Equity Impacts of Wildfire:
Evidence from the California Housing Market

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Abstract

I study the effect of 198 large wildfire events (2016-2018) on nearby house transaction prices, quantities, and quality in order to identify heterogeneity in real estate market responses across risk levels, proximity to wildfire, and time since the wildfire event. Employing an event study strategy, I find that the sale price of homes within 10 miles of a fire event drop by almost 10% for the first 6 months and return to pre-fire levels within a year. Combining price effects with quantity effects, I find that for homes in very-high-risk zones, a positive supply shock dominates, while for homes outside of these zones, a negative demand shock dominates. I also find that the supply shock in very-high-risk zones is driven by homes of lower quality. Using the predicted values of a hedonic regression of house price on house characteristics in the month before a wildfire, I find that the quality of an average home sold in a very-high risk region was around $50,000 "worse" after a fire, implying that less-wealthy homeowners in risky zones are more likely to move after a wildfire than their wealthier counterparts. The quality of homes sold outside of very-high risk zones (including those close to the event) did not change.

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1. Introduction

The costs of wildfire are substantial. From 2011 to 2020, wildfires burned an average of 7.5 million acres of land each year in the United States, roughly 40% of which were in California (CRS Report, 2021). In 2020 alone, 13,887 buildings were destroyed, totaling over $19.884 billion in pure accounting damages. In addition, an estimated 1,975,116 U.S. homes are currently at risk of being destroyed by wildfire, carrying an associated reconstruction cost of $638 billion. Of the the areas most at risk, 76% are in California (Corelogic, 2020). Wildfire size and intensity are projected to increase over the next century as climate change intensifies (Westerling et al. 2006, 2011).

Despite these costs, very little economics research has been conducted on wildfire[2]. Of these, a total of five papers employ the hedonic price model (HPM) formalized by Rosen (1974) to estimate how wildfires are capitalized into house prices. The first of these papers was Loomis (2004), which studied the effect of Colorado wildfires on house prices in the town of Pine and found that prices dropped 15% for homes within 2 miles of a wildfire. Studying homes in Montana, Steller et al. (2010) find a 7.5% decrease for homes within 5k and 13.7% decreae for homes between 5k and 10k. In Southern California (most relevant to this article), Mueller et al. (2009) find a negative effect of 10% for the first fire and 23% for the second fire for homes within 1.75 miles. Donovan et al. (2007) and Hansen and Naughton (2013) find inconclusive results.

My study builds on this body of work by extending the analysis to a number of dependent variables that paint a clearer picture of post-fire real estate market dynamics. In order to understand supply and demand responses, I study quantity changes in addition to price effects. In order to understand the duration of wildfire effects, I employ event study estimation in addition to difference-in-differences.

A common challenge among the aforementioned studies is the ability to disentangle the amenities affected within the hedonic model (Hansen, Mueller, and Naughton, 2014). These

[2] Only six papers have been published on wildfire in leading field journals–*JEEM* and *ERE*–and none by the American Economics Association

studies quantify the effect of wildfire itself rather than the specific amenities (channels) through which wildfires affect house prices. To address this issue, I study risk zones in addition to proximity.

There is also a growing body of literature identifying heterogeneous burdens of natural disasters. Fussel, Sastry, and VanLandingham (2010) find that poorer families were slower to return to their New Orleans homes following Hurricane Katrina. Qiang (2018) finds that poor households more exposed to flood zones in the United States and Winsemius et al. (2018) find that this holds true globally as well. However, to the extent of my knowledge, no paper has studied how wildfires affect communities differently. This paper seeks to fill that gap.

The present article builds on previous literature in three main ways: (1) by identifying heterogeneous housing market (supply-demand) responses to wildfire events, (2) by partially identifying the the channels through which wildfire impacts the housing market, and (3) by exploring the types of homes that respond most to wildfire events.

I find that for homes in very-high-risk zones, a positive supply shock dominates, while for homes outside of these zones, a negative demand shock dominates. I also find that the supply shock in very-high-risk zones is driven by homes of lower quality, implying that poorer homeowners in risky zones respond to wildfire much more than their wealthy counterparts. Using the predicted values of a hedonic regression of house price on house characteristics in the month before a wildfire, I find that the quality of homes sold in very-high risk regions was around $50,000 ”worse” after a fire. The quality of homes sold outside of very-high risk zones (including those close to the event) did not change.

The remainder of this article proceeds as follows. The next section (2. Background & Data) describes the data I use as well as the historical context behind California’s creation of fire hazard severity zones (FHSZ), the main treatment-interaction variable of interest. Section 3 (Model) formalizes the assumptions and testability of my hypotheses. Section 4 (Empirical Strategy) explains the regression models that I use to empirically test my hypotheses. Section 5 (Results) highlights my main findings and combines them with my model assumptions to derive comparative statics interpretations. Section 6 (Discussion) brings additional context to my findings, highlights potential equity concerns, and discusses ways for future research to shed light on what I've found. Lastly, section 7 concludes.

2. Background & Data

2.1 Background

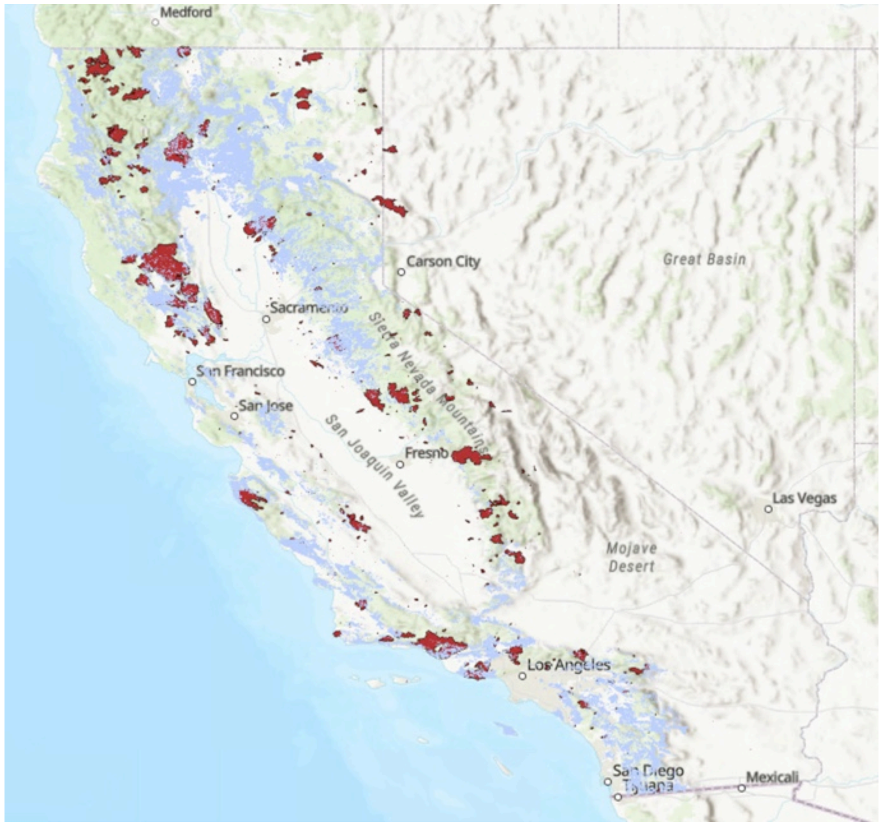
All areas in the state are split into two types of fire risk liability areas: State Risk Liability Areas (SRA) and Local Risk Liability Areas (LRA). While local municipalities are primarily responsible for fires that happen in LRAs, the state is primarily for handling fires in SRAs. As such, LRAs are mostly comprised of (sub)urban regions and SRAs of rural and unincorporated regions.

In 2011, the State of California assigned to every geographical coordinate in the SRA region a fire risk level–moderate, high, very-high, or none–called Fire Hazard Severity Zones (FHSZ). For LRAs, the State only identified very-high FHSZ. Owners of homes in very-high FHSZ, whether in an SRA or LRA, were notified that they live in a very-high fire risk zone. Sellers of homes in very-high FHSZ are legally obligated to disclose that the home is in a very-high FHSZ.

