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Department of Economics Working Paper
WP 2023-01
April 2021

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

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April 13, 2023

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 35 percent in the six-week aftermath of the fire. Effects decay with distance and are statistically insignificant beyond 50 miles. Second, effects are detected within two weeks of the fire, fully materialized within six weeks, and are persistent up to ten months (which exhausts our period of consideration). Third, these effects are specific to low-fire-risk properties. Results are robust to a variety of specifications and modeling assumptions and are corroborated by the observed pattern of displacement.

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, thirteen occurred in the last five 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.[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 beyond a mere disaster:

[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://www.fire.ca.gov/media/t1rdhizr/top20_destruction.pdf

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

[5] https://www.fs.fed.us/pnw/pubs/pnw_gtr870/pnw_gtr870.pdf

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

"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 detailed temporally and spatially granulated data. To satisfy these requirements, we merged geospatial information on the fire's footprint with Zillow's geo-coded 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. 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 35 percent. Effects decay as distance from the fire increases, reaching up to 50 miles away. Prices remained elevated for up to ten months for properties within 50 miles of the fire's footprint (which exhausts the posterior period of consideration). Outside of the fire's footprint, estimated price premiums are much higher for properties located in low or medium wildfire risk zones compared to properties located in high or very high wildfire risk zones. This is notable given the fact that burned homes were all located in areas of high or very high wildfire risk, suggesting that evacuees updated either their risk perceptions or

[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).

their risk preferences in response to the Camp Fire.

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 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.

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

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

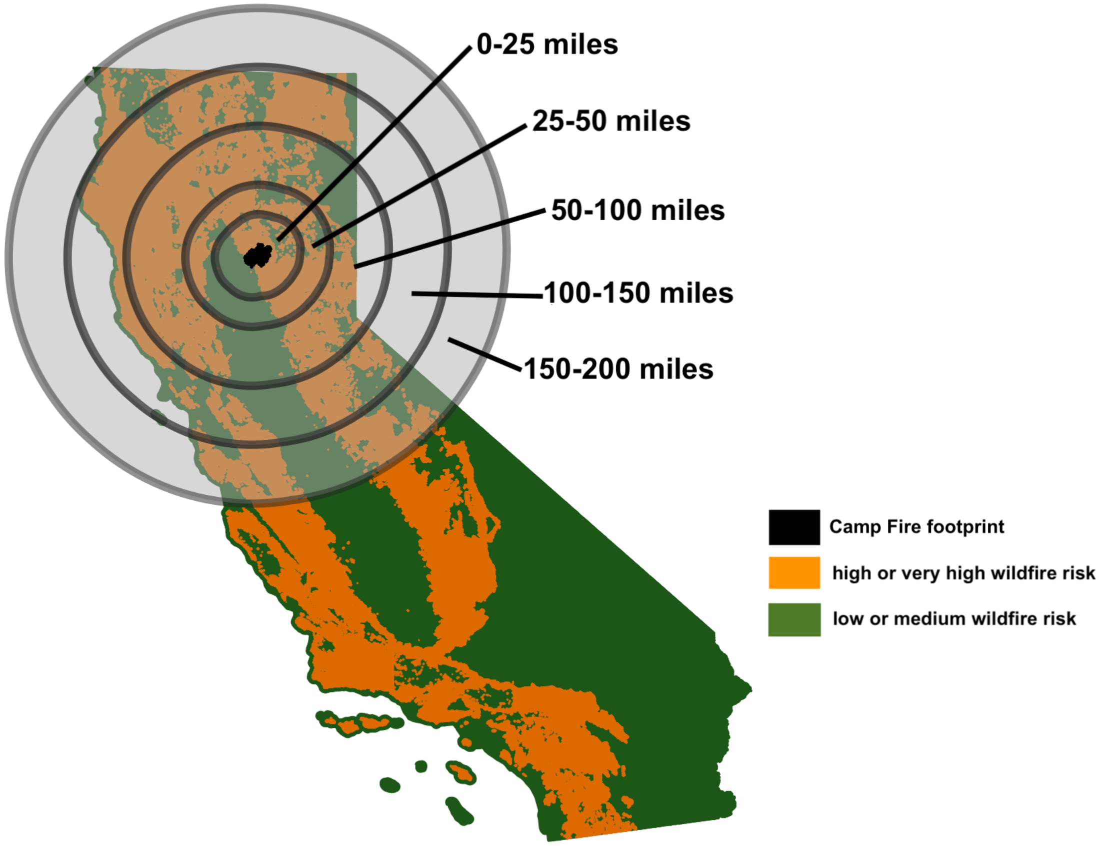
Figure 1 gives the relative location of the Camp Fire, with the fire's footprint overlaid on a map of California. Spatial information on the Camp Fire burn perimeter (footprint) is provided by the California Department of Forestry and Fire Protection (CALFIRE).[12] Mutually exclusive spatial bands around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

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

[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/

Figure 1: Study area & Distance Bins



Note: The area inside the first donut marks the footprint of the Camp Fire. Wildfire risk zones were generated using Cal Fire's Fire Hazard Severity Zone data.

3. Data

3.1 California Real Estate Transactions & Property Characteristics

Property transaction data come from Zillow's Transaction and Assessment Database (ZTRAX). The sample is composed of arms-length transactions of single family homes located within 200 miles of the Camp Fire boundary.

We utilize ZTRAX data for California from 2010 to 2020. The data describe the sale date and location (physical address in addition to latitude and longitude). The sale date corresponds to when escrow closed. In practice, there is roughly 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, and lot size.

Properties with prices less than the first percentile or greater than the 99th percentile of all prices within a given year, and properties with lot sizes greater than one acre were omitted from the sample. We also dropped properties that had multiple recorded transactions on a single day, properties that transacted more than ten times between 2010 and 2020 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 are presented in Table A1.

3.2 Wildfire Risk Zones

Wildfire risk zone information comes from the California Department of Forestry and Fire Protection (CALFIRE).[13] CALFIRE 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. The entirety 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 200 miles of the Camp Fire, seven percent of the properties in our sample are located in a high or very high wildfire risk zone, and 93 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 by clearing trees.

4. Identification Strategy

We identify the effect of the Camp Fire on regional housing prices 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 bin, or donut, based on its straight-line distance from the boundary of the Camp Fire. These donuts are depicted in Figure 1.

Homes within 150 and 200 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 3).

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

Economic shocks, such as the Camp Fire, generate both spatial and temporal effects. We consider both dimensions, designing slightly different estimation equations for each. Both models rely on the key identifying assumption that the timing and location of the Camp Fire are exogenous, conditional on spatial and temporal fixed effects. While fires have generally become a more salient threat to people living in the western part of the United States over the past few years, the reason the Camp Fire occurred on November 8, as opposed to any other day in 2018, was largely due to chance (combined with dry vegetation, high winds, and a transmission tower failure).

