THE EFFECT OF WILDFIRES ON HOUSE SALE PRICES ACROSS RISK ZONES IN THE WESTERN UNITED STATES

by

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ABSTRACT

Wildfires are becoming more prevalent and destructive in the Western United States, especially as residential development expands into fire-prone areas. The interaction between homeowners and wildland increases both ignition risk and structural exposure. This paper examines how housing markets respond to wildfire events and whether these responses vary across areas with different predicted risk classifications. Using repeat sales data from over 230,000 single-family house transactions linked to 276 wildfires, I estimate stacked difference-in-differences models. I compare the change in pre- and post-wildfire house sale prices between nearby and more distant houses. Models are estimated separately for houses in low and high wildfire hazard potential zones to observe whether house sale price responses differ between risk zones. The results indicate that house sale prices increase slightly, by around 1%, after wildfire exposure, with significant effects observed in low-risk zones. In high-risk zones, price responses are consistently insignificant. No clear differences in sale price responses appear between low- and high-risk zones. These findings suggest that housing markets do not reflect the risk information provided from new wildfire events. This result supports the possibility that housing markets already reflect wildfire risk, and new fire events do not provide any additional risk information.

INTRODUCTION

Wildfire activity in the Western United States has increased in both frequency and severity over the past several decades (National Interagency Fire Center, nd). Earlier snowmelt, prolonged droughts, and anthropogenic climate change have contributed to larger and more destructive fire seasons (Holden et al., 2018; Abatzoglou & Williams, 2016). At the same time, residential development has expanded into wildland areas (Radeloff et al., 2005). These trends have increased the number of houses exposed to wildfire hazards and raise questions about whether homeowners adequately account for the risks associated with living in areas of high fire risk.

In theory, housing markets should reflect wildfire hazard if buyers are aware of the information. Risk maps, such as the Wildfire Hazard Potential (WHP) map series published by the USDA Forest Service, serve as one tool for communicating risk to the public. I propose that if homeowners utilize wildfire risk maps and wildfire events when forming expectations, house sale prices in low-risk areas should react more strongly to wildfires than sale prices in high-risk areas. Wildfires in low risk areas may be perceived as unexpected and lead to larger revisions to wildfire risk, which is then reflected in greater changes in house prices.

Prior research suggests that housing prices tend to decrease following wildfire exposure in high wildfire risk areas (Kiel & Matheson, 2018; Adachi & Li, 2023; Nie et al., 2023), though existing studies are often limited to individual wildfire events or small geographic areas. To date, no study has used a complete sample of wildfires across a broad geographic region to assess the impact of wildfires on housing sale prices across predicted wildfire risk zones. Since existing literature covers only select events and local areas, it may not provide a representative estimate of broader house sale price responses to wildfires across predicted

risk zones.

This paper investigates how housing markets in the Western United States respond to wildfire events, and whether the response differs across areas with varying levels of predicted wildfire risk. Specifically, my research question asks: What is the impact of wildfires on house sale prices, and does the effect vary across predicted wildfire risk zones? To answer this, I use repeat sales data comprising over 230,000 single-family house transactions from October 2015, when the first Wildfire Hazard Potential (WHP) maps were released, to August 2021. I estimate stacked difference-in-differences models to evaluate average treatment effects of wildfire exposure on house prices across 276 fires. Models are estimated separately across pre-assigned risk classifications. The results suggest small increases in prices following wildfire exposure, with significant effects concentrated in low-risk zones and little evidence of differential responses by risk classification or distance to the fire. Potential heterogeneity by fire size is observed across risk classifications.

BACKGROUND

A comprehensive understanding of the influence of wildfires on urban–wildland interactions in the U.S. requires both historical context and insight into how wildfire risk has been measured, communicated, and incorporated into housing market analysis. This paper focuses on one form of wildfire risk communication to homeowners: the U.S. Forest Service's Wildfire Hazard Potential (WHP) maps.

Wildfires and the Wildland Urban Interface

Wildfires are a natural phenomenon that have occurred for approximately 430 million years (Glasspool & Gastaldo, 2022). Although their prevalence is long-standing, systematic federal wildfire tracking in the United States began only in recent decades. A major component of this effort was the establishment of the Monitoring Trends in Burn Severity (MTBS) program in 2005 (Monitoring Trends in Burn Severity, ndb). In the year prior to establishment, federal agencies recognized the need for consistent geospatial data to monitor "the environmental impacts of large wildland fires and identify trends in burn severity on all lands across the United States..." (Monitoring Trends in Burn Severity, nda).

The MTBS program is implemented in partnership with the United States Geological Survey's Earth Resources Observation and Science (EROS) Center and the U.S. Forest Service, with funding from the U.S. Forest Service and Department of the Interior agencies (Monitoring Trends in Burn Severity, nda). Today, the MTBS program serves as "the largest and most spatially and temporarily comprehensive post-fire mapping and assessment program conducted by the United States Department of Agriculture Forest Service and the [United States Geological Survey]" (Monitoring Trends in Burn Severity, nda).

Wildfires can ignite naturally, typically by a lightning strike, or as a result of human activity. In the United States, approximately 85% of wildfires are attributed to human

actions (U.S. National Park Service, 2025). Once ignited, the spread of a wildfire is determined by wind, temperature, available fuel, and the dryness of surrounding vegetation (U.S. Environmental Protection Agency, 2025). Among these, wind has the most immediate and pronounced effect, as it increases oxygen availability, dries available fuels, and accelerates fire movement across the landscape (Rothermel, 1972). While wind is a key driver of fire behavior, temperature and fuel conditions also play a critical role in determining fire intensity and spread (Rothermel, 1972).

The Western U.S. is particularly vulnerable to wildfires due to persistent drought conditions and abundant dry vegetation (Holden et al., 2018; Westerling et al., 2006). These conditions have intensified wildfire activity and extended the duration of fire seasons in the West over recent decades (Holden et al., 2018). Earlier snowmelt and less precipitation in the summer have also contributed to longer fire seasons and more severe fire behavior (Westerling et al., 2006). Abatzoglou & Williams (2016) find that anthropogenic climate change has increased both the frequency and severity of wildfires by altering fuel moisture. Figure 1 illustrates the geographic distribution of wildfire activity across the U.S.

Despite increasing wildfire frequency, residential development is expanding into areas that are inherently susceptible to wildfires (Radeloff et al., 2005). The Wildland Urban Interface (WUI) represents the zone where developed areas meet undeveloped, typically forested land prone to wildfires (U.S. Fire Administration, 2022). Radeloff et al. (2005) classify the WUI into two types: intermix and interface. Intermix WUI describes areas where housing density is at least 6.17 housing units per square kilometer and wildland vegetation covers at least 50% of the area, such that homes and vegetation are intermixed within the same landscape (Radeloff et al., 2005).

