota	27	12	14249	0.08
Mississippi	28	2	14249	0.01
Missouri	29	21	14249	0.15
Montana	30	46	14249	0.32
Nebraska	31	4	14249	0.03
Nevada	32	243	14249	1.71
New Hampshire	33	3	14249	0.02
New Jersey	34	3	14249	0.02
New Mexico	35	34	14249	0.24
New York	36	8	14249	0.06
North Carolina	37	27	14249	0.19
North Dakota	38	3	14249	0.02
Ohio	39	19	14249	0.13
Oklahoma	40	31	14249	0.22
Oregon	41	540	14249	3.79
Pennsylvania	42	10	14249	0.07
Rhode Island	44	1	14249	0.01
South Carolina	45	14	14249	0.10
South Dakota	46	6	14249	0.04
Tennessee	47	64	14249	0.45
Texas	48	131	14249	0.92
Utah	49	81	14249	0.57
Vermont	50	11	14249	0.08
Virginia	51	24	14249	0.17
Washington	53	162	14249	1.14
West Virginia	54	1	14249	0.01
Wisconsin	55	5	14249	0.04
Wyoming	56	17	14249	0.12

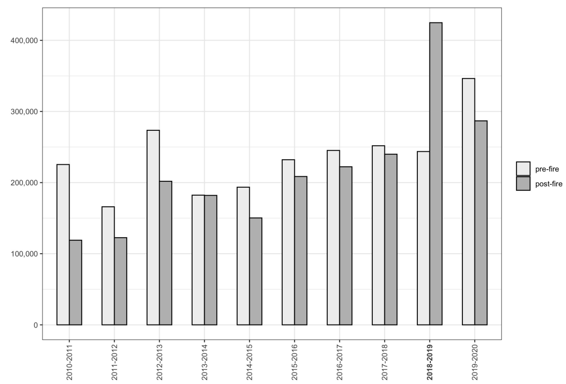
Table A18: Volume estimate

	Dependent variable:
	inhs(sales)
inside campfire - 25 mile bin x 1 quarter after fire x campfire year	0.525***
	(0.113)
inside campfire - 25 mile bin x 2 quarters after fire x campfire year	0.290***
	(0.113)
inside campfire - 25 mile bin x 3 quarters after fire x campfire year	−0.057
	(0.109)
25 - 100 mile bin x 1 quarter after fire x campfire year	−0.004
	(0.036)
25 - 100 mile bin x 2 quarters after fire x campfire year	−0.009
	(0.036)
25 - 100 mile bin x 3 quarters after fire x campfire year	0.076**
	(0.035)
Observations	267,263
R^2	0.730
Adjusted R^2	0.723
Residual Std. Error	0.637 (df = 260088)

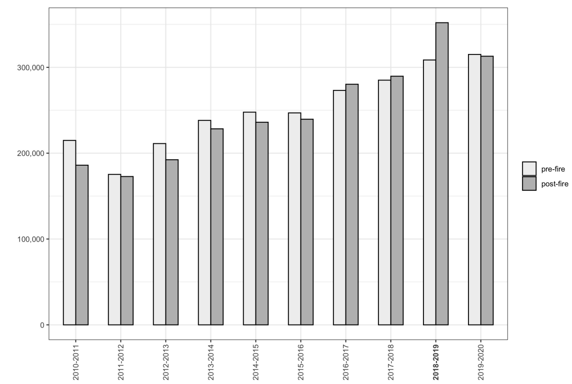
Note: Results of the estimation of sales volume on distance bin, temporal bin and year interaction terms. Estimates correspond to those presented in Figure A5. Treatment effects are conditioned on year, quarter and tract-distance bin fixed effects. For brevity, only the coefficients on the triple interactions are reported. *p<0.1; **p<0.05; ***p<0.01.