Because of the high level of risk, it is generally more difficult for homes in very-high FHSZ to be approved for fire insurance. While insurance companies in California are prohibited from dropping clients, companies are free to not approve coverage to new applicants with risky homes. California homeowners are not legally obligated to purchase fire insurance, but those who want coverage but have been denied by standard insurance companies are entitled to state-run insurance plan (The FAIR Plan) which offers relatively limited coverage.

2.2 Data

Figure 1: FHSZ and Wildfires (2016-2018)

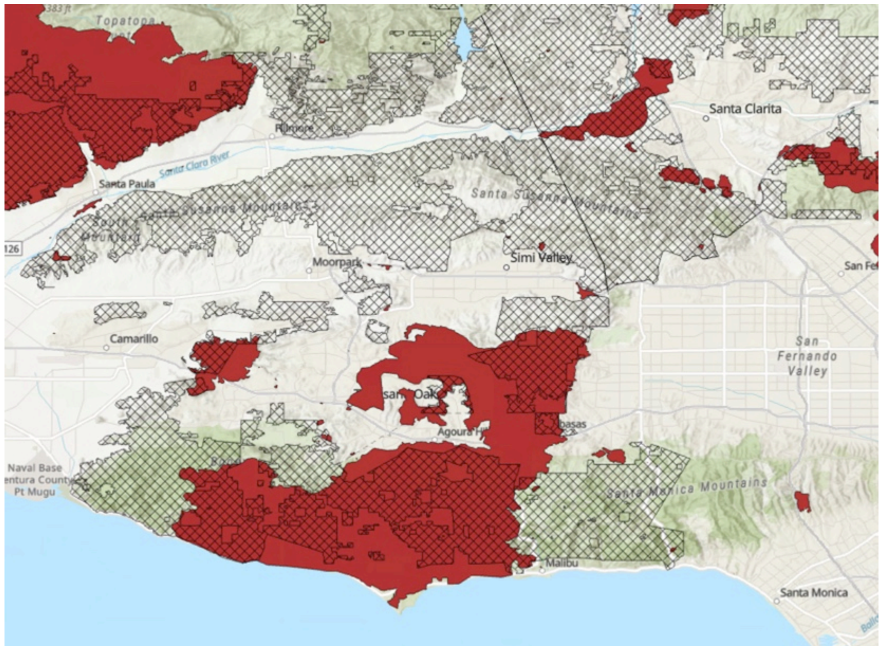


Note: Wildfire perimeters are colored red and FHSZ are colored indigo. FHSZ include all zones–medium, high, and very-high.

Data in my analysis are comprised of three sources: (1) House transactions and house characteristics (2016-2018) provided by Zillow ZTRAX; (2) fire perimeter GIS coordinates and fire event information (2015-2018) from Wildland Fire Interagency Geospatial Services; and (3) Fire Hazard Severity Zone (FHSZ) coordinates (unchanged since 2011) from California Fire and Resource Assessment Program (FRAP). House transactions are for years 2016-2018 since these years seemed to be the most complete in the Zillow data. Importantly, 2017 and 2018 experienced some of the largest fires to date.

I attached to each transaction its legal FHSZ based on GIS coordinates and assigned to each fire event all the house transactions that occurred within a 10 mile buffer of the fire perimeter. I limited the fire event sample to "large fires"–over 1,000 acres, as defined by the EPA (of which there were 211)–and to fires that affected over 1,000 transactions. These

Figure 2: FHSZ and 2017 Woolsey Fire (Malibu area)



Note: Wildfire perimeters are colored red and very-high FHSZ are shaded.

restrictions leave me with 192 wildfire events between 2016 and 2018.

I limited transactions to single family residential properties with a sale price, of which there are 406,481 in my data from 2016 through 2018. I normalized house sale prices to the 2016 Case-Schiller California House Price Index and drop the top and bottom 5 percentiles. Dropping the bottom percentile mostly ensures that I am using arms length transactions and dropping the top 5 percent safeguards against possible typos. This further limited my number of transactions to 365,338.

To each transaction, I assigned an event time indicator based on when the transaction took place with respect to the fire event. Event time of "0" indicates that the property was sold during the fire event. For example, if the fire event was 3 months long, then any transaction that occurred in those 3 months (if within 10 miles of the fire event) would be given an event time of 0. The average fire event in my data lasted two months. I then restricted the data to 12-month event time leads and lags and to only homes that occurred within 10 miles of a fire event.

At this point, the observations are event-transaction level, meaning that one transaction may be assigned multiple wildfire events if it the transaction occurred within a year before or after the event. To ensure that duplicate transactions are not counted as ”untreated”, if a it was assigned both a pre- and post-event time, I kept only the post event time assignments. After doing this, 99,477 transactions were assigned to more than one fire event, of which 54,484 were ”post” and 44,993 were ”pre”. In all, my data contain 211,231 event-transaction observations and 198,204 unique transactions.

Usable transactions were further limited in some regressions by non-missing house characteristics (see Tables 1 and 3). Of transactions that have complete house characteristic data, 10,364 are in very-high FHSZ, 1,164 homes are in high FHSZ, 1,472 homes are in moderate FHSZ, and the remainder, 57,557, are in no FHSZ. As shown in Table 1, homes in very-high FHSZ tend to have more land and be slightly more expensive than those not in a FHSZ. The median home in a very-high FHSZ in my sample sold for $390,000 compared to $369,000 among those not in a FHSZ.

Of transactions that have complete house characteristic data, 4,194 homes are within 2 miles of a fire event, 22,366 homes are within 5 miles (including within 2 miles), and the remainder, 48,191, are 5-10 miles away. As shown in Table 2, homes in close to (within 2 miles of) fire events also tend to be more expensive than those far away (5-10 miles away). The median ”close” home in my sample sold for $410,000 compared to $371,500 among those ”far away.”

3. Model

My hypotheses, empirical strategy, and interpretation of results are formulated under a simple model of housing supply and demand. While housing supply is fixed in the short run, the housing turnover rate—in my study, the number of homes sold each month—need not be. As such, I assume that fire events can affect both current owners (supply) and potential buyers (demand) in three keys ways: environmental aesthetics, smoke pollution, lower perceived future risk, and higher perceived future risk. In addition, I consider the possibility that perceived personal fire risk–the event of one's own house catching fire–may be different from perceived local fire risk–the event where a wildfire occurs somewhere close but does not affect my house directly. Local fire risk would include all associated negative effects of a fire other than the risk of losing one's house, such as increased air pollution during the fire.

I assume that homebuyers and sellers interpret these channels in each time period t with a utility function $U = U(s, a, b)$ where s is smoke pollution during the event, a is aesthetic beauty of the nearby environment, b is an indicator for whether one's home burned. I assume these effects are relatively ephemeral and either last only the duration of the fire or gradually lessen over the course of a year. I also assume that homebuyers and sellers act according to an expected utility function which incorporates the risk of a fire event happening again in the future. Let r represent the perceived probability of b happening in the future and call r one's "personal risk." Let l be the perceived probability of (s, a) happening again in the future and call this "local risk." I assume the relationship between utility U (as well as expected utility, $\mathbb{E}[U]$) and the four channels s, a, r, and l to be

$$\frac{\partial U}{\partial s} < 0 \; , \; \frac{\partial U}{\partial a} > 0 \; , \; \frac{\partial \, \mathbb{E}[U]}{\partial r} < 0 \; , \; \frac{\partial \, \mathbb{E}[U]}{\partial l} < 0.$$

Supply is governed as follows. After a fire event, homeowners must chose to stay or to move. They make this decision based on expected value of living in the location (net of costs). Since I don't include renters in my data, I restrict owners to these two options. If environmental amenities become bad enough (relative to elsewhere), homeowners will decide to move. Supply is determined by the number of homeowners who choose to move in a given period. Since every homeowner values a, s, r and l as described above, the post-fire aggregate supply response will look like

$$\frac{\partial S}{\partial s} > 0 \; , \; \frac{\partial S}{\partial a} < 0 \; , \; \frac{\partial S}{\partial r} > 0 \; , \; \frac{\partial S}{\partial l} > 0.$$

Demand is modeled as follows. Everyone in the state is a potential homebuyer and homebuyers in all FHSZ share the same preferences on average. Potential homebuyers evaluate locations based on their characteristics and on their environmental amenities. If a potential homebuyer finds a home that brings them higher expected value than the place they are currently living, they will buy it. If a location becomes less appealing, then fewer people will desire to live there. Since every homebuyer values a, s, r and l as described above, the post-fire aggregate demand response will look like

$$\frac{\partial D}{\partial s} < 0 \ , \frac{\partial D}{\partial a} > 0 \ , \frac{\partial D}{\partial r} < 0 \ , \frac{\partial D}{\partial l} < 0.$$

In the event of a situation like a wildfire, it is likely that multiple shocks coexist with one another. However, these effects are not entirely confounding. Decreased prices accompanied by decreased quantity sold identify the existence of (at least) a negative demand shock; whereas the reverse would identify a positive demand shock. Decreased prices accompanied by increased quantity sold identify the existence of (at least) a positive supply shock; whereas the reverse would identify a negative supply shock.