Interface WUI refers to regions with similar housing density as intermix WUI but less than 50% vegetation cover, located adjacent to large, contiguous wildland areas (Radeloff et al., 2005). Specifically, these are urban areas within 2.4 kilometers of highly vegetated

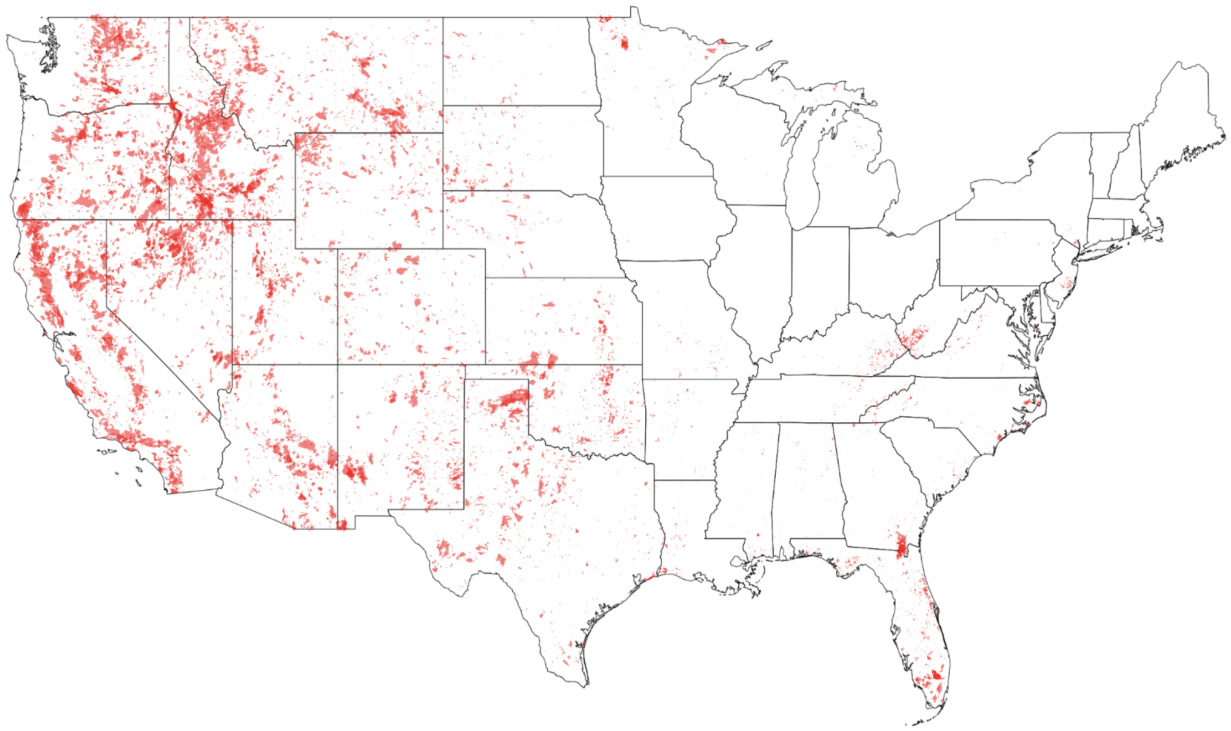


Figure 1: Wildfire Perimeters in the Contiguous U.S. from 1984 to 2020. Source: U.S. Geological Survey & USDA Forest Service (2024)

wildland patches (Radeloff et al., 2005). Radeloff et al. (2005) define these wildland patches as being at least five square kilometers in size and at least 75% vegetated. The 2.4 km buffer extends outward from the edge of wildland vegetation into development, reflecting the potential reach of wildfire embers and the spread of fire into residential zones (Radeloff et al., 2005).

Homeowners in the WUI benefit from highly valued surrounding environmental amenities (Snyder et al., 2008). Athukorala et al. (2019) and Koo & Liang (2022) suggest that residents often prioritize these benefits over the risks of living in wildfire-prone areas. This trade-off has contributed to the rapid expansion of WUI zones, with an average annual growth of two million acres (U.S. Fire Administration, 2022). The number of houses within them has also risen significantly. Between 1990 and 2020, households in the WUI increased by approximately 47% (U.S. Forest Service, 2025). By 2020, over 32% of all U.S. houses were

located in both intermix and interface WUIs (U.S. Forest Service, 2025). This expansion places more houses at risk while also increasing the risk of ignition. As more people settle in fire-prone areas, the potential for human-caused wildfire increases, creating a compounding dynamic in the West.

Wildfire Hazard Potential Maps

Wildfire risk designations serve as a source of information for homeowners about their exposure to wildfire, offering insight into anticipated rather than realized wildfire conditions. In this study, predicted wildfire risk is measured using the Wildfire Hazard Potential (WHP) maps developed by the U.S. Department of Agriculture Forest Service. These maps provide one of the only nationally consistent measures of wildfire risk in the United States.

In April 2020, the USDA Forest Service published Wildfire Risk to Communities, a website developed in response to the Consolidated Appropriations Act, following direction from Congress in 2018. This legislation required the Forest Service to "develop and publish a geospatial map appropriate for community-level use that depicts wildfire hazard severity to inform at-risk communities that are adjacent to [National Forest Service (NFS)] lands or affected by wildland fire, and disseminate such information in a web-based format" (Consolidated Appropriations Act, 2018, § 210; see U.S. Congress, 2018). One of the stated purposes of this legislation is to evaluate and communicate information about wildfire risk to the public.

Prior to 2020, publicly available wildfire risk maps were produced by state agencies or the U.S. Forest Service. However, state-level wildfire risk maps are inconsistent[1]. One of the

[1]CAL FIRE updated their Fire Hazard Severity Zones Map in February 2025. Prior to that, the most recent update was in 2007 (California Department of Forestry and Fire Protection, 2019). The Oregon Department of Forestry published its first statewide wildfire hazard map in 2022, but the map was repealed following public backlash (Ehrlich, 2024). A revised draft was released in 2024. Washington is currently in the process of developing its own wildfire hazard mapping system (Washington State Department of Natural Resources, nd). Other Western states vary in their methods and timelines for mapping wildfire hazard.

earliest efforts to provide a consistent, nationwide measure of wildfire risk was the Wildfire Hazard Potential (WHP) map series. They were first released in 2015 by the U.S. Forest Service. These maps offer a standardized index of wildfire risk across the contiguous United States and have been updated in 2018, 2020, and most recently in 2023. The study period in this paper is 2015 to 2021 and focuses on WHP maps through 2020. Beginning in 2020, the WHP maps have also been published on the Wildfire Risk to Communities website. The 2015, 2018, and 2020 versions of the WHP map are presented in Figure 1.

The WHP index considers both the likelihood and intensity of a wildfire, as well as vegetation and fuels data from LANDFIRE (U.S. Forest Service, 2020). The likelihood of a wildfire, also known as burn probability, is the annual probability of a wildfire burning in a given 270-meter raster cell (U.S. Forest Services, nd). The U.S. Forest Service uses fire behavior simulations across thousands of hypothetical fire seasons to generate estimates of wildfire likelihood (U.S. Forest Services, nd). These simulations factor weather, topography, and ignitions[2] (U.S. Forest Services, nd). The inputs are "based on patterns derived from observations in recent decades" (U.S. Forest Services, nd). Wildfire intensity is the estimated energy a fire releases and is "measured in units of heat transferred per length of fire perimeter"[3] (U.S. Forest Services, nd). Intensity depends primarily on topography and available burnable vegetation (U.S. Forest Services, nd).

Each 270-meter raster cell in the WHP map is assigned a risk level from 1 to 7 based on how its estimated wildfire potential ranks within the national distribution. Levels 1 through 5 correspond to burnable land. Level 1, very low risk, includes values from the 0th to the 44th percentile; level 2, low risk, covers the 44th to 67th percentile; level 3, moderate risk, spans the 67th to 84th percentile; level 4, high risk, the 84th to 96th percentile; and level

[2]The data for these variables are sourced from multiple agencies: weather data from the National Weather Service; topographic data from the U.S. Geological Survey; and historical weather pattern data from GRIDMET and Remote Automated Weather Station (RAWS) records.

[3]Measured in kilowatts per meter (kW/m), this metric is known as fireline intensity. It reflects the rate of heat energy released per unit length of the fire front (Byram, 1959).