We estimate Equation (1) below using more than 200,000 home sales from 2010 to 2019:

$$
\begin{aligned}
\ln\left(\text{Price}_{i,t}\right) = \\
\alpha_0 + \alpha_1 \text{Post}_t + \alpha_2 \text{TreatPeriod}_y + \sum_{b=0}^{4} \alpha_{3b} D_{b,i} + \\
\beta_1 \text{Post}_t \times \text{TreatPeriod}_y + \sum_{b=0}^{4} \beta_{2b}(\text{TreatPeriod}_y \times D_{b,i}) + \sum_{b=0}^{4} \beta_{3b}(\text{Post}_t \times D_{b,i}) + \\
\sum_{b=0}^{4} \pi_b (\text{Post}_t \times \text{TreatPeriod}_y \times D_{b,i}) + \\
\text{Period}_y \times \text{County}_i + \gamma \mathbf{X}_i \times \text{County}_i + \\
\epsilon_{i,t}
\end{aligned}
\tag{1}
$$

where $b(\in 0, 25, 50, 100, 150)$ indexes spatial 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.

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 (six weeks after the fire) in each year from 2010 to 2020.[14] Each year, therefore, provides a single "period", and we observe ten of them (e.g. Period 1: September 27, 2010 - November 7, 2010 and December 6, 2010 - January 17, 2011; Period 2: September 27, 2011 - November 7, 2011 and December 6, 2011 - January 17, 2012; and so on). TreatPeriod_y is equal to one for homes sold in the period coinciding with the Camp Fire (September 27, 2018 - November 7, 2018 and December 6, 2018 - January 17, 2019); zero otherwise. Post_t is equal to one for homes sold between December 6 and January 17 in

[14] Transactions occurring the four weeks after November 8 are excluded from the analysis to account for what is typically a one month escrow period.

any given period; zero otherwise.

Modeled this way, Post_t captures the fixed effect of a home being sold in winter rather than fall, TreatPeriod_y captures the fixed effect of a home being sold in 2018/2019 rather than another year and $D_{b,i}$ captures the effect of a home being located in bin b relative to the reference bin (located between 150 and 200 miles from the footprint of the fire). The interaction of Post_t and TreatPeriod_y accounts for seasonal effects that vary by year and are common to all bins. The interaction of TreatPeriod_y and $D_{b,i}$ accounts for a treatment year effect unique to each bin, but common to both the pre- and post-period. The interaction of Post_t and $D_{b,i}$ accounts for seasonal effects unique to each bin and common to all years. Our primary coefficient of interest is on the interaction term $Post_t \times TreatPeriod_y \times D_{b,i}$, which is the "additional" effect of a sale occurring in the post-period of the treatment year, and within a designated bin.

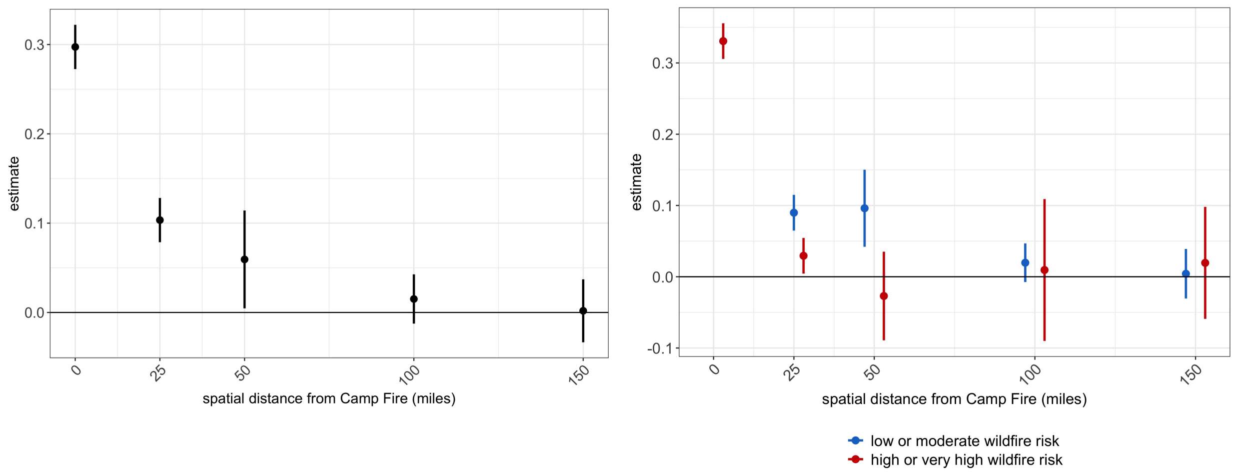
A reasonable concern is that the fire altered the composition of housing being purchased. If evacuees favored higher quality homes after the fire, prices may reflect the variation in the quality of housing rather than a pure demand effect that we aim to estimate. And in fact, we see some evidence of this. For example, Figures A3 - A6 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 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 property sale prices. To address bias resulting from compositional changes, we condition effects on home size, lot size, home age, and home age squared. To account for spatial heterogeneities in the effect of these home attributes (small homes near cities might be more expensive than large homes in rural areas), we interact each of these attributes with county indicators. We additionally condition on period-by-county fixed effects to account for long run, county-specific variation in home prices.

Equation (1) is well suited to measure the spatial distribution of the effects of the Camp Fire. To shed light on the temporal distribution, we estimate variants of Equation (1) in which we replace spatial bins with temporal ones and interact them with indicators for being within 50 miles and between 50 and 100 miles of the Camp Fire perimeter. We continue to condition on home characteristics interacted with county fixed effects, as well as period by county fixed effects. Errors in all estimations are clustered at the county level.

5. Results

Spatial Estimates

Figure 2



(a) Baseline spatial effects (b) By wildfire risk zone

Note: Spatial distribution of the short-term effect of the Camp Fire on property prices in California. Points indicate point estimates and vertical lines indicate 95 percent confidence intervals. In panel (a), treatment groups are defined by their distance to the Camp Fire boundary (inside the fire's footprint, just outside the footprint to 25 miles from the Camp Fire, 25-50 miles, etc.). In panel (b), treatment groups are defined by their distance from the fire and their wildfire risk. For both estimations, the comparison group is all properties located 150 - 200 miles from the Camp Fire. Note that inside the Camp Fire footprint, all of the transacted properties have either a high or very high wildfire risk.

The results from the estimation of the spatial model Equation (1) are provided in panel (a) of Figure 2. In the six weeks after fire, home prices within the footprint increased by 35 percent.[15] To put this result into context, the fire-induced price premium is approximately $80,000 for the average property inside the fire's footprint. We document smaller increases in home prices within 25 miles (11 percent) and 50 miles (seven percent) of the fire. One-hundred miles from the fire we measure a positive treatment effect of three percent, though the estimate is not statistically distinguishable from zero. We estimate that the fire had no statistically significant impact on housing prices 150 miles from the fire.