Furthermore, the channels through which these shocks occur can be narrowed through testable dimensions. In this case, my hypothesis is that if buyers and sellers are concerned about worse aesthetics near the wildfire site or perceive lower fire risk near the wildfire site (possibly due to less flammable material), then event proximity will be a relevant dimension for post-wildfire transactions.

If smoke pollution is relevant, then I expect all buyers and sellers to respond regardless of where the home is located (within 10 miles of the fire event). Smoke pollution is known to span large geographical areas–even across state borders–and thus is unlikely to be correlated with the treated groups (FHSZ and proximity) any more than with the control group.

If buyers and sellers perceive higher risk after the fire relative to before, then all buyers and sellers might respond, however those in very-high FHSZ will respond more. So the effect of wildfire on homes in very-high FHSZ can be attributed entirely to changes in risk perception. On the other hand, for the untreated group, the channels of ”smoke pollution” and ”higher perceived risk” are indistinguishable from each other.

My hypothesis can thus be described succinctly by the following table:

Channel	**Demand response**	**Supply response**	**Testable dimension**
worse aesthetics	$\Downarrow$	$\Uparrow$	proximity
lower perceived risk	$\Uparrow$	$\Downarrow$	proximity
higher perceived risk	$\Downarrow$	$\Uparrow$	FHSZ
smoke pollution	$\Downarrow$	$\Uparrow$	all

4. Empirical Strategy

The purpose of the empirical portion of this article is twofold. The first is to identify which of the channels outlined in Section 3 (Model) is most dominant in the housing market after a recent wildfire event and whether demand or supply responded stronger. The second is to explore one possible reason as to why demand and supply response magnitudes differ across FHSZ.

To address the first , I use the following difference-in-differences and event study regressions with price and quantity dependent variables:

Diff-in-diff:

$$
\begin{aligned}
Y_{i,c,t} = \beta_0 &+ \beta_1 \mathbb{1}_t^{post} \mathbb{1}_i^{treat} + \beta_2 \mathbb{1}_t^{post} + \beta_3 \mathbb{1}_i^{treat} \\
&+ \sum_{n=4}^{N} \beta_n x_{n,i,c,t} + \alpha_c + \gamma_t + \epsilon_{i,c,t}
\end{aligned} \tag{1}
$$

Where Y can be log(house price) or log(number of house sales). For house price regressions, i is house and for house sales regressions, i is event geographical region (area within 10 miles of event). In both cases, c is county, t is month-year, x_n are house characteristic controls, α_c is county fixed effects, and γ_t is month-year fixed effects. The indicator $\mathbb{1}_t^{post}$

takes on a value of one if the transaction occurred during or after a nearby fire event and the indicator $\mathbb{1}_i^{treat}$ takes on a value of one if the house is in a treated zone. What is considered a ”treated zone” varies depending on the regression of interest. Some regressions use distance as the treated variable, in which case, the treated zone includes any home sold within 2 miles of a fire event. In others, the treated zone is very-high Fire Hazard Severity Zone (FHSZ). In my triple differences regressions, I include both treatments as well as their interactions. However, in these regressions, my interest is less in the triple interaction and more in the diff-in-diff estimators, having controlled for one another.

The event study regressions are essentially the same as the difference-in-differences model but with an event time indicators $\mathbb{1}_t^{t=\tau}$ on the interaction term rather than $\mathbb{1}_t^{post}$. Note that t is technically a month-year, but, within a given event geographical area, corresponds to an event time $\tau \in [-12, 12]$.

Event study:

$$\begin{aligned} Y_{i,c,t} = \beta_0 + \sum_{\tau=-12;\tau\neq-1}^{12} \beta_{\tau 1} \mathbb{1}_t^{t=\tau} \mathbb{1}_i^{treat} \\ + \beta_2 \mathbb{1}_t^{post} + \beta_3 \mathbb{1}_i^{treat} \\ + \sum_{n=4}^{N} \beta_n x_{n,i,c,t} + \alpha_c + \gamma_t + \epsilon_{i,c,t} \end{aligned} \tag{2}$$

In order to examine possible reasons why demand and supply response magnitudes differ across FHSZ (my second empirical goal), I track the quality of houses sold in event time. This explanation is entirely motivated by an empirical observation I made while carrying out the above regressions. Specifically, I noticed that including house characteristics significantly altered the effect of wildfire on prices, but only for homes in high risk FHSZ. Observing this, I generated a proxy for house quality using the following regression, restricted to transactions that took place in event time -1.

Predictive hedonic regression:

$$log(house\,price)_{i,c,t} = \beta_0 + \sum_{n=1}^{N} \beta_n x_{n,i,c,t} + \alpha_c + \gamma_t + \epsilon_{i,c,t} \tag{3}$$

Where i is house, c is county, t is month-year, x_n are house characteristics, α_c is county fixed effects, and γ_t is month-year fixed effects. With the estimated coefficients, I predicted the house prices of homes that were sold in other event time periods in order to track the "quality" of houses sold over time to give me an idea of what types households respond to nearby wildfire.

5. Results

5.1 General Findings

I find that all house transactions within 10 miles of a recent wildfire event and sold within a year were affected by the event. The average home price dropped nearly 10% in the first six months following a fire (Figure 4) and the number of home sales per month decreased by 25% during that same period for homes not in very-high FHSZ (Figure 11). These changes reflect what one would expect to see in the event of a demand decrease.

Most surprising, however, was the response of transactions in very-high FHSZ areas. Home prices fell by the same amount as in non-FHSZ homes (10%) in the first six months following a fire (Figure 4), but the number of sales *increased* by 50%, suggesting that the equilibrium was caused by an outward shift in supply. In addition, prices in very-high FHSZ appear to return to pre-fire levels faster than those not in FHSZ. Once accounting for house characteristics, however, the price effect nearly disappears for these homes, particularly after 5 months. This implies that a major effect of the wildfire on high risk areas is on the types of houses being sold. Figure 10 and Table 6 show that the quality of homes sold in very-high FHSZ after a wildfire event is noticeably lower quality (predicted hedonic log house price) compared to in the same region before. In fact, the predicted pre-fire price of very-high FHSZ homes is 12% lower (equivalent to $42,000 in ”quality”) after a fire than before. Meanwhile, homes sold outside of a FHSZ appear to have the exact same quality before and after the fire event.

On the other hand, I find no evidence that geographical proximity to a recent wildfire changes consumer and seller behavior in any meaningful way. Proximity only seems to matter for the non-interaction term since homes closer to wildfires tend to be nicer to begin with. However, the interaction term in my difference-in-differences and/or event study regressions consistently yields statistically insignificant coefficients. Likewise—and in contrast to FHSZ neighborhoods—average house quality in close neighborhoods appears to be unaffected by wildfire events.

5.2 Mechanism Channels

In in Section 3 (Model), I list four possible channels through which wildfire events might affect house prices–aesthetics, lower perceived risk, higher perceived risk, and smoke pollution. There, I propose that if aesthetics and/or lower perceived risk are relevant channels, then proximity will be an important dimension (”post x close” in Table 3). If higher perceived risk is relevant, then FHSZ will be an important dimension (”post x very-high FHSZ” in Table 3). If smoke pollution is relevant, then being sold after a fire event will be relevant to all homes (”post” in Table 3).