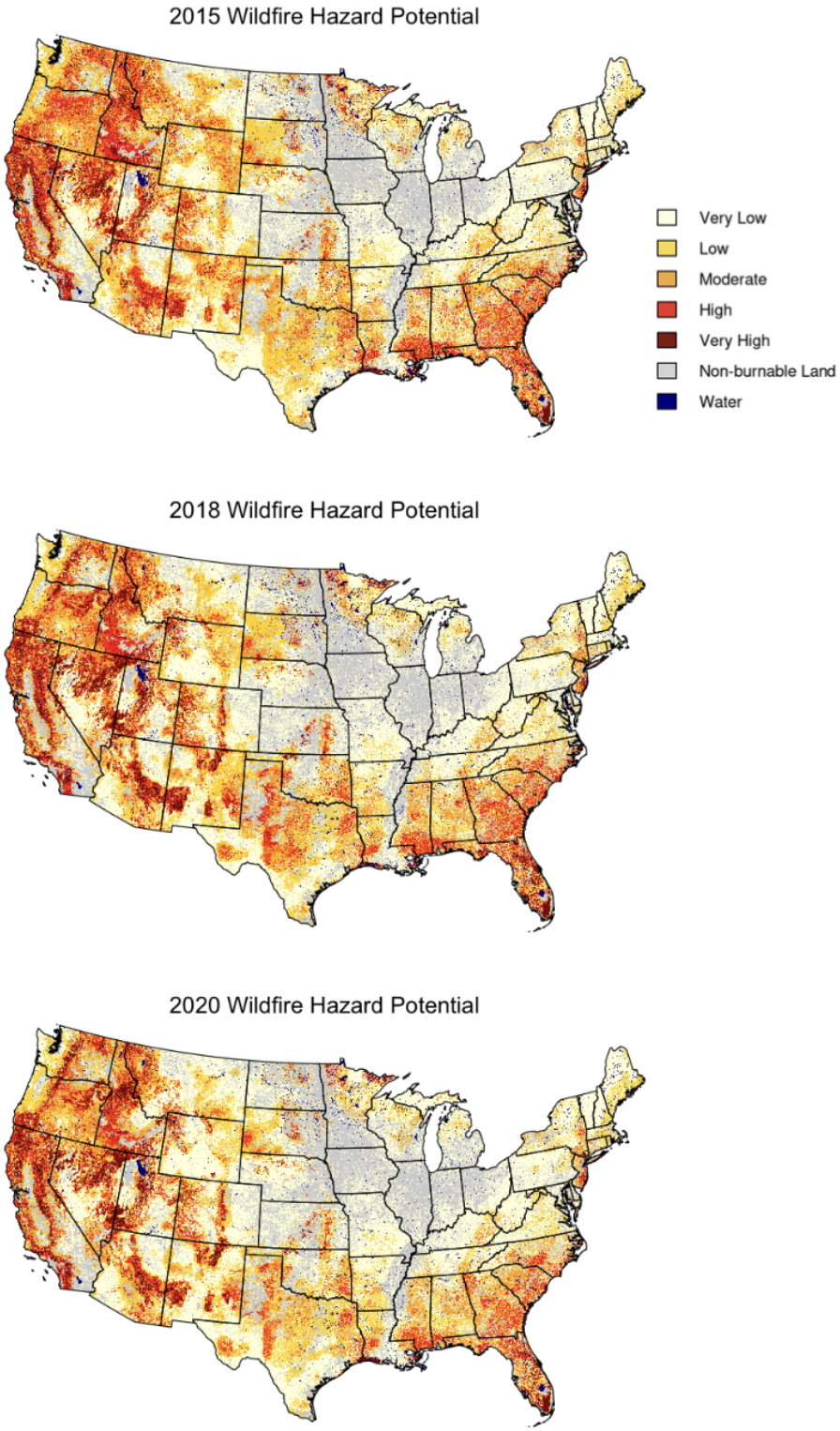


Figure 2: The 2015, 2018, and 2020 Wildfire Hazard Potential for the United States. Source: U.S. Forest Service (2015, 2018, 2020)

5, very high risk, includes values above the 96th percentile (Dillon et al., 2015). Level 6 denotes non-burnable land, which includes urban areas, agricultural land, bare ground, or areas covered by snow or ice, while level 7 represents water bodies (Dillon et al., 2015).

The WHP classification system is designed to reflect how wildfire potential is distributed across the contiguous United States. Approximately two-thirds of the landscape is assigned to very low or low wildfire potential classes, with two-thirds of this group classified as very low and one-third as low (Dillon et al., 2015). Of the remaining one-third of the landscape, half is assigned to the moderate class, while the other half is split such that two-thirds fall into the high class and one-third into the very high class (Dillon et al., 2015).

The WHP dataset provides a measure of wildfire hazard that supports comparisons of "relative wildfire risk among communities nationally or within a state or county" (U.S. Forest Service, 2020). Although it is not designed to replace state, regional, or local estimates of risk, it may be useful in areas where local models are unavailable. The WHP is not a forecast and "does not include any information on current or forecasted weather or fuel moisture conditions" (U.S. Forest Service, 2020). Instead, it is meant to support "long-term strategic fuels management" based on landscape characteristics (U.S. Forest Service, 2020).

LITERATURE REVIEW

The effect of wildfire risk designations on housing markets has been examined in only few studies. A small but growing body of work explores how wildfire risk zones and perceptions of wildfire risk influence home prices.

Limited papers specifically analyze how risk designations affect home values, focusing either on the initial publication or on updates to existing designations. Garnache (2023) uses CoreLogic data to examine how CAL FIRE's 2007 updates to Fire Hazard Severity Zones affected single-family home prices in California. Using regression discontinuity, difference-in-discontinuities, and difference-in-differences designs, the author observes no change in housing prices within the newly designated zones. However, when including homes farther from the risk zone boundaries, Garnache (2023) finds a 2.5% decrease in prices for homes that are assigned to a higher risk zone. Garnache (2023) concludes that homeowners update their beliefs about wildfire risk in line with actual hazard levels.

Leveraging the initial publication of wildfire risk designations, Donovan et al. (2007) focus on a localized setting in Colorado Springs. In 2000, the Colorado Springs Fire Department assigned wildfire risk levels to 35,000 homes and published this information online (Donovan et al., 2007). Before the wildfire risk designations were published, the authors observed a positive relationship between wildfire risk and home prices. However, using maximum likelihood estimation, Donovan et al. (2007) find that this relationship disappeared after the website was launched. The results suggest that the risk designations increased homeowner awareness of wildfire risk (Donovan et al., 2007).

Champ et al. (2009) use the same study setting as Donovan et al. (2007) but reach a different conclusion: wildfire risk zones do not affect home prices. Rather than using county sales data, the authors distribute a household survey to properties that sold between July 2002 and September 2004 in Colorado Springs. The survey results indicate that most

homeowners are unaware of their wildfire risk (Champ et al., 2009). However, the study does not employ econometric methods to estimate price effects, and non-response bias is a potential concern due to the self-administered nature of the survey.

Rather than observing risk designations, Ma et al. (2024) study how fire hazard disclosure requirements affect home prices in California. State law requires disclosure if a home is located in a moderate, high, or very high fire hazard zone in areas where the state is responsible for wildfire management (Ma et al., 2024). In contrast, only homes in very high risk zones require disclosure when fire management falls under local jurisdiction (Ma et al., 2024). Using a boundary discontinuity design and Zillow data from 2015 to 2022, the authors find that homes subject to fire hazard disclosure sell for 4.3% less, on average, than homes not subject to the requirement. That is, homes just inside the zone where disclosure is required sell for less than similar homes just outside the boundary (Ma et al., 2024). The authors conclude that wildfire risk disclosures provide new information to buyers in the housing market.

Stetler et al. (2010) take a novel approach by using visibility of the wildfire burn area as a proxy for perceived risk to examine how homeowner perceptions of wildfire risk affect home prices. Using OLS estimation and housing data from the Northwest Montana Association of Realtors, the authors find that home prices in northern Montana decrease with increased perceived wildfire risk between June 1996 and January 2007. Stetler et al. (2010) also find that perceived risk is higher when a burned area is visible from the property. Specifically, having a view of a wildfire-burned area reduces the mean sale price of a home by $6,610 compared to homes without a view (Stetler et al., 2010). Stetler et al. (2010) suggest that when wildfire damage is not visible, buyers tend to overlook or underestimate the associated risk.