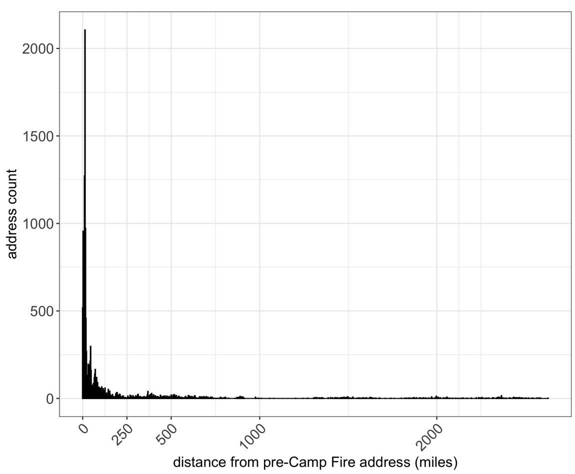
Having established the spatial dimensions of the average treatment effect of the fire, we turn our attention to heterogeneous effects. Specifically, we partition our donuts from Equation (1) into two mutually exclusive areas as defined by CALFIRE: (1) high or very high wildfire risk and (2) medium or low wildfire risk. These results are provided in panel (b) of Figure 2. All of the properties remaining after the fire within the fire's footprint either have high or very high risk, therefore we cannot estimate heterogeneous effects among this group. Within 25 and 50 miles of the fire, we find that the fire increased housing prices by

[15] A coefficient estimate of 0.3 implies a $e^{0.3} - 1 = 34.9$ percent increase in price.

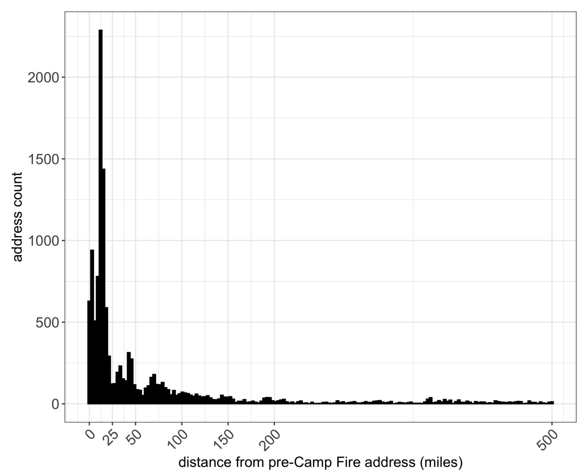
roughly ten percent, but only among lower risk properties. In fact, for higher risk properties, we estimate the Camp Fire increased housing prices within 25 miles by just 2.5 percent, and had no effect on higher risk property prices farther awa.

Taken together, our results hold two key findings. First, evacuees preferred to relocate close to where they lived prior to the fire. This is demonstrated by the fact that we estimate diminishing price effects as properties' distance from the footprint of the fire increases. This interpretation is corroborated by the observed migratory behavior of Camp Fire evacuees. As described in panels (a) and (b) of Figure 3, the large majority of evacuees remained within 50 miles of the footprint of the fire.[16] Second, outside of the fire's footprint, evacuees preferred properties with lower wildfire risk, as indicated by the larger price premiums on these properties. This is notable given the fact that the burned homes were all located in areas of high or very high wildfire risk, indicating that evacuees updated either their risk perceptions or their risk preferences in response to the Camp Fire. It's challenging to interpret treatment effects within the Camp Fire's footprint because the fire both reduced the supply of housing and caused a temporary reduction in real wildfire risk. Outside of the footprint, these factors were held constant.

Figure 3: Observed Migratory Behavior



(a) All Addresses



(b) Address within 500 miles

Note: Spatial analysis of the distance that people moved from the footprint of the Camp Fire, comparing pre-fire addresses to post-fire addresses. Data are from the United States Postal Service Change-of-Address database.

Temporal Estimates

[16]United States Postal Service change-of-address data on the location of Camp Fire evacuees was graciously shared with us by Peter Hansen at California State University, Chico. A description of how these data were generated is given in Chase and Hansen (2021).

We now turn our attention to temporal effects. We start by estimating the effect of the fire in one week intervals, the result of which is provided in panel (a) of Figure 4. We also report pre-treatment estimates ($t-6$ to $t-2$) to reveal any pre-trends. The week prior to the fire serves as the reference category in this estimation. Within 50 miles of the fire, it took four weeks on average for home prices to begin to rise. Assuming a four week escrow window, these results are consistent with fairly sudden effects on home prices. We see similar temporal patterns among homes between 50 and 100 from the fire, however, statistical significance is limited to the six week bin.

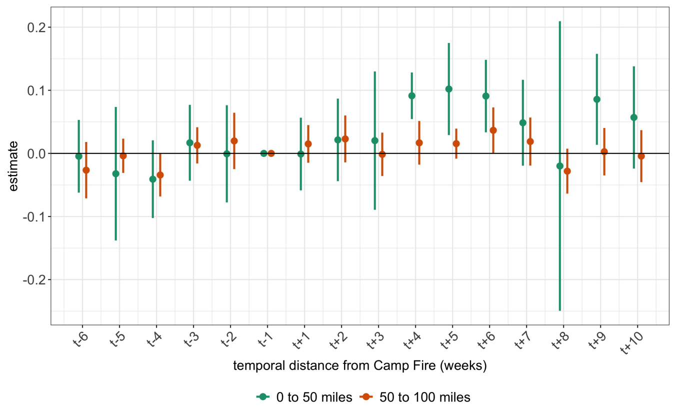
We also estimate temporal effects according to wildfire risk zones. These results are provided in panels (b) and (c) of Figure 4. For homes within 50 miles of the fire, and in low or medium risk zones, we observe an increase in price just two weeks after the fire. This effect is surely a lower bound estimate on the true magnitude of the effect of the fire given that some of the homes in this group likely entered escrow prior to November 8th, the start of the Camp Fire. Interestingly, there is some evidence of a decline in home prices in high or very high risk zones immediately after the fire. We are hesitant to draw strong conclusions, however, given the imprecision of the estimate. Comparing panels (c) and (d), it is clear that homes within 50 miles of the fire were impacted more significantly than those between 50 and 100 miles away.

To estimate longer-run effects, we use an estimation strategy that is very similar to that used to estimate short-run effects, with months replacing weeks. Our reference group of homes are those sold in the six-week pre-period, September 27th to November 7th. To avoid overlap between our treatment months and the reference group, we restrict the analysis to the ten months during and after the fire, i.e. November 8th to September 8th.

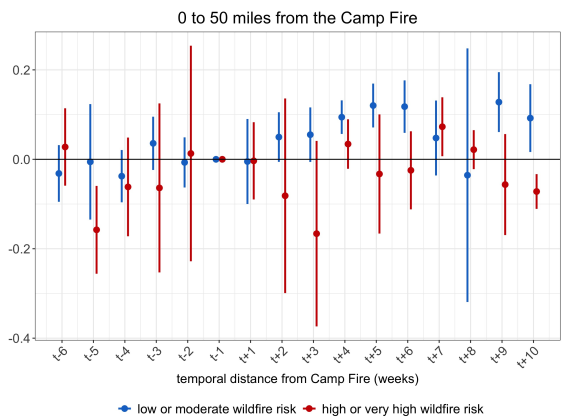
In the ten months after the fire, treatment effects are persistent among homes within 50 miles of the footrprint of the fire (panel (a) of Figure 5). It is interesting to note that, whereas these effects are relatively stable (a treatment effect of roughly eight percent across all ten months), homes further away initially see a two percent premium but this disipates by month three. Then, five months after the fire, treatment effects start to rise again. One speculative interpretation of this pattern is that some displaced people waited until the following summer (five months after the fire coincides with May 2019) to purchase homes away from the burned area. This could potentially reflect labor market frictions (it takes time to find a new job) or the academic calendar (parents may have waited to move their children to a new school district).