Appendix Figures

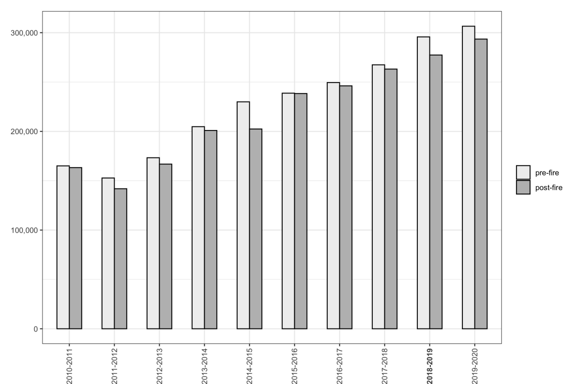
Figure A1: Mean price by treatment and temporal group (nominal USD)



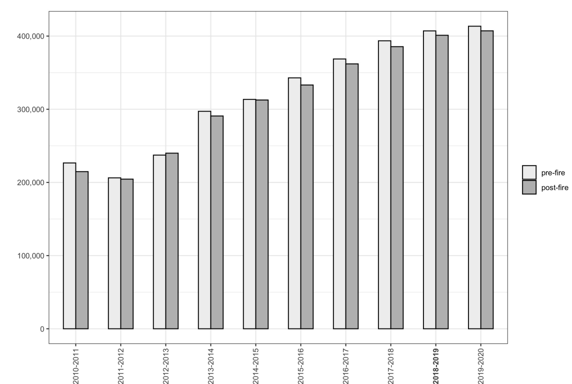
(a) Within the Camp Fire boundary



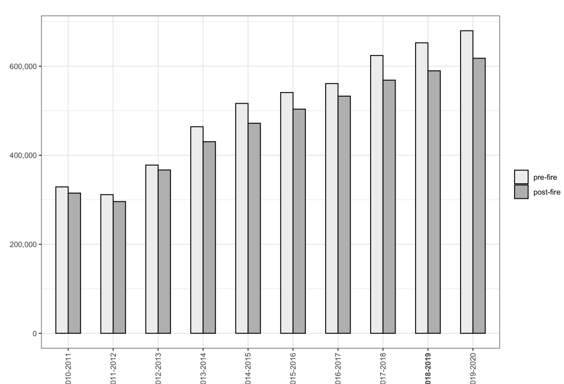
(b) Between 0 and 25 miles from the Camp Fire boundary



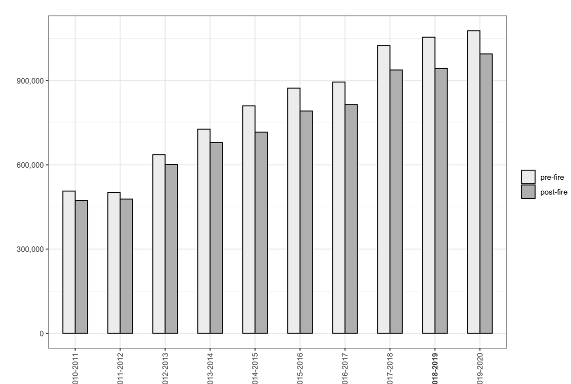
(c) Between 25 and 50 miles from the Camp Fire boundary



(d) Between 50 and 100 miles from the Camp Fire boundary



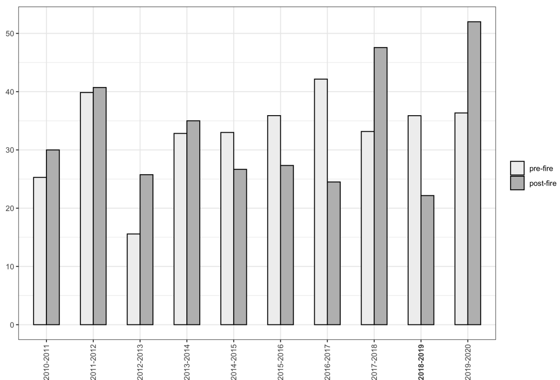
(e) Between 100 and 150 miles from the Camp Fire boundary