To the best of my knowledge, only in the past seven years have researchers begun estimating the effects of wildfires based on the predicted risk of a home. Nie et al. (2023)

focus on high wildfire risk zones to estimate the impact of wildfires on home prices, drawing on a severe wildfire season in California in 2015. Using a synthetic difference-in-differences design and CoreLogic home sale transaction data, Nie et al. (2023) find a 7.5% decline in average home prices in high-risk areas after 2015, relative to pre-2015 levels. Their analysis relies on Wildfire Hazard Potential maps developed by the U.S. Forest Service.

Kiel & Matheson (2018) use a difference-in-differences approach to estimate the impact of wildfires on home prices in Boulder County, Colorado. To incorporate wildfire risk, the authors utilize a rating system from the Boulder County GIS website. Using housing data from the Warren Group, they observe a 21.9% decrease in sales prices for homes located in the highest-risk zone following a wildfire, relative to homes in low-risk zones. The authors note that homes in medium-risk areas sell at a smaller discount, while estimates for high-risk zones are not statistically significant. Kiel & Matheson (2018) suggest that homeowners in the highest-risk zones are the most likely to update their risk perceptions following a wildfire.

Looking outside the U.S., Adachi & Li (2023) use the same empirical method as Kiel & Matheson (2018) and draw on APM housing data. They find a 4.96% decrease in home prices within designated bushfire-prone areas (BPAs) compared to homes outside the BPA following the 2015 Sampson Flat Bushfire in South Australia. The discount persists for at least two years (Adachi & Li, 2023). Adachi & Li (2023), similarly to Kiel & Matheson (2018), broaden their search to include medium-risk BPA. Unlike Kiel & Matheson (2018), Adachi & Li (2023) find that medium-risk zones incur greater price discounts than high-risk zones.

Findings by McCoy & Walsh (2018) support those of Adachi & Li (2023), but offer a more nuanced view of how perceived wildfire risk evolves after a wildfire. Using a difference-in-differences approach and housing data from DataQuick Information Systems, the authors study the Colorado Front Range between 2000 and 2012. McCoy & Walsh (2018) find that negative housing price shocks in high-risk zones dissipate within two to three years. McCoy

& Walsh (2018) define three treatment groups based on proximity to wildfire, visibility of burned areas, and whether the property is located in an area with high latent risk. Their results suggest that wildfires produce a short-term increase in risk salience among homeowners in high-risk areas. However, this heightened perception appears to fade over time, implying that homeowner responses to new information about risk may be temporary (McCoy & Walsh, 2018).

Of the studies reviewed, most find that wildfire risk designations and perceived wildfire risk influence housing markets. The most rigorous research studies find that homeowners tend to update their perception of risk when presented with new information, particularly when that risk is made visible. However, studies that differentiate responses across risk zones are limited to individual states or localized markets. In addition, findings vary regarding which risk zone experiences the largest decline in home values following a wildfire.

This paper builds on the existing literature by examining how housing market responses vary across designated wildfire risk zones in the contiguous western United States. In doing so, it contributes to the emerging literature on how spatially defined wildfire risk, shaped by standardized zoning, affects property values. It also broadens the scope of prior research by assessing whether homeowner responses to wildfire differ systematically by risk designation at a regional scale.

CONCEPTUAL FRAMEWORK

Understanding why housing prices respond to wildfires, and why this response may differ across areas with varying projected risk levels, is essential for identifying how individuals perceive and respond to environmental hazards. Home prices reflect more than just the physical characteristics of a property; they capture how people value the safety and long-term stability of a location. When prices change following a wildfire, it signals a shift in how residents interpret and respond to risk. By examining how housing prices change after a wildfire across risk zones, this study provides insight into whether homeowners consider risk classifications when forming expectations and how new information alters those expectations.

A wildfire provides a visible and immediate signal of local hazard. For nearby homeowners, especially in areas where wildfires are not expected, the event can prompt reassessment of future risk. As homeowners receive new information, they may revise their beliefs about the likelihood or severity of future exposure. A perceived increase in risk can reduce demand for homes in the affected area, resulting in lower home prices. Even without direct property damage, a wildfire may reduce the desirability of a neighborhood due to concerns about air quality, loss of environmental amenities, or the potential for future events. As such, I propose that home prices will decrease following a wildfire due to a loss in the desirability of the surrounding neighborhood.

How homeowners respond to a wildfire depends on the information they already possess. According to Bayes' Theorem, individuals beliefs about the probability of a future event are shaped by both prior information and new signals. In this study, wildfire risk classifications and fire history act as priors, and wildfire exposure acts as a signal. If neither fire history nor risk classifications are known or considered, the homeowner has no prior and the wildfire serves as the first salient signal of hazard. In such a case, the wildfire would prompt a similar update to beliefs about the probability of a future event across areas regardless of

their assigned classification, and prices would fall uniformly across zones. The absence of prior expectations implies that all homeowners interpret the wildfire as the first signal of risk, leading to similar shifts in beliefs.

Most homeowners, however, are likely aware of local fire history. Such awareness can arise from personal experience and education, long-term residency, or communication within the community. In this context, prior fire history shapes expectations about future exposure. In areas with repeated previous exposure to wildfires, the prior suggests a higher probability of future wildfire exposure. In contrast, in areas with minimal or no prior wildfire activity, the prior suggests a lower probability of future wildfire exposure.

Along with historic wildfire activity, wildfire risk designations serve as another source of prior information for homeowners. Similarly, in areas with a high predicted risk of wildfires, the prior suggests a higher probability of future wildfire exposure. In areas with a low predicted risk of wildfires, the prior suggests a lower probability of future wildfire exposure. When homeowners experience a wildfire event, responses will vary depending on prior beliefs of wildfire risk. If the signal aligns with the prior, little updating occurs because information aligns with expectations. If the signal contradicts the prior, the signal may lead to a larger revision in expectations. Thus, when a wildfire event occurs, housing price responses reflect the revision in homeowner beliefs about the potential for a future wildfire event.

I propose three potential ways homeowners may respond, depending on how they weigh their priors and signals. First, if homeowners have "complete information," they only weigh priors, such as risk classifications, and view the fire as consistent with overall risk. In this case, prices do not change following a wildfire in both low- and high-risk zones. Second, if homeowners update beliefs with new information, they will incorporate both the priors and the new signal of fire risk in their updating of beliefs. This would result in prices diverging across risk zones, with greater effects observed in the low-risk zones since their prior suggests a low probability of a wildfire event. Finally, if homeowners diverge from neoclassical models,

they may ignore, or be unaware of, prior classifications and respond only to the fire event. In this case, prices decrease significantly across both risk zones. The three potential outcomes illustrate how housing markets may respond differently to wildfire events depending on how homeowners revise their beliefs in response to new information.

The exact mechanisms through which homeowners engage with information about their wildfire risk is unclear. This study uses Wildfire Hazard Potential (WHP) classifications as a source of predicted risk. While WHP classifications are designed to provide information on wildfire risk, it is not evident how widely they are used or how frequently they factor into home buying decisions. Some prospective buyers may be informed of predicted wildfire risk through disclosures during the sales process, conversations with real estate agents, or personal research. Others may not be aware of the information. Additionally, homeowners could learn about their wildfire risk through state agencies, which may publish the content of WHP maps on separate platforms. In states where locally developed risk maps are unavailable, WHP maps may be the primary source of official wildfire risk information available to the public.

Variation in housing market responses across predicted risk zones following wildfire exposure reveals how homeowners engage with information about environmental risk when forming expectations. Depending on how homeowners weigh prior beliefs, such as risk classifications, and new information from wildfire events, price responses may differ across risk zones, remain unchanged, or change uniformly. By examining how prices vary in response to wildfires across risk zones, this study evaluates how households interpret wildfire hazard signals and whether predicted risk classifications guide residential decision making.