Panel (b) of Figure 5 reports monthly effects within 50 miles of the footprint of the fire by wildfire risk zone. These results show a fairly consistent and persistent ten percent treatment effect among properties with low or medium fire risk. Among properties with high or very

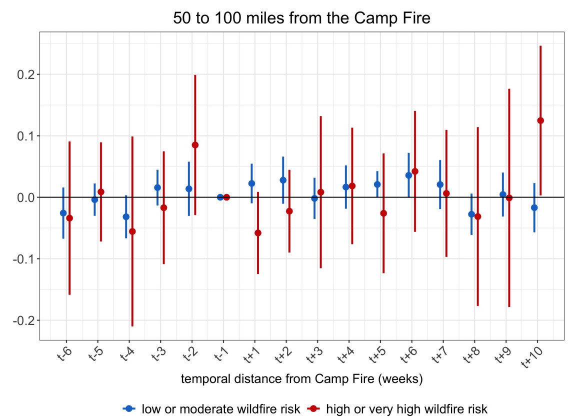
Figure 4: Temporal effects in the short-term



(a) Pooled



(b) 0 to 50 miles

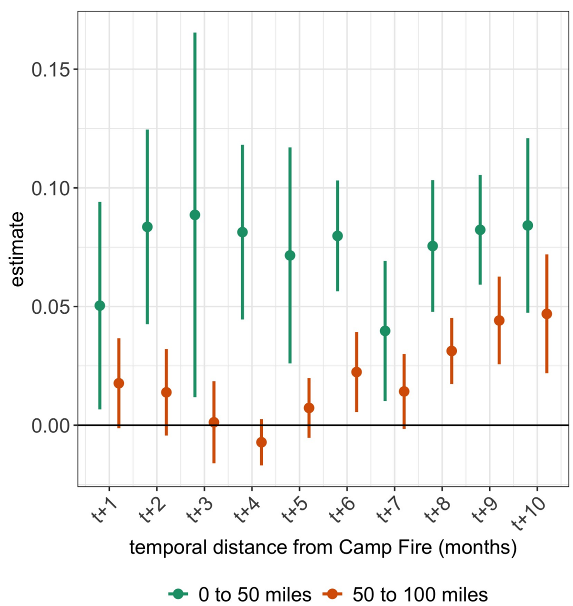


(c) 50 to 100 miles

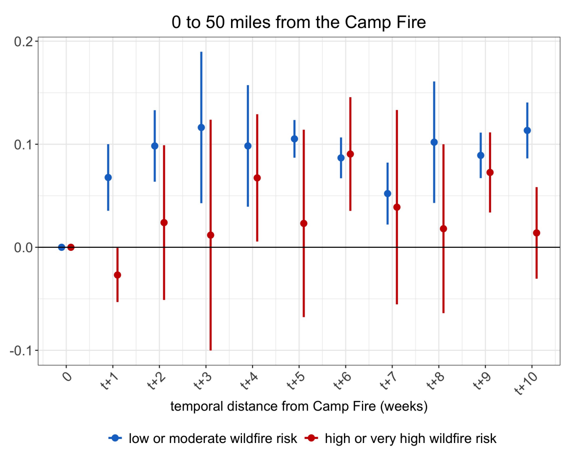
Note: Weekly temporal effects of the Camp Fire on property prices in California up to ten weeks post-fire (i.e. January 16, 2019). Points indicate estimates and vertical lines indicate 95 percent confidence intervals. The comparison group is properties located greater than 100 miles and less than 200 miles from the Camp Fire. Panel (a) gives estimates pooling properties across wildfire risk zones. Panels (b) and (c) report estimates for homes within low-fire-risk zones and high-fire-risk zones, respectively. Estimates are zeroed at property prices one week prior to the Camp Fire.

high fire risk, effects are less precisely estimated, but are mostly smaller in size. Between 50 and 100 miles from the fire (panel (c) of Figure 5), we again see a "u" shaped distribution of treatments effects, particularly among lower-risk properties. Whereas the fire caused an immediate and longer-term increase in lower-risk properties, it had no discernible short or long-run effect on higher-risk properties.

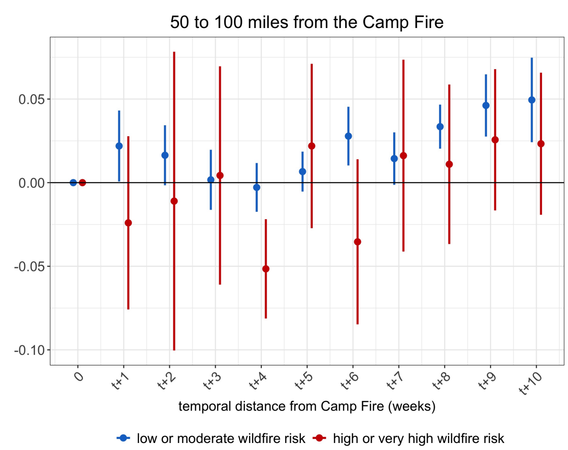
Figure 5: Temporal effects in the medium-term



(a) 0 to 50 miles



(b) 0 to 50 miles



(b) 50 to 100 miles

Note: Temporal analysis of the monthly effects of the Camp Fire on property prices in California up to ten months post-fire (i.e. September 7, 2019). Points indicate estimates and vertical lines indicate 95 percent confidence intervals. In panel (a), properties are pooled across wildfire-risk-zones. In panels (b) and (c), one treatment group is properties located in low or medium fire risk zones and a second treatment group is properties located in high or very high risk zones. The comparison group is properties located greater than 100 miles and less than 200 miles from the Camp Fire. Estimates are zeroed at property prices for the two months prior to the Camp Fire.

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 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 or proximity to particular amenities), our estimates of the pure demand effect would be upward biased.

To paint a clearer picture of whether the estimated price effect is the result of increased demand for housing, or simply a compositional change in the characteristics of homes being purchased, 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 block by distance donut, year-period, pre- and post-November 8th. The sales count variable — transformed with hyperbolic sine — serves as the dependent variable in the estimation.[17] The explanatory variables are identical to that of Equation (1), meaning we include indicator variables and their interactions for each donut, the post-November 8th variable and the 2018-2019 treatment-year period. Contrary to Equation (1), we spatially aggregate to 50 mile-wide donuts and temporally aggregate to three-month quarters to assure sufficient sample size in each spatial-temporal bin. The estimation also includes period, quarter, and tract-donut fixed effects, the latter of which ensures that estimation of the sales volume effect is derived from within-tract-donut variation in sales count. Results from the estimation are shown in Figure A1. The Camp Fire caused an increase in the volume of home sales within 50 miles of the fire. In the first quarter, sales volume increased by nearly 38 percent. In the second quarter, the effect is more than halved and statistically significant at the ten percent level. For properties 50 to 100 miles from the Camp Fire, we do not observe a change in sales volume. 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 in this study's primary analysis we use homes sold between 150 and 200 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 between 100 and 150 from the Camp Fire), we use a series of alternative

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

reference bins and re-estimate our baseline results for added robustness. These results are provided in Figure A2. The results show that changing the distance from the reference bin to the fire has virtually no effect on our estimates.