Combining these hypotheses with my results, I conclude that aesthetics and lower perceived risk are likely not very relevant to buyer or seller decisions after a wildfire since ”post x close” has an insignificant coefficient in all of my regressions (see Tables 3, 4, 6, and 7). I can think of two reasons why I find no evidence of consumers responding in these ways. The first is that home buyers are buying for the long-run. Aesthetic changes are temporary and consumers are perfectly willing to put up with a charred hillside for a few months or years and any potential risk reduction caused by the fire burning up nearby flora is just as ephemeral. The other reason is that I may not be looking close enough. Perhaps homes 2 miles away are unable to see the wildfire damage. However, my study is limited by statistical power and, alas, restricting the "close" area to be homes under 1 mile from a wildfire event significantly decreased my power. My sample contains fewer than 1,000 transactions within 1 mile of a wildfire event.

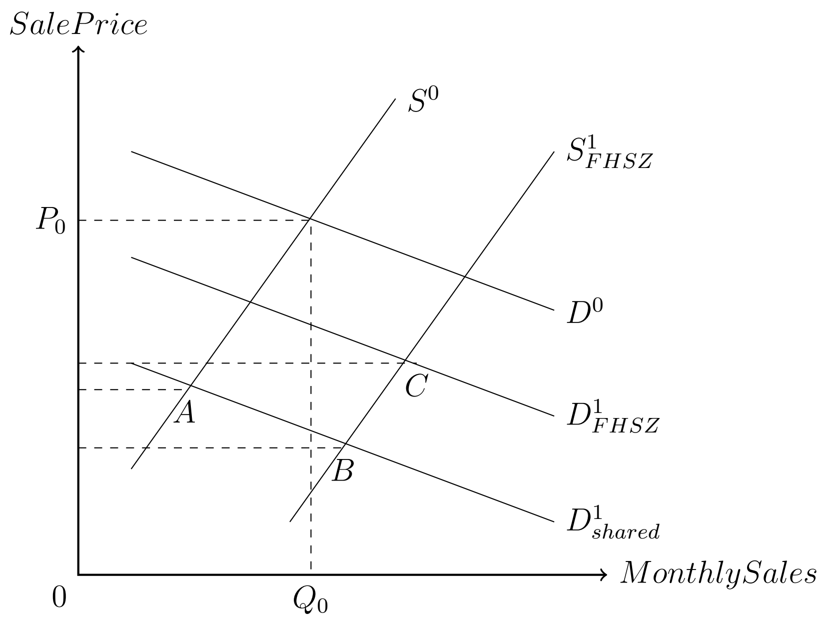
On the other hand, I do find evidence that higher perceived risk and smoke pollution are relevant to buyer and seller decisions since "post" and "post x very-high FHSZ" have significant coefficients in all of my regressions (see Tables 3, 4, and 7). One reason why these channels may be more salient than those in the above paragraph is that these are more long-term. Smoke pollution may only be present during the event itself, but if people update their expected more fires to occur nearby in the future, they will also expect to experience more smoke pollution in the future as well.

5.3 Comparative Statics: Model Interpretation

Under the assumption that very-high FHSZ and not very-high FHSZ face potential buyers with the same preferences, the demand shift that was experienced in non-FHSZ homes (as identified in the previous section) was also experienced by very-high FHSZ homes. However, if homes in very-high FHSZ experienced a positive supply shift (as identified in the previous section) in addition to this shared negative demand shift, then post-fire very-high FHSZ prices should have been even lower than post-fire non-FHSZ prices after controlling for house characteristics and zone (node B in Figure 3 below). As can be observed in Figure 4 and Table 3, this is not the case. Instead, there is a post-fire, very-high FHSZ premium.

If we keep the assumption that very-high FHSZ and not very-high FHSZ homes are in the same market, then a possible consistent explanation of this price premium is that sellers in very-high FHSZ face two pools of buyers–one that is shared with non-FHSZ and one that is not. The one that is shared generated the common negative demand shift (D^1_{shared} in Figure 3). The not-shared group reacted to the fire with a positive demand shift (D^1_{FHSZ} in Figure 3). This would shift the new static equilibrium to node C in Figure 3 below.

Figure 3: Comparative Statics



Note: Assuming that homes in very-high and not-very-high FHSZ are in the same housing market, they both start off at the equilibrium point P_0 and Q_0 (after controlling for housing characteristics and zone differences). Prices and quantities not to scale.

5.4 Comparative Statics: Alternative Interpretations

Three other explanations (that are also consistent with my empirical findings) arise if we instead assume potential buyers in very-high FHSZ and not very-high FHSZ are completely separate groups to begin with–i.e. that homes in different risk zones do not share any of the same potential buyers[3]. However, without the guiding parameters of a more restrictive model (as in the above section), I cannot distinguish between these three scenarios based only on my results.

The first is that high-risk zone buyers do not respond at all to fire events. In this scenario, homes outside of very-high FHSZ only experience a demand shock (D^1_{shared} in Figure 3) and

[3]Concerning supply, I also implicitly assume (1) that sellers in very-high FHSZ and not-very-high FHSZ are distinct and (2) that sellers in the not-very-high FHSZ did not respond with a positive supply shift. While these may not perfectly hold, they aren't particularly confounding either. The only supply-related assumption that needs to hold in order for my results to make sense is for the positive demand shift to be stronger in the very-high FHSZ than in not-very-high FHSZ, which is easy to believe. Since the demand shifts are less obvious, I spend more time discussing demand.

homes in very-high FHSZ only experience a supply shock (S^1_{FHSZ} in Figure 3). In this case, the price "premium" is just an artifact of the fact that the positive supply shift was not as "strong" as the negative demand shift. The second is that high-risk buyers did respond negatively, just not as much as not-very-high-risk buyers (D^1_{FHSZ} in Figure 3). The third is that high-risk buyers actually responded positively to the fire event (not depicted in Figure 3) but not enough to pull prices above P_0 in Figure 3.

Of these three alternative explanations, I find the second to be most persuasive, if only by process of elimination. The first is unconvincing since, if buyers outside of the very-high FHSZ are affected by fire events, then why wouldn't buyers within very-high FHSZ be affected at all? The third could make sense if, for some reason, only investors are interested in very-high fire risk zones. On the other hand, the third situation could come about if very-high FHSZ potential buyers' elasticity of demand is less elastic (for whatever reason) than that of not-very-high FHSZ potential buyers.

6. Discussion

6.1 Demographic Shifts

What I observe in very-high FHSZ after a wildfire event is that, in addition to selling *more* homes (Figure 12 and Table 7), the homes being sold are of significantly lower quality (Figure 10 and Table 6). As I suggest in Section 5 (Results), these changes support the hypothesis that there was a supply shock in very-high FHSZ, particularly among owners of lower quality homes. These patterns run in stark contrast to what happens in areas in not-very-high FHSZ which see a decrease in quantity sold after a fire (Figures 12 and 13, and Table 7) and no changes in quality of homes (Figure 11 and Table 6).

One explanation for high-risk zone emigration could be that relatively poorer households in high-risk zones are not as adequately insured as wealthier households. A direct connection between insurance rates and household income in these high-risk areas is beyond the scope of this article. However, even if poorer and wealthier households were equally insured, poorer households would not be as able to afford fire damage repairs. Witnessing a nearby fire event and knowing that they live in a very-high FHSZ may cause these households to reevaluate a risk they previously thought was low.

6.2 Efficiency v. Equity

From the perspective of strict efficiency (think Tiebout sorting), it good that those who can't afford to pay for fire damages (including insurance) or have high risk aversion move away from risky areas. If nearby wildfires cause owners to reevaluate their perceptions of fire risk and acting accordingly, this is likely economically efficient behavior.

However, from the perspective of equity, this behavior potentially raises a number of concerns. The first is perhaps the most obvious–that post-wildfire migration burdens are disproportionately experienced by the poorer households. Poorer households move out of risky zones while richer households are able to afford to stay. This type of behavior is not simply attributable to different ”preferences” for risk since risk aversion is endogenous to household wealth.