DATA

Single-Family Residential Transactions

Parcel-level transaction data were purchased from CoreLogic, a proprietary source that provides comprehensive nationwide home sale data. The dataset was acquired in 2021, which is the final year included in this analysis. Each parcel is geolocated using block-level centroid coordinates, corresponding to the U.S. Postal Service address associated with the property. Properties with zero or undefined coordinates are excluded from the sample. Sale price is inflated using the monthly consumer price index from the U.S. Department of Labor and Statistics. Transactions are recorded from November 9, 2015, which is the release date of the first WHP map, and extend through August 3, 2021.

Key variables in the transaction dataset include the sale date, sale amount, and the block-level centroid coordinates. The transaction date used in this analysis is the sale-derived date[1], rather than the deed signing date or the recording date. A CoreLogic data consultant recommended using the sale-derived date as the transaction date, and I assume that it is an accurate reference point for when the transaction occurred.

Property attributes are sourced from a separate CoreLogic dataset containing assessment records, which include housing characteristics and block-level centroid coordinates. Since the assessment and transaction data lack a consistent temporal identifier, each sale is matched to the closest available assessment year, with priority given to assessments that occur before the sale. This process allows each transaction to be paired with the most relevant housing characteristics. In cases where the transaction and assessment occur in the same year, it is unknown whether the assessment occurred before or after the sale. I assume

[1]CoreLogic defines the sale-derived date as the "proprietary sale date derived from the original public record filing, representing the date that the Deed was prepared in advance of being notarized and prior to being recorded" (CoreLogic (2021), received as part of proprietary data transfer).

that assessments recorded in the same year are reflective of property conditions at the time of sale. Sales with no assessment information are excluded from analysis. More detail on data processing is provided in the Appendix.

Only properties with sale prices between $20,000 and $10,000,000 are retained[2]. Figure 3 displays a histogram of the log-transformed sale amount. Mobile homes and non-arm's length[3] transactions, such as short sales, bank foreclosures, and inter-family transfers, are excluded. The analysis is restricted to a repeat-sales sample, where each home is observed at least twice during the study period.

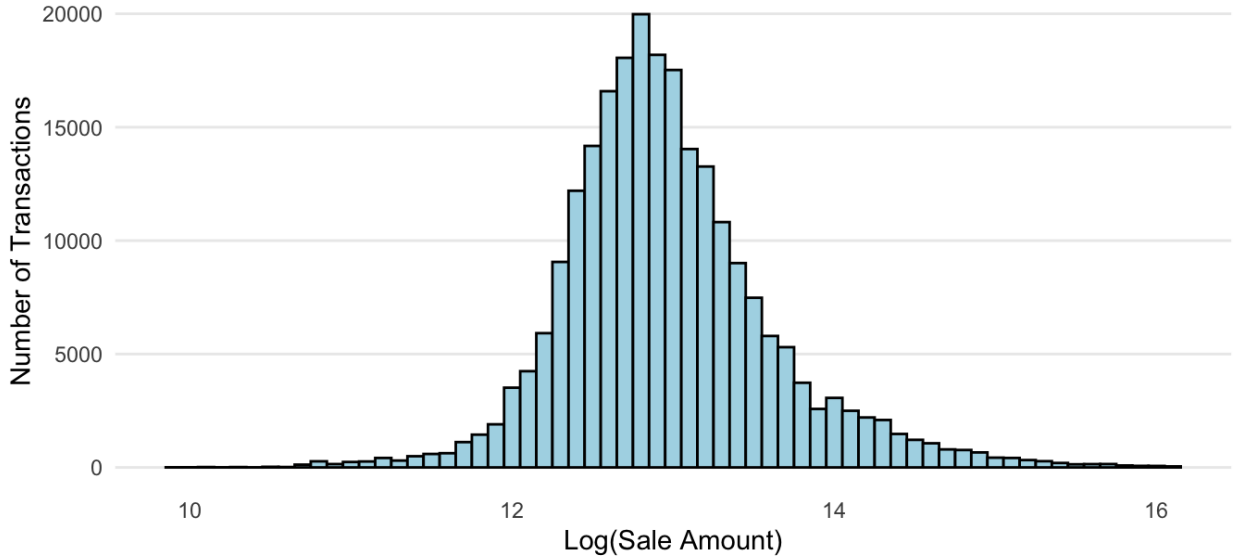


Figure 3: Histogram of Log-Transformed Sale Amount. Source: CoreLogic (2021)

Each home is assigned to a single wildfire, defined as the first observed exposure during the study period. I retain only the first post-treatment sale for each home, along with any

[2]Nie et al. (2023) exclude home sale prices below $20,000 and above $25,000,000; Donovan et al. (2007) drop sales below $25,000 and above $2,500,000; Huang & Skidmore (2024) restrict their sample to sales between $10,000 and $10,000,000. Since my study spans multiple states and housing markets, I adopt a price range that represents a middle ground between these approaches, capturing most home sales while excluding extreme outliers.

[3]A non-arm's length transaction occurs when the buyer and seller have a pre-existing relationship (e.g., family or friends), whereas an arm's length transaction reflects a market-based exchange between unrelated parties.

sales that occurred prior to the fire. Once a home is classified as treated, it does not appear in the control group for any subsequent wildfire. Homes in the control group may appear in multiple control groups if they are not treated prior to appearing in the control group. The final sample consists of 237,702 unique, arm's-length, single-family residential transactions, representing 73,044 unique homes.

Wildfire Boundaries

The Monitoring Trends in Burn Severity (MTBS) program provides long-term data on wildfire burn perimeters to support policy analysis, fire management, and scientific research (Eidenshink et al., 2007). The program is jointly managed by the U.S. Geological Survey's Earth Resources Observation and Science (EROS) Center and the USDA Forest Service's Geospatial Technology and Applications Center (GTAC) (Monitoring Trends in Burn Severity, ndb). The primary dataset used to identify wildfire exposure is the Burned Area Boundaries dataset, retrieved directly from the MTBS website as part of its publicly available geospatial products.

The data include spatial perimeters for large wildfires across the United States. Fires are included in the dataset if they exceed 1,000 acres in the western U.S. or 500 acres in the eastern U.S. (Monitoring Trends in Burn Severity, ndb). Each fire record includes a spatial polygon outlining the burned area, along with the ignition date, and the burned area in acres. Burned area boundaries are derived from pre- and post-fire imagery captured by Landsat and Sentinel-2 satellites[4]. The data are provided in 30-meter resolution.

Despite its broad coverage, the MTBS dataset has several limitations that may affect its completeness and accuracy. Fires can be excluded from the data if they are missing from

[4]The Landsat program, jointly managed by the U.S. Geological Survey and NASA, provides continuous satellite imagery to monitor Earth's land surface (U.S. Geological Survey, 2025). The Sentinel-2 program, developed by the European Space Agency (ESA), offers imagery of land and vegetation and has supported MTBS mapping since 2015 (European Space Agency, nd; Monitoring Trends in Burn Severity, ndb).

official records or if the fire is low severity and not detected in the imagery (Monitoring Trends in Burn Severity, nda). In some cases, inaccurate ignition dates or locations may prevent proper alignment with satellite imagery (Monitoring Trends in Burn Severity, nda). Additionally, cloud cover or poor image quality can interfere with the ability to detect burned area (Monitoring Trends in Burn Severity, nda). With a 1,000-acre threshold in the West, the MTBS data captures roughly 95% of the annual burned area.