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.[18]

Catastrophic wildfires have the potential to create significant spatial and temporal spillovers, in which the effects of wildfires extend beyond the immediate location and time of the fire. Spillovers can take different forms, including health effects of environmental changes such as wildfire smoke (Borgschulte et al., 2022) and economic effects of disrupted supply chains (Boehm et al., 2019). Measuring spillovers reveals the indirect consequences of disasters that may not be immediately visible or apparent. By understanding the wider scope of a disaster's impact, decision-makers can make more informed and comprehensive assessments of the costs, benefits, and trade-offs of different interventions and policies.

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 in November 2018, the Camp Fire destroyed the town of Paradise in northern California, killing 85 people, destroying thousands of homes, and displacing 50,000 people. We find that the fire had large effects on nearby real estate markets, causing prices to rise within 50 miles of the fire's footprint. Prices remained elevated for at least ten months after the fire. The largest price effects were detected in areas of low or medium wildfire risk, indicating that evacuees preferred properties that were minimally susceptible to wildfire. This is important because all of the properties that burned were located in either high or very high wildfire risk zones, suggesting that evacuees updated either their risk perceptions or their risk preferences in response to the Camp Fire.

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 lower wildfire risk areas outside of the fire's

[18] https://www.fire.ca.gov/media/t1rdhizr/top20$_{d}\mathit{estruction.pdf}$

footprint were indirectly affected as thousands of evacuees purchased homes — or attempted to purchase homes — in their locations. In addition to the Camp Fire 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.[19]

While rising housing prices provides some benefits to homeowners in host communities, 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 that can increase the supply of housing to evacuees both in the immediate and longer-run. 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.[20] 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 and costless 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 precise effects of future events as such effects will depend upon the density and distribution of housing specific to those areas. That being said, we think certain patterns in our data could reasonably be applicable elsewhere. Specifically, our results suggest that low wildfire risk jurisdictions in close proximity to high wildfire risk

[19]This number should not be confused with the total value of homes purchased by fire evacuees. Rather, it is only the additional money spent on housing that resulting from rising prices. More specifically, the figure was computed as follows. We first estimated the 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 (1)). 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 bin in the six weeks prior to the fire ($229,722, $307,909, and $299,704, respectively). Finally, we multiply the resulting value changes within each bin by the respective number of home sales in the ten months following the fire (which were 166, 1,830, and 1,988, respectively).

[20]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.

ones are highly susceptible to the migratory spillover effects of catastrophic wildfires. Policy makers should consider implementing wildfire adaptation strategies that take into account the wildfire risk of their neighbors and the broader social, economic, and environmental context in which wildfires tend to occur.

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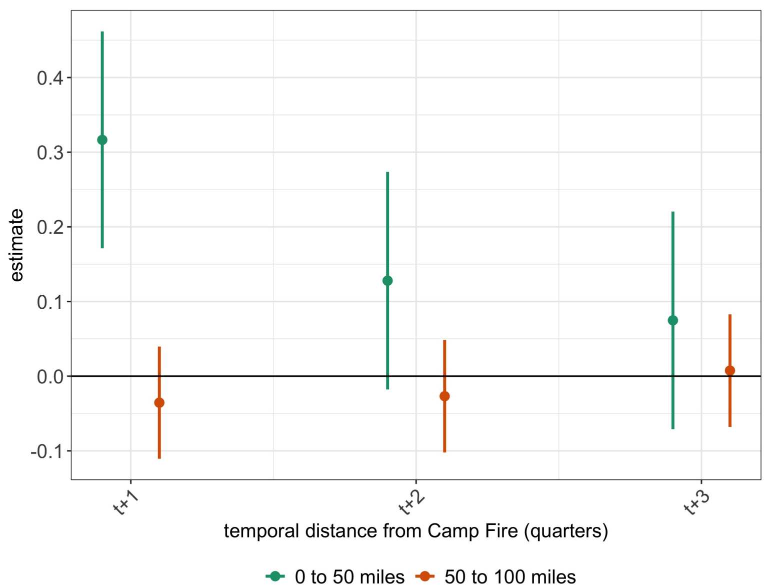
8. Appendix

Table A1: Summary Statistics

Statistic	Mean	St. Dev.	Min	Max
Sales price	\$490,688	\$496,619	\$25,000	\$3,992,500
Inside Camp Fire footprint	0.001	0.027	0	1
Inside 0-25 mile donut	0.015	0.123	0	1
Inside 25-50 mile donut	0.022	0.147	0	1
Inside 50-100 mile donut	0.296	0.456	0	1
Inside 100-150 mile donut	0.431	0.495	0	1
Inside 150-200 mile donut	0.229	0.420	0	1
High or very high wildfire risk	0.073	0.260	0	1
Low or moderate wildfire risk	0.927	0.260	0	1
Sale occurred after the Camp Fire	0.429	0.495	0	1
Lot size (acres)	0.184	0.126	0.003	1.00
House size (square feet)	1,779	700	24	24,156
Age of house	40	27	0	170

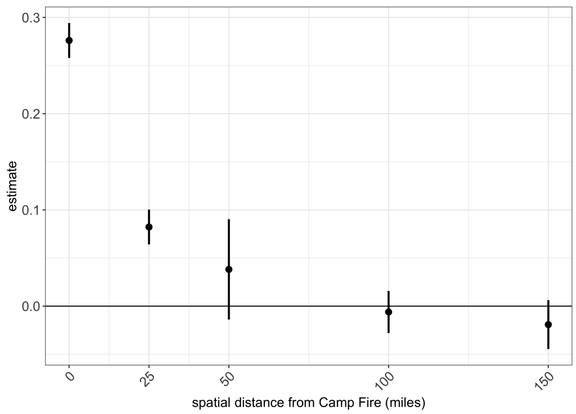
N = 219,594

Figure A1: Sales volume

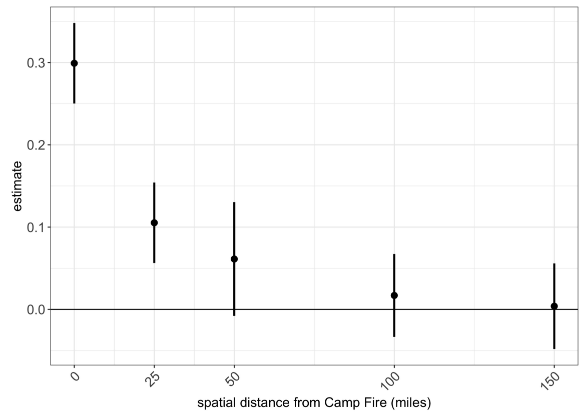


Note: Temporal analysis of the quarterly effects of the Camp Fire on property prices in California up to ten months post-fire (i.e. September 7, 2019). The first month after the fire is excluded from the sample. Points indicate point estimates and vertical lines indicate 95 percent confidence intervals. One treatment group is properties located 50 miles or less from the Campfire footprint and a second treatment group is properties located 50 - 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.