A second concern arises from the possibility that these less-wealthy sellers might be over-responding to fire risk. One perspective is that these sellers Bayesian-updating. If this is the case, then sellers are ”rationally” responding to wildfire events and reconsidering their own risk accordingly. Another possibility is that they are experiencing ”availability bias”. Or in other words, fire risk a more salient concept right after a wildfire but is less salient between fire events. This hypothesis suggests that sellers might significantly overestimate the risk of fire immediately after a nearby event. If this is the case, then sellers may regret selling so soon either because (1) their (not too far-) future self might perceive risk more accurately or (2) because they might be able to sell their home for more money in only a few months once the hype has worn off. If very-high FHSZ households are in fact selling to investors, this would support the ”availability bias” scenario.

A third concern for equity is that non-wealthy emigration may exacerbate wealth-based residential segregation going forward as fires increase in severity and frequency with climate change. If less-wealthy households are replaced by wealthier households after each fire event, then wildfires may encourage wealth-based residential segregation. However, the reality of this concern is uncertain and largely depends on buyer demographic trends which I have not explored in this article.

6.3 Rational Updating or Availability Bias?

From the event study figures of log sale price (Figures 4, 4, 5, and 6), we observe that prices drop immediately after a wildfire event but steadily rise back to pre-fire levels around a year after the event. The event study figures of log quantity sold (Figures 12, 13, 14 and 15) suggest that quantity sold after a fire remains relatively constant for at least a year following the event, suggesting that price changes might be driven by increased demand over this period.

In any case, what is driving this dynamic response is unclear and a thorough analysis of it is beyond the scope of this paper. One perspective is that buyers and sellers may be ”rationally” responding to wildfire events by reevaluating fire risk. On the other hand, fire risk may be a more salient concept right after a wildfire but is less salient between fire events. This second scenario is what behavioral economists refer to as ”availability bias”. Anderson, Plantinga, and Wibbenmeyer (2020) find evidence of availability bias among policy makers in the wildfire setting. Testing this phenomenon in the housing market may be explainable in future work with a Bayesian learning model following the blueprint of Gallagher (2014).

7. Conclusion

Using event study and differences strategies, I study the effect of wildfire events on nearby house transaction prices, quantities, and quality. I find that the sale price of homes within 10 miles of a fire event drop by almost 10% for the first 6 months and return to pre-fire levels within a year. Combining price effects with quantity effects, I find that for homes in very-high-risk zones, a positive supply shock dominates, while for homes outside of these zones, a negative demand shock dominates.

In order to partially identify the channels through which wildfire affects buyers and sellers, I explore how responses differ across risk level, proximity to wildfire, and time since the wildfire event. Since risk level (very-high FHSZ) is an important dimension in my empirical analysis, I conclude that market participants perceive higher wildfire risk after a fire. Since proximity appears to not be important (at least without more statistical power), I fail to reject the null hypothesis that market participants don't perceive lower perceived risk and/or don't care about the aesthetic impacts of wildfire.

I also find that the supply shock in very-high-risk zones is driven by homes of lower quality. Using the predicted values of a hedonic regression of house price on house characteristics in the month before a wildfire, I find that the quality of an average home sold in a very-high risk region was around $50,000 ”worse” after a fire, implying that less-wealthy homeowners in risky zones are more likely to move after a wildfire than their wealthier counterparts. The quality of homes sold outside of very-high risk zones (including those relatively close to the event) did not change.

These results may have inequitable implications. First, post-fire migration costs appear to be disproportionately carried by the less-wealthy sellers. Second, post-fire sorting may exacerbate residential wealth-based segregation. And third, wildfire salience/myopia may lead to suboptimal sales timing, leading to hasty or regrettable decisions for less-wealthy sellers. As climate change progresses, wildfires will continue to affect households of all demographics. More research will be needed to understand the heterogeneous impacts of these fires on our communities going forward.

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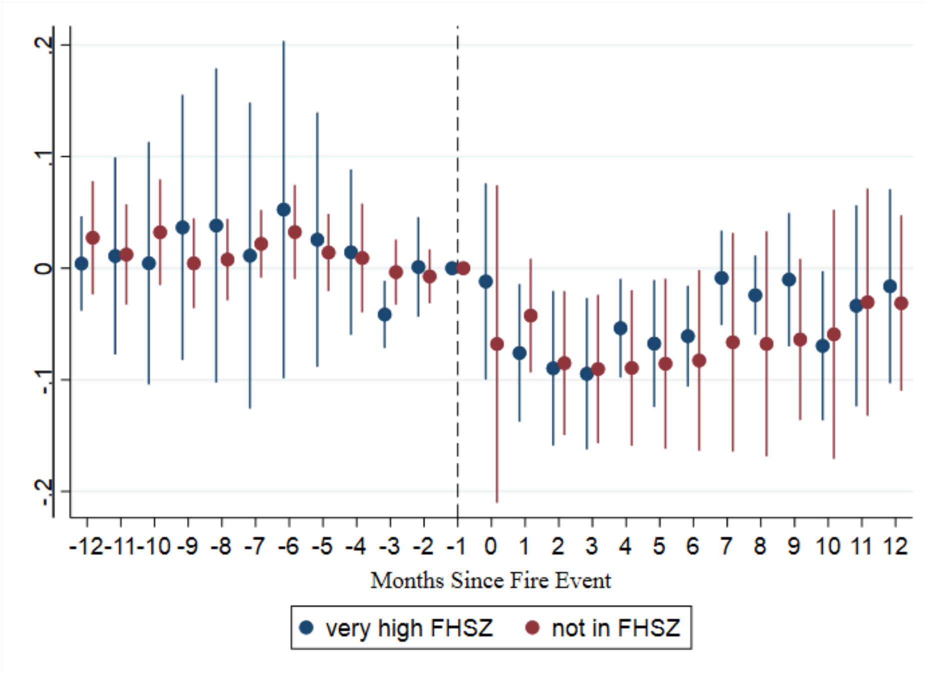
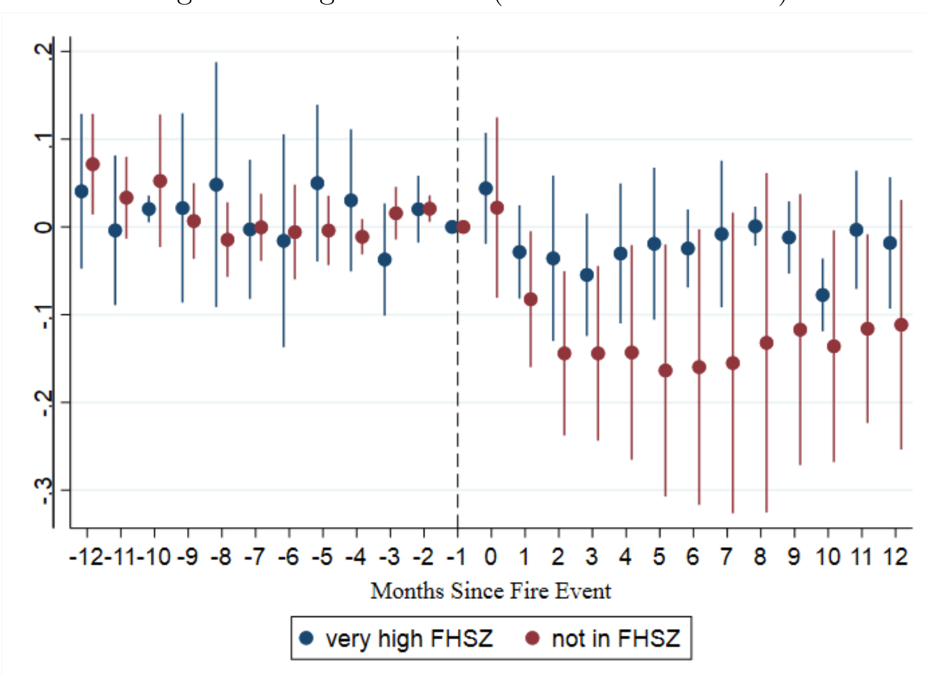
Appendix: Figures and Tables

Figure 4: Log Sale Price (no house char. controls)