I restrict the dataset to fires classified as Wildfires that occurred within the 11 Western U.S. states. A 30-kilometer buffer is created around each fire's perimeter to define treatment, following Huang & Skidmore (2024), and a 50 to 70-kilometer buffer is used to define the control group. Wildfire perimeters and 70-kilometer buffers for fires included in this analysis are displayed in Figure 4. For each home located within the treatment and control buffers, I calculate the Euclidean distance to the nearest point on the perimeter of the intersecting fire. See the Appendix for details on the spatial assignment process.

Table 1 presents the summary statistics and difference in means for select variables across the control and treatment groups. Select housing characteristics include lot size, building square footage, and number of bedrooms and bathrooms. These are presented solely to compare treated and control homes; they are not included as model covariates.

Table 1: Balance Table by Treatment Status

	Control		Treated				
Variable	Mean	SD	Mean	SD	Diff	SMD	p-value
Lot Size (acres)	1.05	30.70	1.02	51.69	0.03	0.00	0.885
Building Sq. Feet	2,642	1,203	2,569	1,154	73	0.06	<0.001
No. of Bedrooms	3.35	0.96	3.37	0.91	-0.02	-0.02	0.026
No. of Bathrooms	2.57	0.92	2.50	0.93	0.07	0.08	<0.001
Sale Amount ($)	559,445	593,145	565,240	639,072	-5,795	-0.01	0.039

Note: This table presents the mean and standard deviation of housing characteristics for homes in the control and treated groups, as well as the difference in means. Standardized mean difference (SMD) is computed as the difference in means divided by the pooled standard deviation.

The difference in means indicate that treated and control homes exhibit minimal variation across select housing characteristics. Mean values for lot size, number of bedrooms, and sale amount are similar between groups, with small standardized mean differences and statistically insignificant differences. Although the number of bathrooms and building square footage differ statistically at the 1% level, the magnitude of these differences is small and may be attributable to high rates of missing data in these variables. The difference in means results suggest that the control group provides a reasonable counterfactual for treated homes.

Fires are retained in the data if at least one housing centroid intersects with the 30-kilometer buffer and at least one housing centroid intersects with the 50 to 70-kilometer buffer. In total, 276 unique wildfires are identified, with ignition dates ranging from December 26, 2015 to June 25, 2021. Table 2 displays transaction counts by treatment group and timing, where post-treatment transactions are defined as those occurring on or after the wildfire ignition date.

Table 2: Transaction Counts by Treatment Timing and Status

Treatment Status	Pre-Fire	Post-Fire	Total
Treated	16,092	15,377	31,469
Control	105,424	100,809	206,233
Total	121,516	116,186	237,702

Note: This table reports the number of repeat-sale transactions by treatment status and timing relative to wildfire exposure. Treatment is defined based on proximity to a wildfire. Transactions are classified as post-fire if the sale occurs after the wildfire ignition date and as pre-fire if the sale occurs before. Totals are reported by row and column.

I considered an additional measure of wildfire severity based on the number of structures burned in each fire. Due to processing limitations, this variable is not included in the analysis. The Appendix provides details on the data source and construction of this variable.

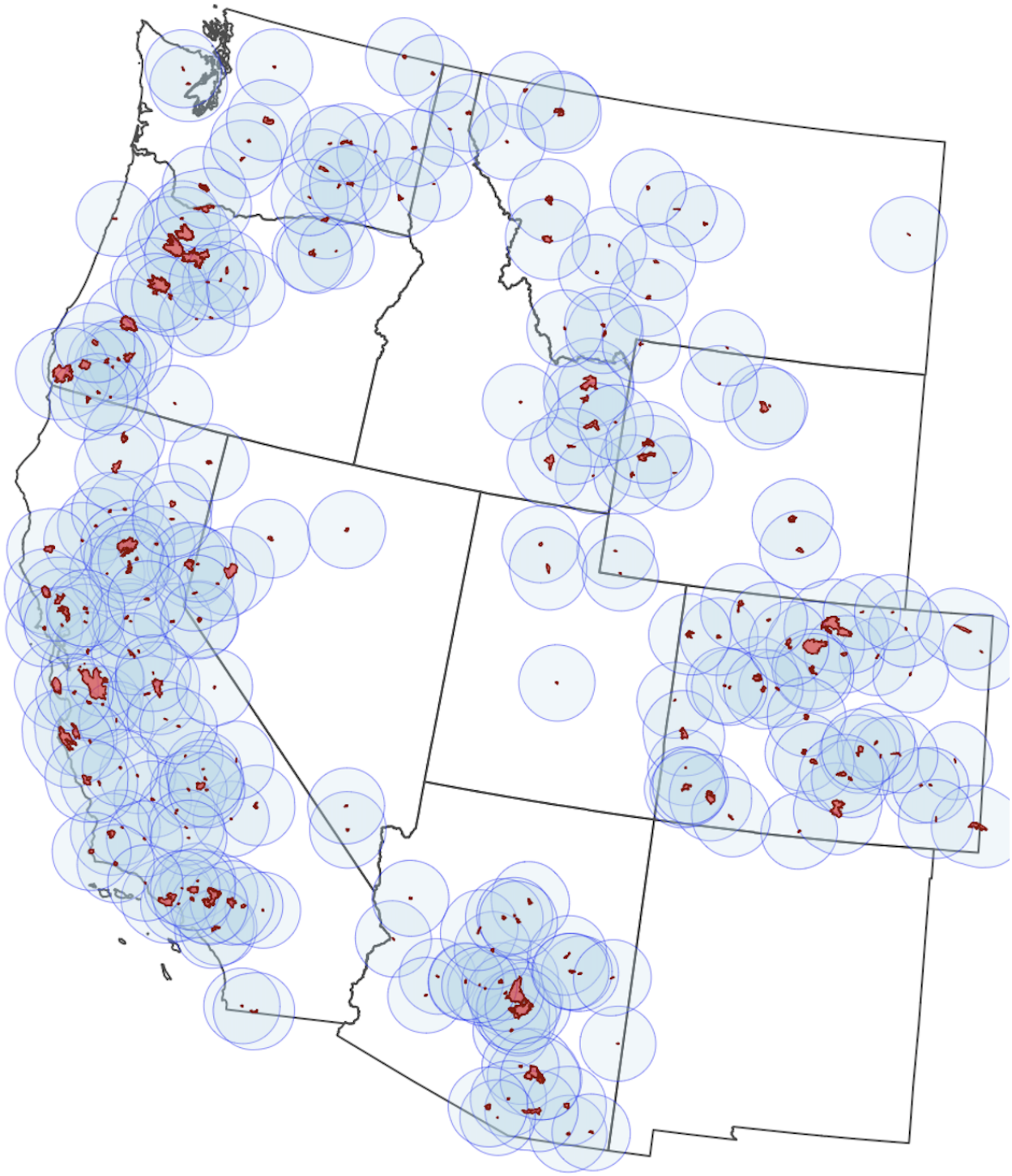


Figure 4: Wildfire Boundaries and 70 Kilometer Buffers. Source: U.S. Geological Survey & USDA Forest Service (2024)

Wildfire Hazard Potential Maps

Wildfire Hazard Potential (WHP) maps are developed by the U.S. Department of Agriculture Forest Service and retrieved from the agency's public data archive. These maps are provided as 270-meter resolution raster files and are available in both continuous and classified formats. The continuous format reflects a numeric index of wildfire hazard potential, while the classified format assigns each raster cell to one of five risk categories: very low, low, moderate, high, and very high. I use the classified version, which reflects the wildfire hazard potential as published and limits the need for custom thresholds or subjective interpretation.

To ensure sufficient sample size and facilitate comparison across risk gradients, I aggregate the five WHP classes into two broader zones: low-risk (very low and low) and high-risk (moderate, high, and very high). This grouping follows the logic of the WHP classification system, which assigns approximately two-thirds of U.S. land area to the low-risk categories and one-third to higher risk categories (Dillon et al., 2015). Further, this retains the intuitive ordering of risk while simplifying the analysis into two clearly defined groups that align with how homeowners may interpret wildfire risk, distinguishing between "safe" and "unsafe" areas when evaluating property decisions. Table 3 reports the number of transactions by treatment status and WHP classification.