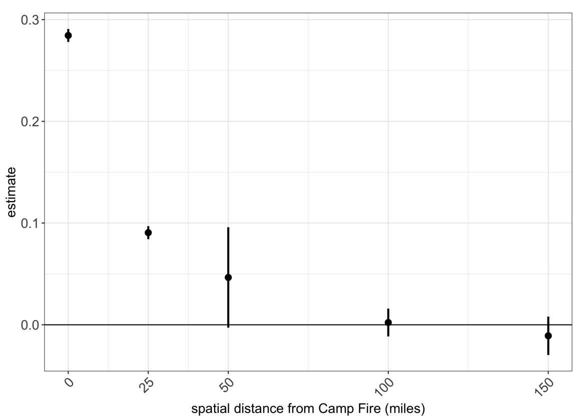
Figure A2: Spatial Effects: Alternate Reference Bins



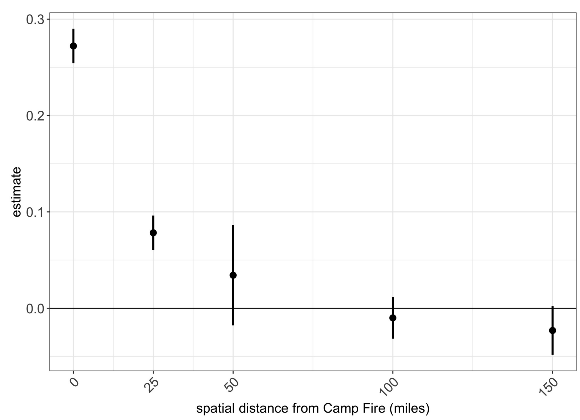
(a) control properties are 200-250 miles from boundary



(b) control properties are 250-300 miles from boundary



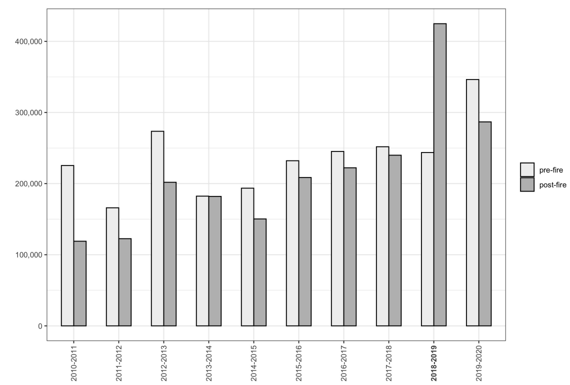
(c) control properties are 300-350 miles from boundary



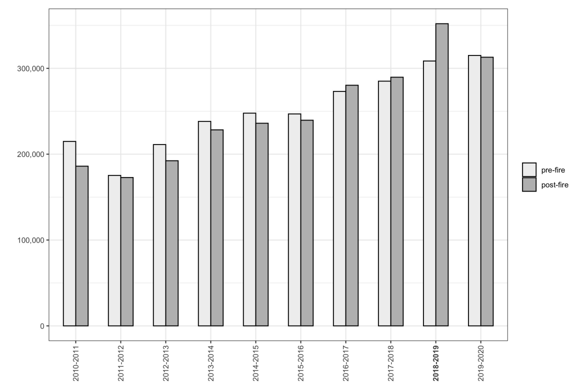
(d) control properties are 350-400 miles from boundary

Note:

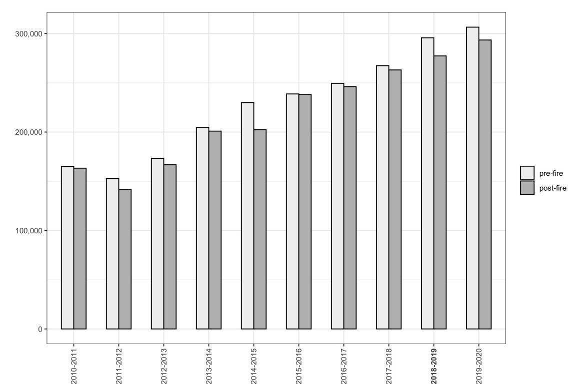
Figure A3: Mean price by treatment and temporal group (nominal USD)



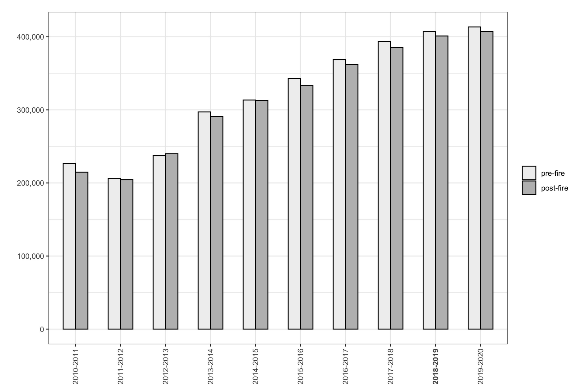
(a) Within the Camp Fire boundary



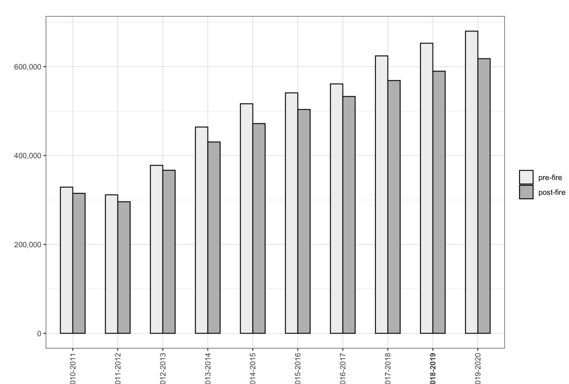
(b) Between 0 and 25 miles from the Camp Fire boundary



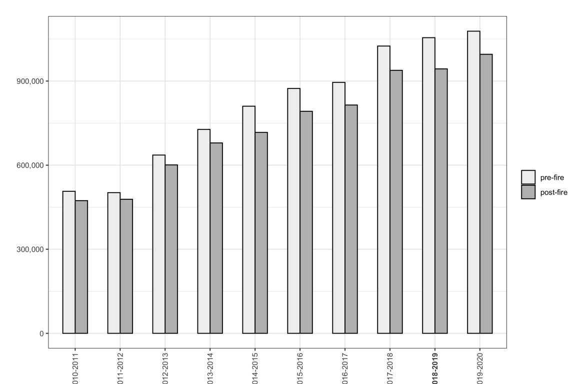
(c) Between 25 and 50 miles from the Camp Fire boundary