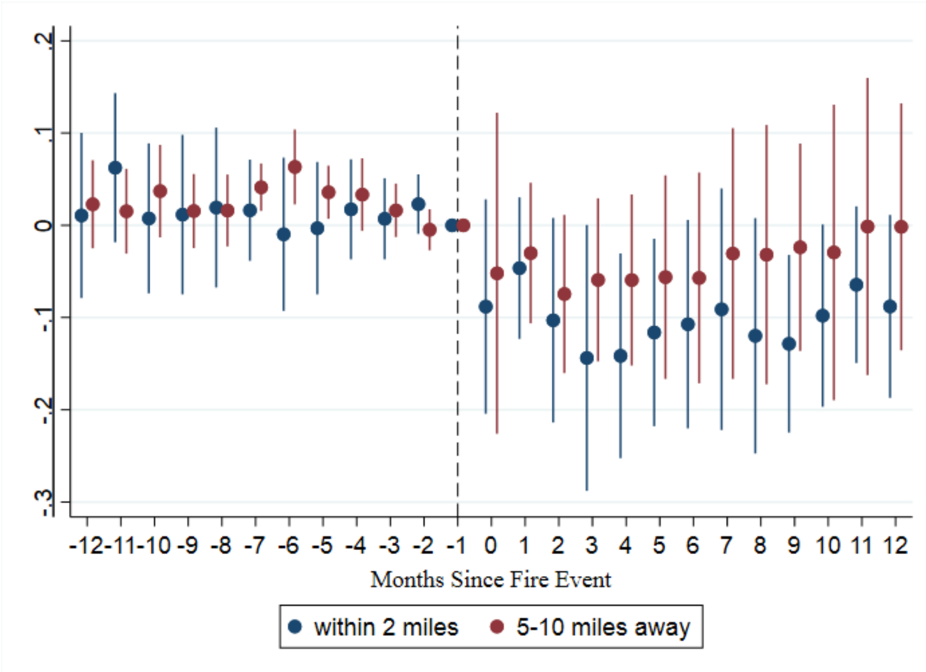
Note: Regressions ran separately for each sample and do not include controls other than county (FIPS) and month-year fixed effects.

Figure 5: Log Sale Price (house char. controls)



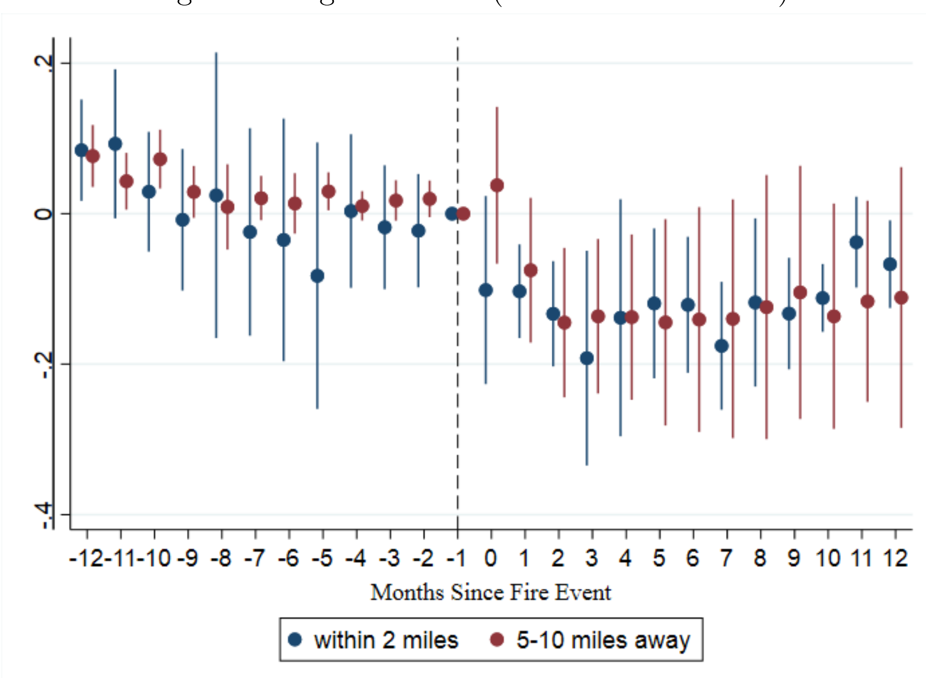
Note: Regressions ran separately for each sample and include house characteristic controls and county (FIPS) and month-year fixed effects.

Figure 6: Log Sale Price (no house char. controls)



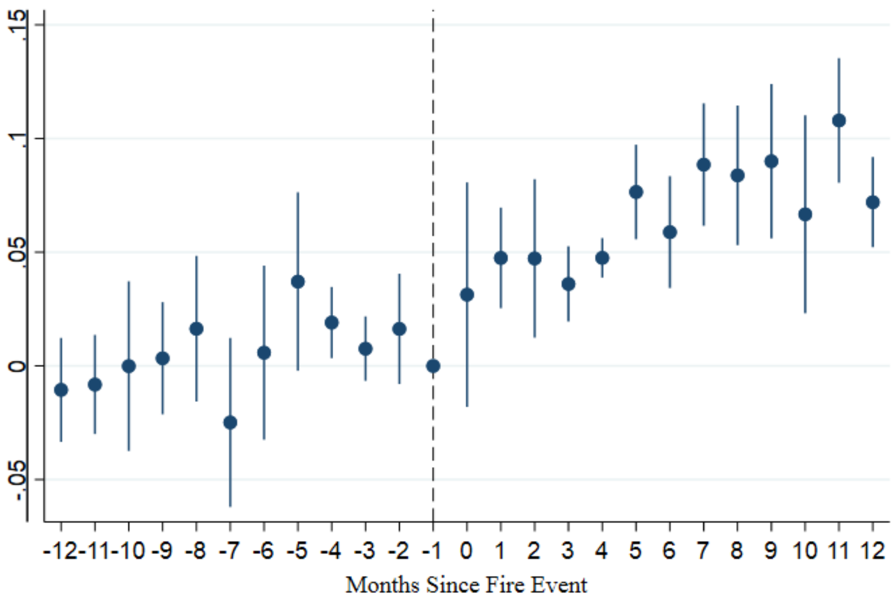
Note: Regressions ran separately for each sample and do not include controls other than county (FIPS) and month-year fixed effects.

Figure 7: Log Sale Price (house char. controls)



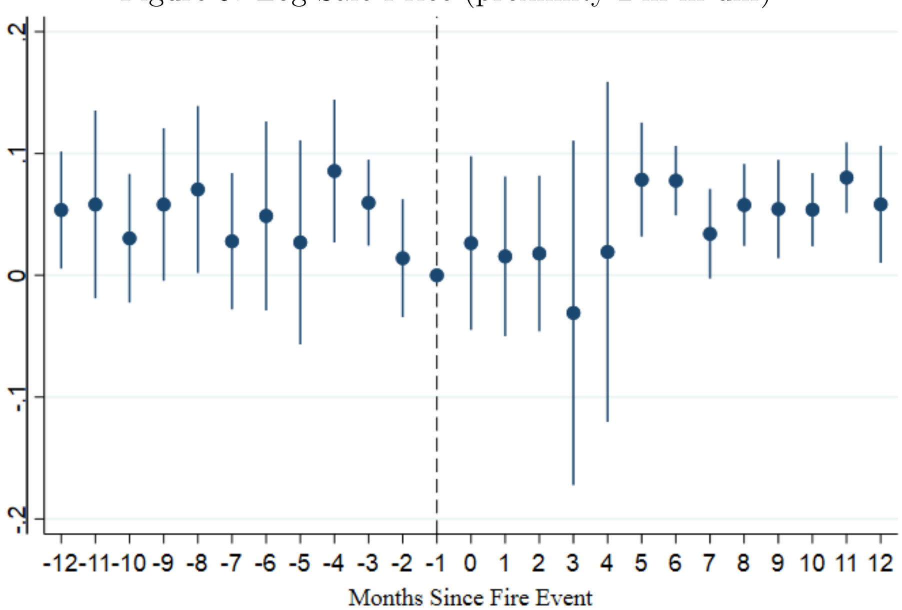
Note: Regressions ran separately for each sample and include house characteristic controls and county (FIPS) and month-year fixed effects.