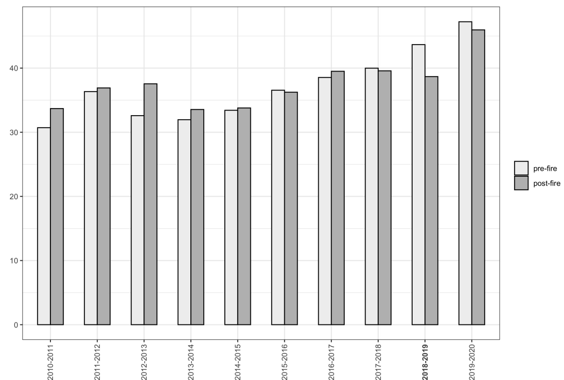
(f) Between 150 and 200 miles from the Camp Fire boundary

Note: For all year groupings, the pre period is September 27th to November 7th. The post period is December 6th to January 16th.

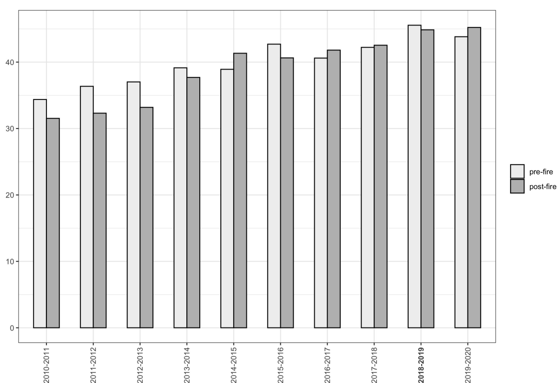
Figure A2: Mean structure age by treatment and temporal group (years)



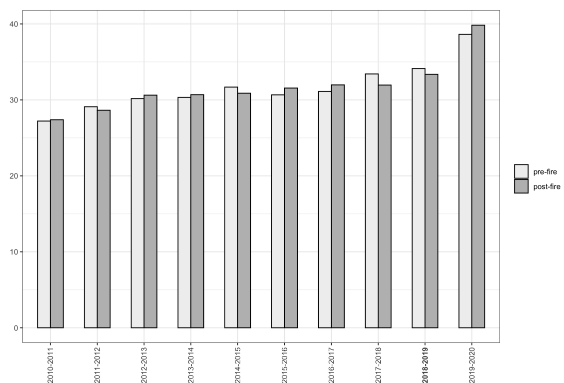
(a) Within the Camp Fire boundary



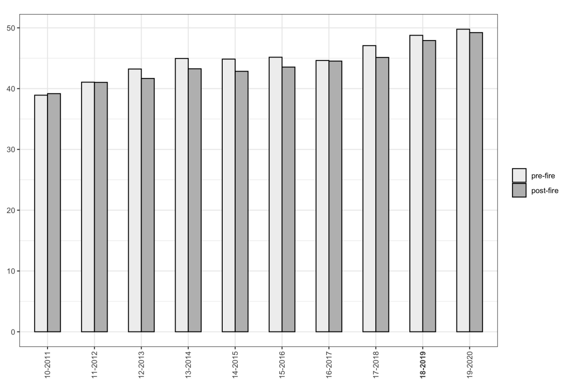
(b) Between 0 and 25 miles from the Camp Fire boundary



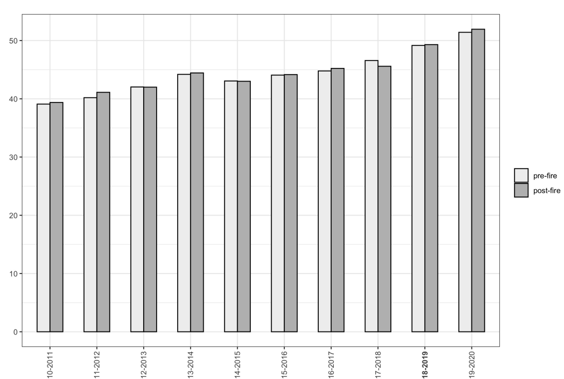
(c) Between 25 and 50 miles from the Camp Fire boundary