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



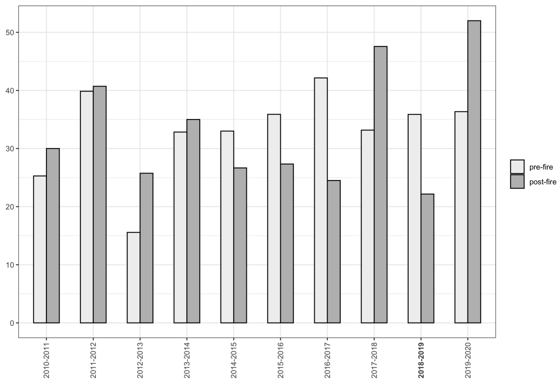
(e) Between 100 and 150 miles from the Camp Fire boundary



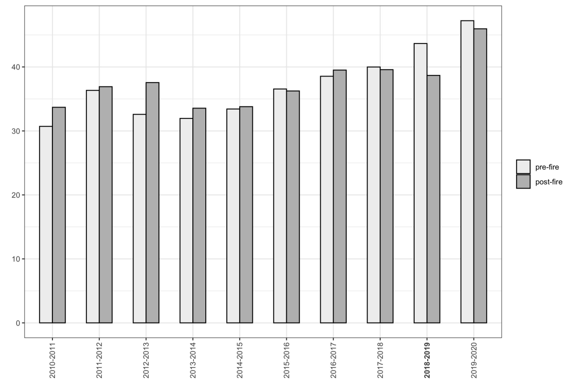
(f) Between 150 and 200 miles from the Camp Fire boundary

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

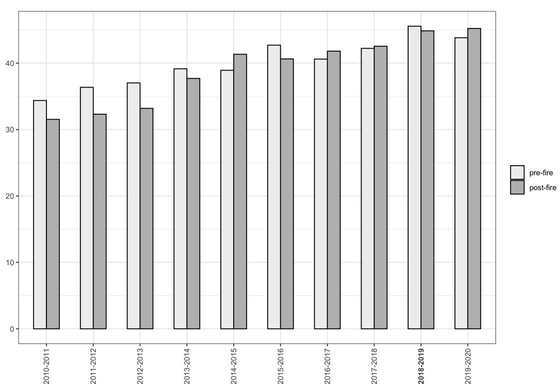
Figure A4: Mean structure age by treatment and temporal group (years)



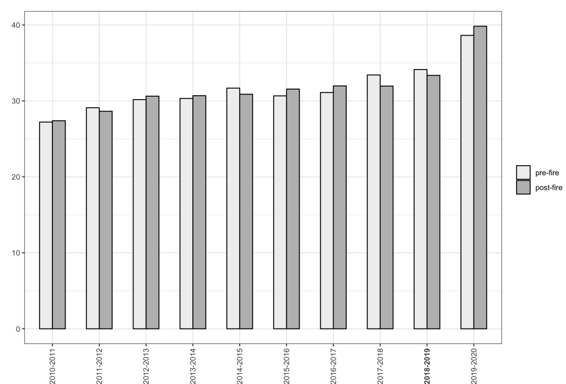
(a) Within the Camp Fire boundary



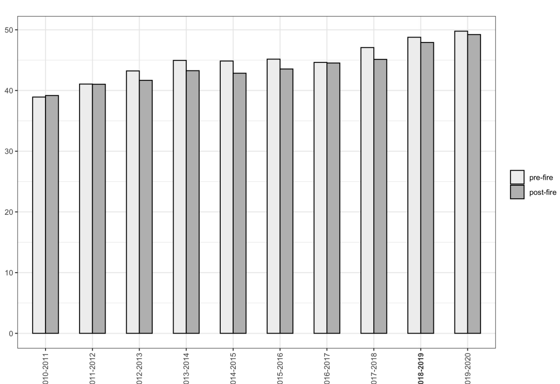
(b) Between 0 and 25 miles from the Camp Fire boundary



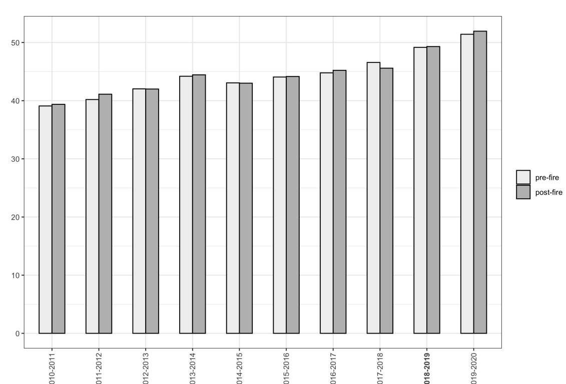
(c) Between 25 and 50 miles from the Camp Fire boundary



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



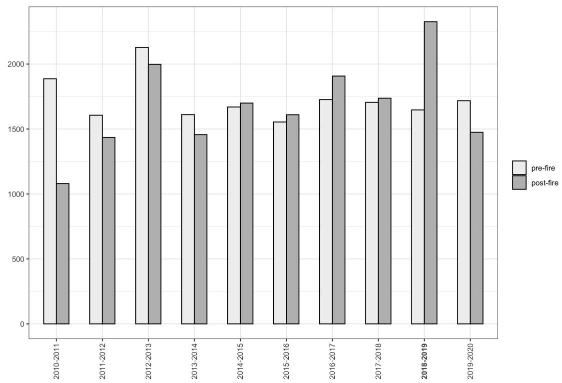
(e) Between 100 and 150 miles from the Camp Fire boundary



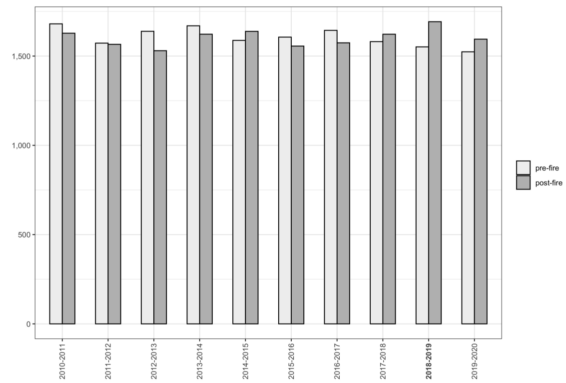
(f) Between 150 and 200 miles from the Camp Fire boundary

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

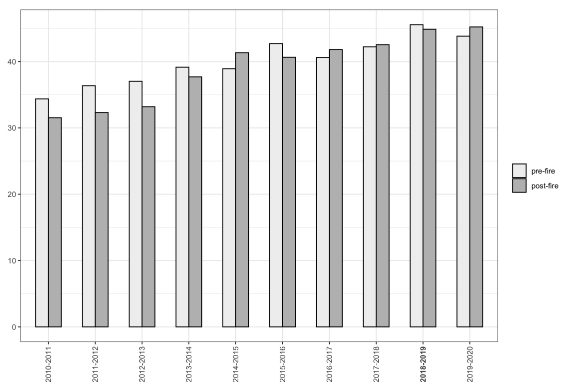
Figure A5: mean structure size by treatment and temporal group (square feet)