Table 3: Transaction Counts by WHP Zone and Treatment Status

WHP Zone	Treated Homes	Control Homes	Total	Share (%)
Low	22,869	119,424	142,293	59.9
High	8,600	86,809	95,409	40.1
Total	31,469	206,233	237,702	100.0

Note: This table reports the number of treated and control transactions across aggregated WHP zones. Low-risk zones include very low and low WHP classes. High-risk zones include moderate, high, and very high WHP classes. Totals are reported by row and column, and the percent share is reported by WHP class.

The WHP classification system includes two additional categories beyond the five risk classes: non-burnable and water. Properties located in non-burnable areas are excluded from the analysis, as these locations typically contain sparse or no vegetation and are not considered meaningfully exposed to wildfire risk. In cases where a property centroid intersects a raster cell classified as water, the home is reassigned to the highest-classified neighboring raster cell. If no adjacent cell contains a valid WHP classification, the observation is dropped from the sample.

Three editions of the WHP maps were released during the study period: the 2015 edition on November 9, 2015; the 2018 edition on October 10, 2018; and the 2020 edition on November 20, 2020. The Appendix outlines key methodological differences across the three WHP map versions. Since the effect of wildfire exposure is measured through post-treatment home sales, each home is assigned the WHP classification corresponding to its post-fire transaction. This approach reflects the information available to prospective buyers at the time of purchase after the wildfire. Accordingly, each WHP value is assigned to housing observations by overlaying the raster files with house centroids at the time of sale.

Final Datasets

The final sample consists of three panel datasets: a full sample of repeat-sale transactions, a subsample restricted to low-risk zones, and a subsample restricted to high-risk zones. Each dataset is constructed so that every observation represents a unique pairing between a single-family residence transaction and an intersecting wildfire event. If a home is treated by multiple wildfires during the study period, it is assigned to the earliest observed fire, and subsequent intersections are excluded. Treatment status is assigned based on the home's distance from the wildfire perimeter, while treatment timing is determined by the number of days between the fire ignition date and the home sale date.

Summary Statistics

Table 4 reports summary statistics for the final datasets used in this analysis. The full sample and low-risk zone subsample span November 9, 2015, to August 3, 2021, while the high-risk zone subsample ends on August 2, 2021. The full sample includes 237,702 single-family residential transactions matched to 276 wildfires. The low-risk zone subsample contains 142,293 transactions and 274 fires, while the high-risk zone subsample includes 95,409 transactions and 247 fires.

Table 4: Summary Statistics

Variable	Mean	SD	Min	Max
Full Sample				
Sale Amount ($)	551,738.3	599,431.3	20,000	10,000,000
Post	0.489	0.500	0	1
Near Fire	0.132	0.339	0	1
Fire Size (acres)	24,771.6	53,220.1	1,001	405,787
Distance to Fire (km)	55.2	14.1	0.14	70.0
Low Risk Zone				
Sale Amount ($)	544,266.9	608,561.3	20,000	10,000,000
Post	0.488	0.500	0	1
Near Fire	0.161	0.367	0	1
Fire Size (acres)	26,642.5	56,929.5	1,001	405,787
Distance to Fire (km)	54.0	15.2	0.14	70.0
High Risk Zone				
Sale Amount ($)	562,881.2	585,376.4	21,500	9,950,000
Post	0.490	0.500	0	1
Near Fire	0.090	0.286	0	1
Fire Size (acres)	21,981.4	47,011.1	1,001	405,787
Distance to Fire (km)	57.0	12.2	5.9	70.0

Note: This table reports summary statistics for key variables for the full sample, the low-risk zone subsample, and the high-risk zone subsample. Risk zone classification is aggregated into low and high based on the WHP raster map assigned to each home at the time of post-fire sale.

The average sale price across all transactions is approximately $552,000, with values

ranging from $20,000 to $10,000,000. Around 49% of sales occur after wildfire ignition, and 13% of transactions are classified as near the fire, or treated. On average, treated homes are exposed to wildfires that burn approximately 25,000 acres, and the mean distance to fire is 55 kilometers.

Subsample comparisons reveal slight differences between low-risk and high-risk zones. Homes in high-risk zones sell for around $19,000 more on average, but are seven percentage points less likely to be treated. Homes are on average three kilometers closer to a wildfire in high-risk zones, while average fire size is around 4,600 acres smaller. The proportion of post-treatment sales remains similar across zones, with just under half of transactions occurring after fire exposure. These summary statistics indicate that treatment and control groups are relatively balanced across zones, though treatment is more prevalent in low-risk areas.

THEORETICAL FRAMEWORK

The hedonic pricing model provides the foundational framework for estimating how environmental factors, such as wildfire exposure, influence housing prices. To isolate the effect of wildfire events from other determinants of home value, researchers apply the hedonic pricing model. In its basic form, the hedonic pricing model can be expressed such that the price (P) of house i in time t is a function of structural attributes (X), neighborhood characteristics (N) and environmental factors (E):

$$P_{i,t} = f(X_{i,t}, N_{i,t}, E_{i,t})$$

Introduced by Rosen (1974), the hedonic pricing model assumes that the market operates in equilibrium, such that home sellers and home buyers maximize their utility and profits. In theory, the hedonic pricing model encompasses all attributes that influence a home's value, capturing the full bundle of housing and neighborhood characteristics. However, this is rarely achieved in practice due to data limitations and unobserved factors. In traditional OLS applications, estimates are biased when relevant variables are missing. Researchers often address concerns about bias by applying research designs, such as fixed effects or matching, to account for unobserved heterogeneity. While core housing characteristics like lot size and number of bedrooms are commonly included, researchers adapt the model to the context of their setting.

In wildfire economics, the hedonic pricing model is used to estimate how wildfire events influence property values. These models often incorporate environmental variables alongside traditional housing and neighborhood attributes to isolate the effects of wildfires on house values. Common measures of environmental quality are proximity to wildfire burn areas, forest cover, elevation, and distances to natural and infrastructural features. To further account for unobserved spatial and temporal heterogeneity, most studies also adopt fixed effects specifications.

Hansen & Naughton (2013), for instance, apply the hedonic pricing model framework to house sales on Alaska's Kenai Peninsula. Their model includes standard housing attributes, proximity to wildfires, forest cover, elevation, seasonal climate conditions, and city fixed effects. Mueller et al. (2018) uses similar variables while estimating the impact of wildfire and post-wildfire flooding on housing prices in Arizona. Instead of fixed effects, Mueller et al. (2018) utilize non-parametric matching techniques to compare pre- and post-wildfire sales, while conditioning on observable housing characteristics and the distance to the Schultz Fire perimeter.

Huang & Skidmore (2024) estimate the impact of both wildfires and wildfire-induced air pollution on house prices across the U.S. The authors use a series of wildfire exposure measures, such as fire frequency, size, cause, and distance to the fire. Due to missing data, their model includes limited time-varying housing characteristics. Instead, Huang & Skidmore (2024) utilize a repeat-sales framework and rely on parcel and county-by-year fixed effects to account for unobserved heterogeneity. Mueller et al. (2009) similarly rely on a reduced set of time-varying housing characteristics in their study of repeated wildfire exposure in Los Angeles County during the 1990's. To account for environmental quality, Mueller et al. (2009) use distance to U.S. Forest Service land. Neighborhood characteristics are captured using local unemployment rate, median household income, and the percentage of residents without a high school degree, not utilizing any fixed effects (Mueller et al., 2009).