(d) Between 50 and 100 miles from the Camp Fire boundary



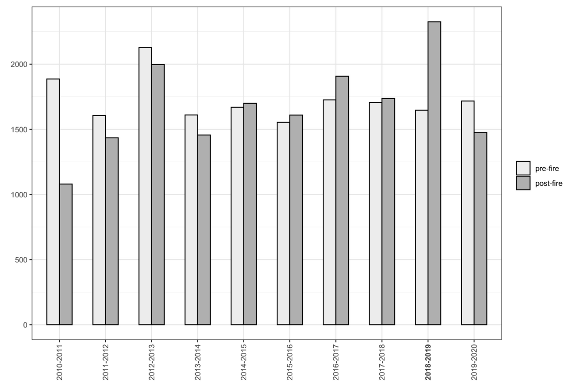
(e) Between 100 and 150 miles from the Camp Fire boundary



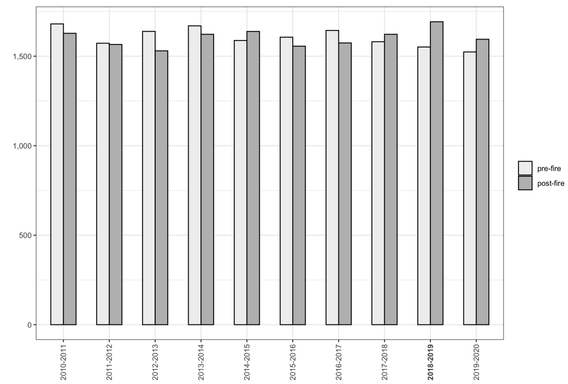
(f) Between 150 and 200 miles from the Camp Fire boundary

Note: For all year groupings, the pre period is September 27th to November 7th. The post period is December 6th to January 16th.

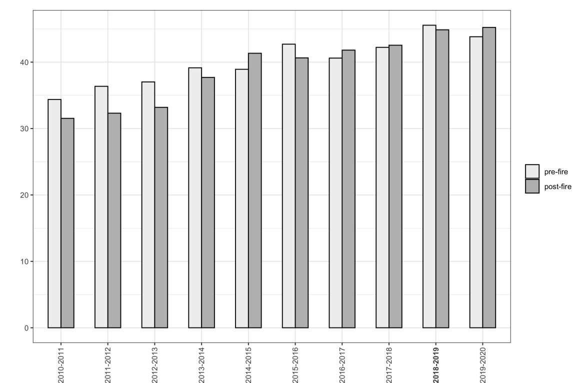
Figure A3: mean structure size by treatment and temporal group (square feet)



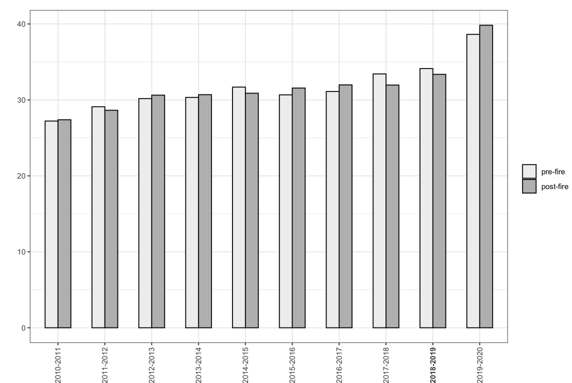
(a) Within the Camp Fire boundary



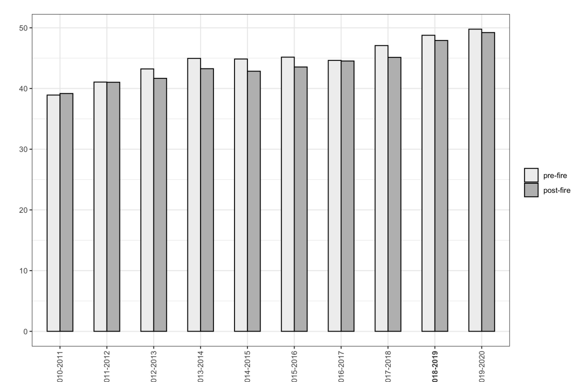
(b) Between 0 and 25 miles from the Camp Fire boundary