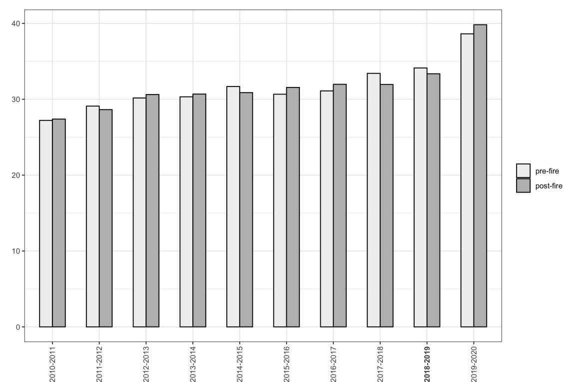
(a) Within the Camp Fire boundary



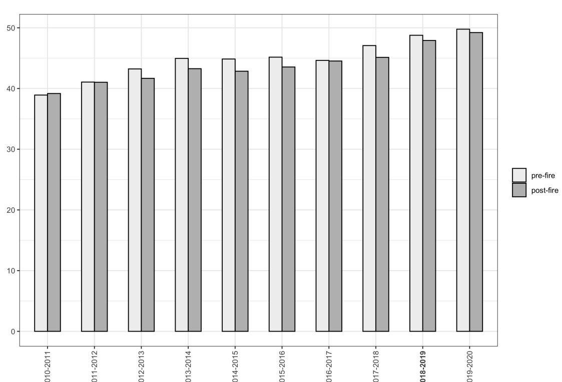
(b) Between 0 and 25 miles from the Camp Fire boundary



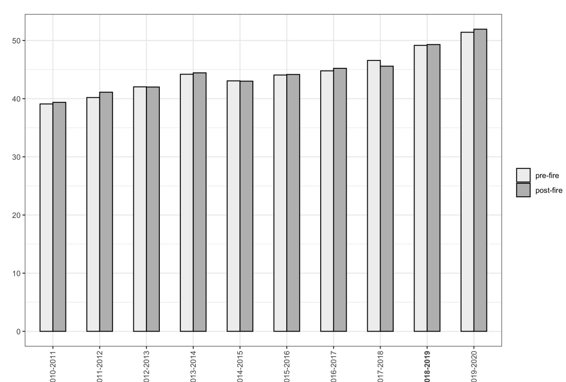
(c) Between 25 and 50 miles from the Camp Fire boundary



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



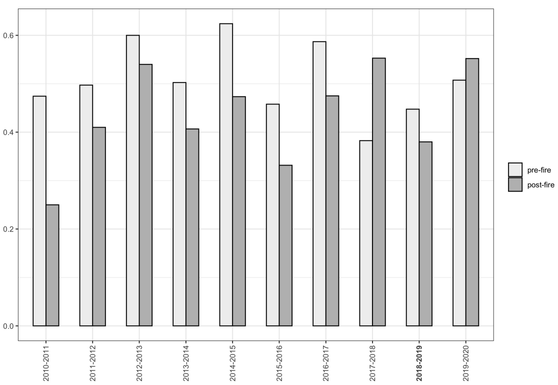
(e) Between 100 and 150 miles from the Camp Fire boundary



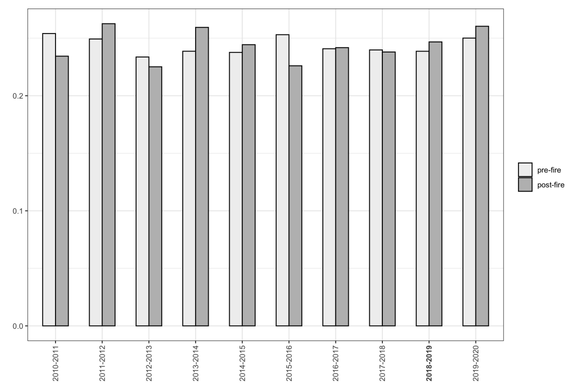
(f) Between 150 and 200 miles from the Camp Fire boundary

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

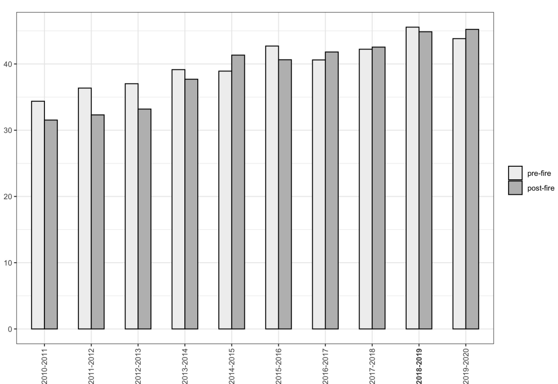
Figure A6: Mean lot size by treatment and temporal group (acres)



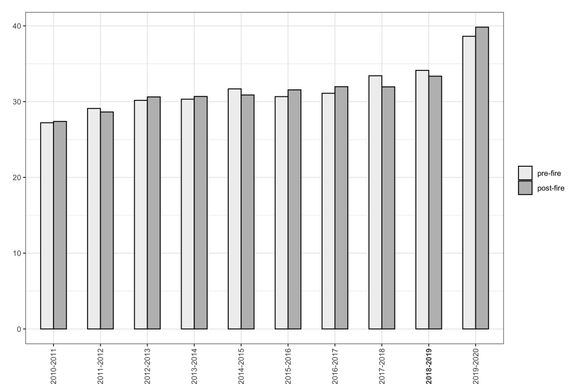
(a) Within the Camp Fire boundary



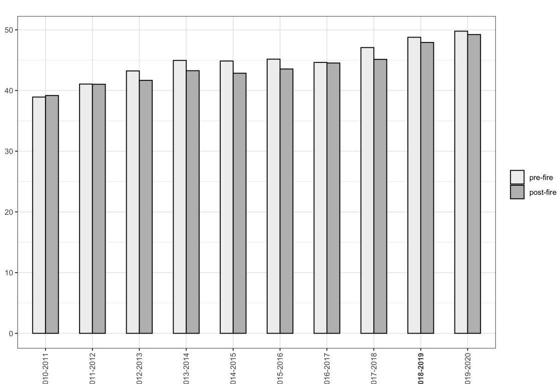
(b) Between 0 and 25 miles from the Camp Fire boundary



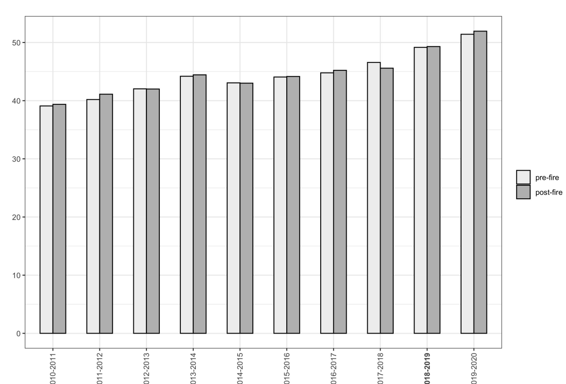
(c) Between 25 and 50 miles from the Camp Fire boundary



(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.