Figure 8: Log Sale Price (very-high FHSZ Diff-in-diff)



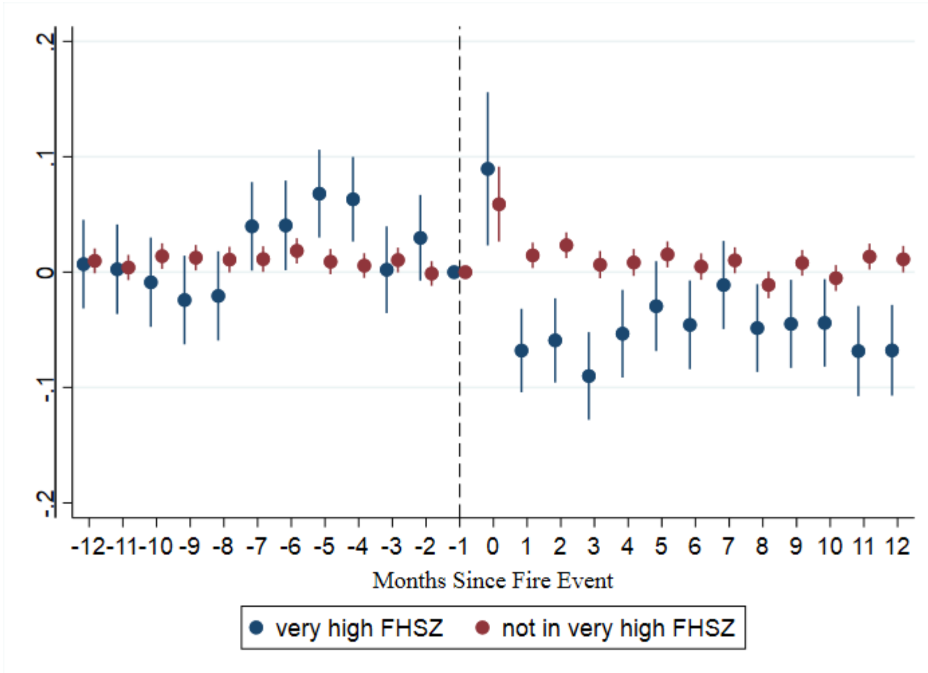
Note: In addition to the "event x very-high FHSZ" interaction displayed here, regression includes post dummy; "very-high FHSZ" dummy; "within 2 miles" dummy; "post x within 2 miles" dummy; house characteristic controls; and county (FIPS), month-year, and fire event fixed effects. For the pre-post diff-in-diff equivalent, see column 2 of Table 3.

Figure 9: Log Sale Price (proximity Diff-in-diff)



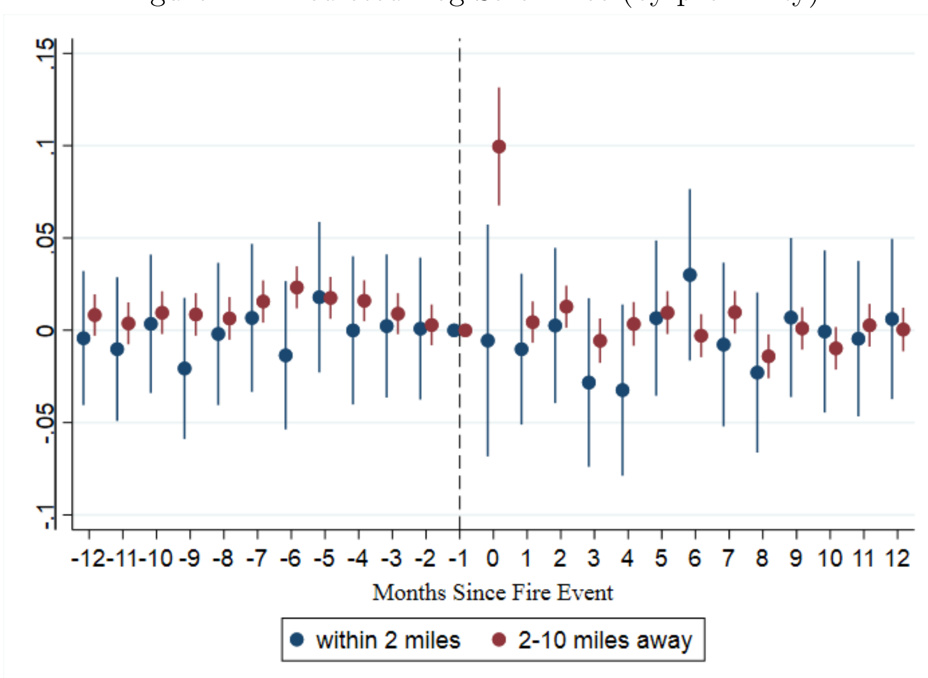
Note: In addition to the "event x within 2 miles" interaction displayed here, regression includes post dummy; "very-high FHSZ" dummy; "within 2 miles" dummy; "post x very-high FHSZ" dummy; house characteristic controls; and county (FIPS), month-year, and fire event fixed effects. For the pre-post diff-in-diff equivalent, see column 2 of Table 3.

Figure 10: Predicted Log Sale Price (by FHSZ)



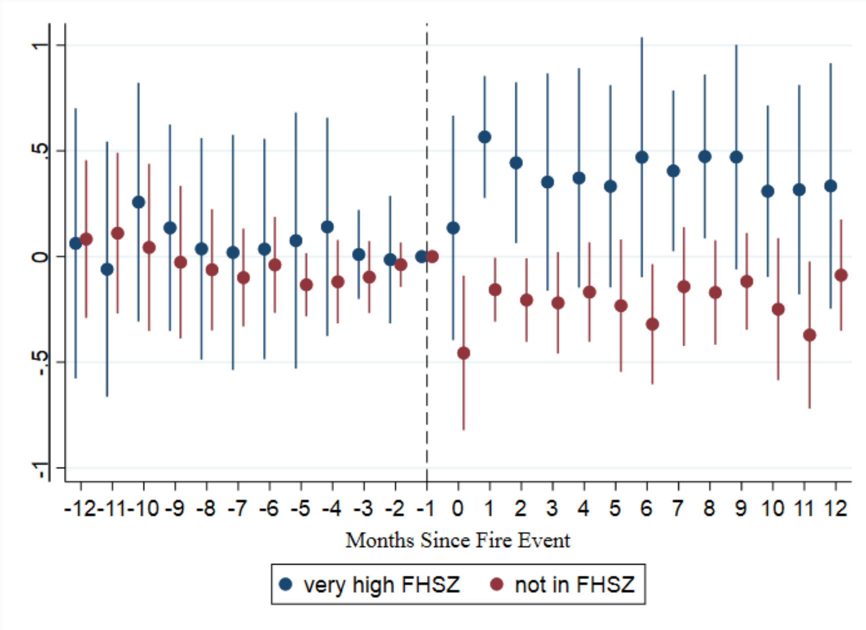
Note: Regressions ran separately for each sample and include house characteristic controls and county (FIPS) and month-year fixed effects. Predictions made using Hedonic regression with only transactions in event period -1 (see Table 5). For pre-post period diff-in-diff equivalent, see Table 6.