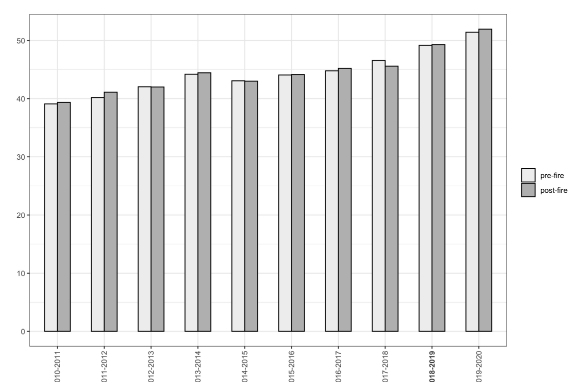
(c) Between 25 and 50 miles from the Camp Fire boundary



(d) Between 50 and 100 miles from the Camp Fire boundary



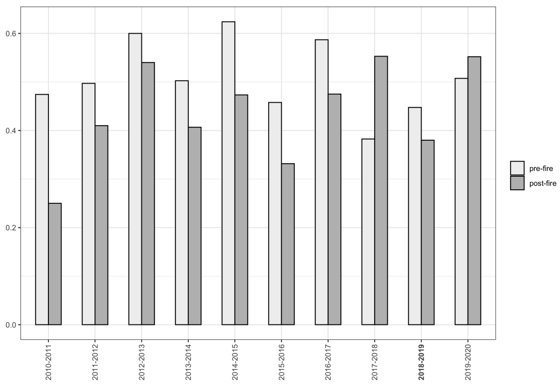
(e) Between 100 and 150 miles from the Camp Fire boundary



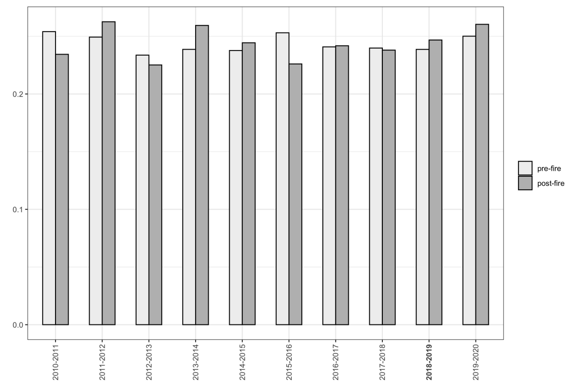
(f) Between 150 and 200 miles from the Camp Fire boundary

Note: For all year groupings, the pre period is September 27th to November 7th. The post period is December 6th to January 16th.

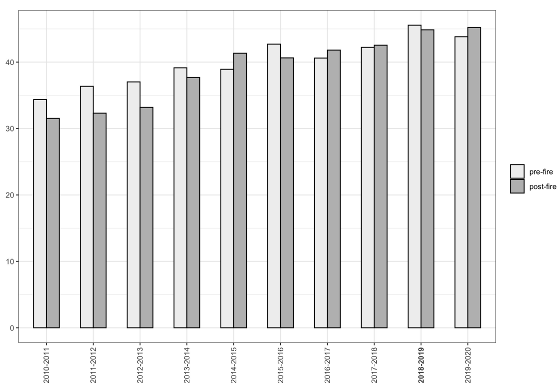
Figure A4: Mean lot size by treatment and temporal group (acres)



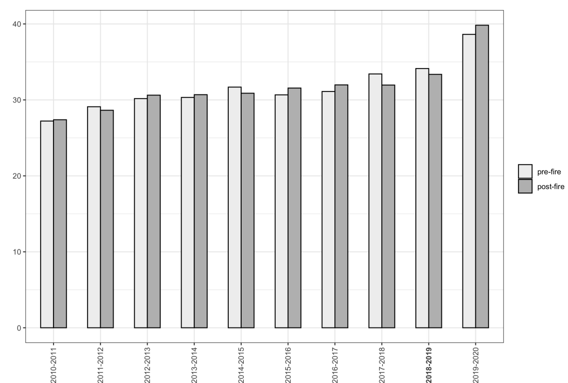
(a) Within the Camp Fire boundary



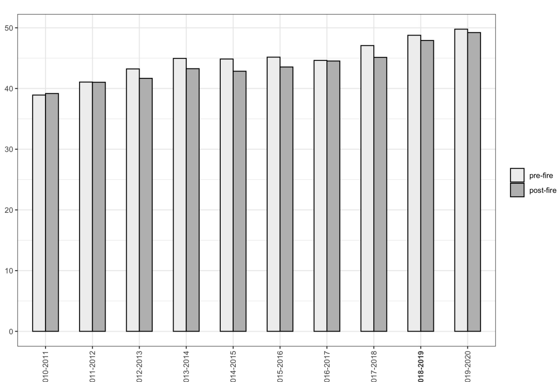
(b) Between 0 and 25 miles from the Camp Fire boundary



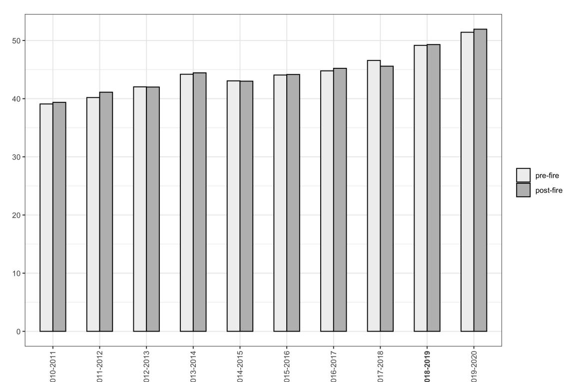
(c) Between 25 and 50 miles from the Camp Fire boundary



(d) Between 50 and 100 miles from the Camp Fire boundary



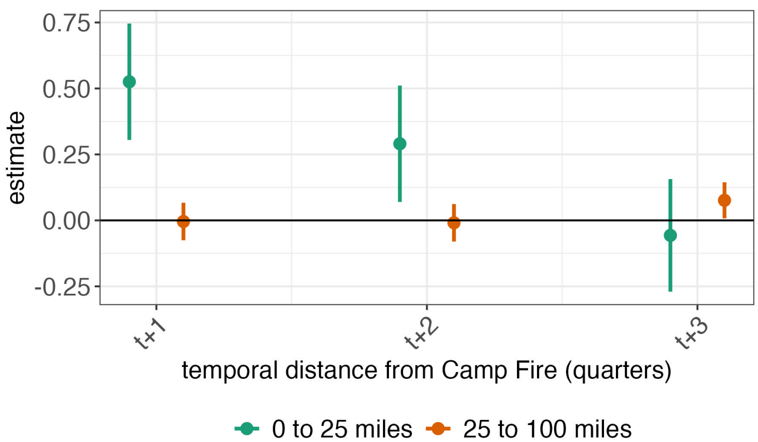
(e) Between 100 and 150 miles from the Camp Fire boundary



(f) Between 150 and 200 miles from the Camp Fire boundary

Note: For all year groupings, the pre period is September 27th to November 7th. The post period is December 6th to January 16th.

Figure A5: Sales volume



Note: Temporal analysis of the quarterly effects of the Camp Fire on volume of sales in California up to three quarters post-fire (i.e. September 7, 2019). The first month after the fire is excluded from the sample. Points indicate point estimates and vertical lines indicate 95 percent confidence intervals. One treatment group is properties located 25 miles or less from the Campfire footprint and a second treatment group is properties located 25 - 100 miles from the Camp Fire footprint. The comparison group is properties located greater than 100 miles from the Camp Fire. Estimates are zeroed at sales volume for the two months prior to the Camp Fire.