Figure 11: Predicted Log Sale Price (by proximity)



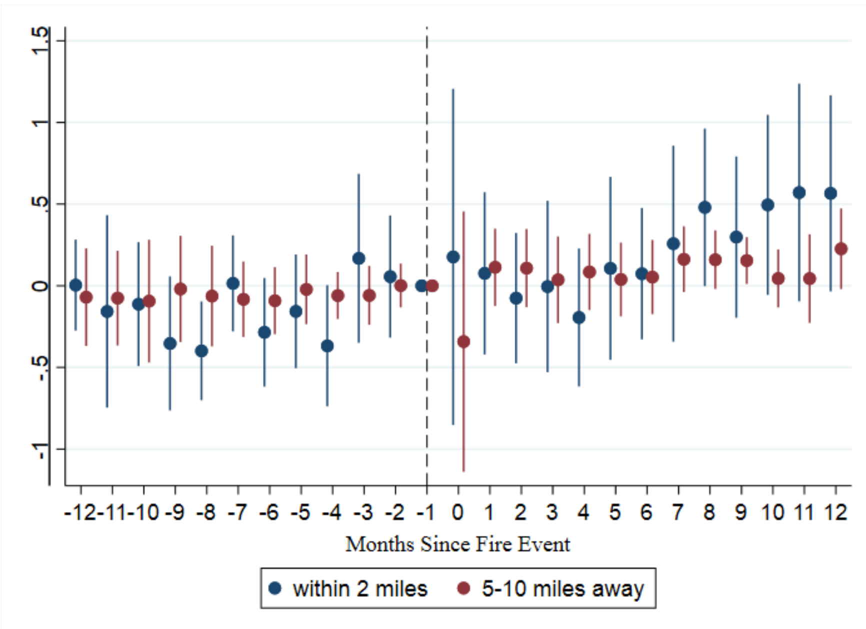
Note: Regressions ran separately for each sample and include house characteristic controls and county (FIPS) and month-year fixed effects. Predictions made using Hedonic regression with only transactions in event period -1 (see Table 5). For pre-post period diff-in-diff equivalent, see Table 6.

Figure 12: Log House Sales (by FHSZ)



Note: Regressions ran separately for each sample and include county (FIPS) and month-year fixed effects. Samples made by aggregating number of transactions to the fire-event geographical area (within 10 miles of fire event) by event-time by FHSZ level. County (FIPS) is the mode FIPS of transactions for the aggregated unit. For the pre-post diff-in-diff equivalent, see column 1 of Table 7.

Figure 13: Log House Sales (by proximity)



Note: Regressions ran separately for each sample and include county (FIPS) and month-year fixed effects. Samples made by aggregating the number of transactions to the fire-event geographical area (within 10 miles of fire event) by event-time by proximity level. County (FIPS) is the mode FIPS of transactions for the aggregated unit. For the pre-post diff-in-diff equivalent, see column 2 of Table 7.

Table 1: Transactions Summary Statistics (by FHSZ)

	not very high FHSZ	very high FHSZ	Total
sales price	400718.1	428412.0	404786.0
	(203424.7)	(240854.7)	(209570.0)
lot size (sq.ft)	12467.8	24833.4	14284.2
	(34178.6)	(89982.2)	(46957.1)
year built	1992.1	1990.8	1991.9
	(20.89)	(21.93)	(21.05)
# bedrooms	3.497	3.267	3.463
	(0.906)	(1.079)	(0.937)
# baths	2.405	2.393	2.403
	(0.689)	(0.902)	(0.724)
# stories	1.451	1.550	1.465
	(0.517)	(0.515)	(0.518)
building quality	2.591	2.480	2.574
	(0.494)	(0.509)	(0.498)
Observations	60193	10364	70557

Note: Observations are transaction-level. Aside from air conditioning and heating types, this table includes all house characteristics that are used in ”log sale price” regressions that include house characteristics (Tables 3, 4, and 5).

Table 2: Transactions Summary Statistics (by proximity)

	2-10 miles away	within 2 miles	Total
sales price	402205.8	445613.2	404786.0
	(208776.0)	(217750.1)	(209570.0)
lot size (sq.ft)	13945.3	19647.0	14284.2
	(44498.0)	(75725.4)	(46957.1)
year built	1991.8	1993.9	1991.9
	(21.13)	(19.71)	(21.05)
# bedrooms	3.470	3.350	3.463
	(0.937)	(0.931)	(0.937)
# baths	2.401	2.436	2.403
	(0.726)	(0.686)	(0.724)
# stories	1.466	1.461	1.465
	(0.518)	(0.520)	(0.518)
building quality	2.579	2.497	2.574
	(0.497)	(0.507)	(0.498)
Observations	66363	4194	70557

Note: Observations are transaction-level. Aside from air conditioning and heating types, this table includes all house characteristics that are used in ”log sale price” regressions that include house characteristics (Tables 3, 4, and 5).

Table 3: Price Diff-in-diff (by house characteristics)

	(1) Sale Price	(2) Sale Price
post x close	-0.0866	-0.00287
	(0.0524)	(0.0333)
close	0.0440	0.0332*
	(0.0275)	(0.0182)
post x very high FHSZ	0.0328**	0.0597***
	(0.0137)	(0.00751)
very high FHSZ	0.131***	0.0626***
	(0.0259)	(0.0196)
post	-0.0168	-0.0398**
	(0.0108)	(0.0136)
House char. controls		X
FID FE	X	X
FIPS FE	X	X
month-year FE	X	X
Observations	211231	80478

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: House characteristics include those described in Table 1 as well as air conditioning and heating types. For relevant figures, see Figures 1, 2, 3, 4, 5, and 6. Observations are event-transaction level.

Table 4: Price Diff-in-diff (by fire event controls)

	(1) Sale Price	(2) Sale Price	(3) Sale Price
post x close	0.0122	0.0119	-0.00287
	(0.0173)	(0.0187)	(0.0333)
close	0.0617*	0.0620**	0.0332*
	(0.0290)	(0.0282)	(0.0182)
post x very high FHSZ	0.0433*	0.0434*	0.0597***
	(0.0224)	(0.0231)	(0.00751)
very high FHSZ	0.0103	0.0106	0.0626***
	(0.0278)	(0.0257)	(0.0196)
post	-0.133**	-0.134**	-0.0398**
	(0.0539)	(0.0544)	(0.0136)
House char. controls	X	X	X
Fire area control		X	
FID Fixed Effects			X
FIPS FE	X	X	X
month-year FE	X	X	X
Observations	80478	80478	80478

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: "FID" is a unique indicator for each of the 220 fire events studied in this article, to which all homes within 10 miles of the fire event are assigned regardless of whether the home was sold before or after the event. "Fire area control" is a measure of the geographical area of the wildfire perimeter. Column 3 is my preferred regression as it can account for more fire-specific characteristics other than the geographical size of the fire. Observations are event-transaction level.

Table 5: Predictive Hedonic Regression (event time = -1)

	log sale price
lot size (sq.ft)	0.000000404
	(0.000000220)
year built	0.00167
	(0.000975)
# bedrooms	0.0529***
	(0.00758)
# baths	0.164***
	(0.0106)
building quality	-0.169***
	(0.0300)
# stories	-0.00402
	(0.0179)
FHSZ level	0.0230**
	(0.00521)
Observations	3204

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Regression was run using only transactions that took place a month before a fire event (event time -1) for the purpose of predicting "house quality" before and after the fire event (see Table 6). Included in this regression but not in the table are indicators for air conditioning and heating types. Observations are event-transaction level.

Table 6: Quality Diff-in-diff

	predicted log sale price
post x very high FHSZ	-0.124**
	(0.0362)
very high FHSZ	0.128**
	(0.0373)
post x close	0.0282
	(0.0211)
close	0.00423
	(0.0200)
post	-0.00962
	(0.00750)
Observations	80480

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: "Predicted log sale price" was constructed for each transaction in each period by predicting log sale price using only event time -1 transactions (see Table 5). As such, I use "predicted log sale price" in this regression to estimate how house quality responded to fire events. Because house characteristics, county (FIPS), and month-year fixed effects were used to construct "predicted log sale price", this regression does not include any variables other than those included here. For relevant figures, see Figures 7 and 8. Observations are event-transaction level.

Table 7: Quantity Diff-in-diff

	(1) log sales per month	(2) log sales per month
post x very high FHSZ	0.734**	
	(0.228)	
very high FHSZ	-0.850*	
	(0.411)	
post	-0.256**	0.0717
	(0.0819)	(0.128)
post x close		0.144
		(0.181)
close		-2.239***
		(0.247)
FIPS FE	X	X
month-year FE	X	X
Observations	3218	1897

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Column 1 sample was made by aggregating the number of transactions to the fire-event geographical area (within 10 miles of fire event) by event-time by FHSZ level. Column 2 sample was made by aggregating the number of transactions to the fire-event geographical area (within 10 miles of fire event) by event-time by proximity level. County (FIPS) is the mode FIPS of transactions for the aggregated unit. For relevant figures, see Figures 9, 10, 11, and 12.