Prior studies illustrate how the hedonic pricing model can be adapted to quantify the impacts of wildfire exposure on housing markets. By incorporating environmental variables into the hedonic pricing function, researchers can evaluate how natural hazards shape the housing market. This framework motivates the empirical strategy developed in the following section.

EMPIRICAL FRAMEWORK

This study examines whether housing market responses to wildfire exposure differ systematically across wildfire hazard potential zones. To test this, I compare changes in single-family residence sale prices following wildfire exposure between nearby and more distance houses across risk zones using a stacked difference-in-differences and event study framework.

Identification Strategy

To estimate the causal effect of wildfire exposure across predicted wildfire risk zones, I implement a stacked difference-in-differences framework that exploits within-property variation in sale prices before and after wildfire exposure. Specifically, I stack repeat sales data from multiple wildfires and restrict the sample to houses located near the wildfire perimeter. I estimate models separately by wildfire risk zone, using houses near fire as the treated group and houses further away from fire as the never-treated group. The resulting estimates capture zone-specific average treatment effects on the treated (ATT).

A key advantage of the stacked difference-in-differences approach is that it mitigates concerns with traditional two-way fixed effects models under staggered treatment timing. Since fires occur at different times, a traditional two-way fixed effects model would introduce negative weighting and contaminated comparisons. The stacked approach prevents bias from staggered treatment by aligning observations relative to the timing of each fire, ensuring that treated homes are compared only to control homes within the same wildfire event.

The identifying assumption underlying the difference-in-differences framework is that single-family house prices in treated areas would have followed the same trends as those in the control group, had the treatment group not been treated. Specifically, sale prices for houses exposed to a wildfire would have followed the same trend as houses that were further

away from the wildfire, had the treated houses not been exposed. While the parallel trends assumption cannot be directly tested, event studies enable a visual and statistical assessment of pre-treatment trends. A lack of statistically significant differences between the treatment and control group in the pre-period supports the parallel trends assumption and the validity of the difference-in-differences design.

A potential threat to identification is spillover effects. If wildfires influence house prices beyond the directly affected treatment area, then houses considered not treated may be partially treated. Houses that are partially treated would serve as an invalid control. To reduce this concern, I implement a "doughnut" control design that excludes houses located within the zone surrounding the treatment boundary. This approach ensures that never-treated houses are minimally affected by spillovers from the wildfire. I define treatment as within 30 kilometers of the wildfire perimeter, following Huang & Skidmore (2024), and use houses located 50–70 kilometers away as the control group. Mueller et al. (2018) found a 31% and 6% decrease in housing prices within 5 kilometers and 20 kilometers, respectively, of a wildfire perimeter. Based on their findings, a 50-kilometer buffer seems conservative.

Repeated wildfire exposure poses another potential threat to identification. Mueller et al. (2009) find that house prices decline after a wildfire and fall by an additional 22.68% when located within 1.75 miles of a second wildfire event. This evidence suggests that housing markets are highly responsive to repeated wildfire exposure. To avoid conflating effects from repeated treatment, I assign each home to its first observed exposure during and before the study period. Specifically, I incorporate data on wildfires that occurred in the three years prior to the observation window to identify homes that were treated before the study period begins. This ensures that earlier fires do not contaminate the estimation of wildfire effects by allowing time for local housing markets to adjust. The three-year window is determined based on findings by McCoy & Walsh (2018), which suggest that perceptions of wildfire risk dissipate after two to three years.

A final potential threat to identification is measurement error. In the case of the MTBS wildfire dataset, missing fires may arise from misreported fire size, inaccurate ignition dates or locations, poor satellite imagery, missing agency-reported fire occurrence data, or low-severity burns that are not visible in imagery (Monitoring Trends in Burn Severity, nda). If misreports are not random, there would be systematic measurement error in the treatment. In particular, if smaller fires are more likely to be missing, treated homes would be incorrectly classified as untreated. While small fires are less likely to have a significant impact on the housing market and thus may not substantially bias the results, their omission still raises concern in this analysis.

Time-varying variables that are omitted from the model are absorbed into the error term and can bias causal inference if they are correlated with both wildfire exposure and housing prices. Although wildfires are often considered a quasi-random event, they may coincide with other changes that affect housing markets. Examples include increased defensible space regulations, local fuel reduction programs, or increased state and federal funding to wildfire prevention. If these factors are not captured by fixed effects, they could bias the estimated treatment effects.

Structural characteristics are captured through house-by-fire fixed effects. Rather than using house fixed effects alone, I employ house-by-fire fixed effects because control homes may appear in multiple fire events if they remain in the control group. This approach ensures that comparisons are made within the same wildfire event, which is essential for the stacked difference-in-differences design. House-by-fire fixed effects absorb all time-invariant attributes of a property within each fire, including unobserved locational and structural features. This accounts for persistent differences across homes and isolates within-home price changes around each wildfire event. House-by-fire fixed effects do not account for structural changes within a property over time, such as major renovations or rebuilds. By limiting the analysis to the first sale post-treatment, the likelihood that observed price changes reflect

long-term structural modifications rather than immediate responses to wildfire exposure is reduced. Even so, it remains possible that observed changes in home value are influenced by repairs or upgrades unrelated to the fire. Without direct information on property improvements, this source of bias cannot be fully ruled out.

Fire-by-month-by-year fixed effects control for time-varying confounders at the level of each wildfire event. This specification allows each fire to have its own time trend, absorbing shocks that may simultaneously affect wildfire occurrence and local housing markets. It also ensures comparisons are made within fire cohorts defined by the timing of treatment. Fire-by-month-by-year fixed effects account for national factors such as interest rates, inflation, and macroeconomic cycles, as well as seasonality in home sales. By absorbing both broader housing market dynamics and fire-specific timing shocks, the specification helps isolate the treatment effect.

Although house-by-fire and fire-by-month-by-year fixed effects absorb much of the spatial and temporal heterogeneity, some bias may persist from local initiatives that vary across time and geographic area. For example, defensible space policies or changes to local building codes within the study period may influence both wildfire exposure and housing values. These factors are difficult to account for without removing too much variation from the model. The fixed effects specification and repeat-sales framework help mitigate concerns about bias by accounting for unobserved factors likely to weaken identification.

Empirical Strategy

To first estimate the effect of wildfires on housing prices across all wildfire hazard potential (WHP) zones, I implement a stacked difference-in-differences model of the form:

$$ln(Price_{i,f,t}) = \beta_0 + \beta_1(\text{NearFire}_{i,f} \times \text{Post}_{f,t}) + \delta_{i,f} + \lambda_{f,m,y} + \varepsilon_{i,f,t}$$

where $ln(Price_{i,f,t})$ is the log sale price of single-family residence i at time t, associated with fire f. The indicator $\text{NearFire}_{i,f}$ equals one if residence i is located within 30 kilometers of wildfire f, and zero if it is located between 50 and 70 kilometers of wildfire f. $\text{Post}_{f,t}$ is an indicator equal to one if the sale occurs on or after the ignition date of fire f, and zero otherwise. The model includes house-by-fire fixed effects, $\delta_{i,f}$, to account for time-invariant characteristics of each house within each fire, and fire-by-month-by-year fixed effects, $\lambda_{f,m,y}$, to account for housing market trends across time for each fire. The coefficient β_1 captures the average treatment effect on the treated (ATT). Specifically, β_1 is the difference in log sale prices before and after the fire for treated homes, relative to the corresponding change for control homes.

I cluster standard errors at the wildfire level to allow for correlation in unobserved shocks among homes exposed to the same fire. This follows common practice in difference-in-differences designs, where standard errors are clustered at the level at which treatment is assigned. Since wildfire exposure is defined at the fire level, price shocks among nearby homes may not be independent. Clustering standard errors at the wildfire level adjusts inference to account for potential within-group correlation.

To examine heterogeneous treatment effects by wildfire hazard potential (WHP) zone, I estimate the model separately for homes located in low-risk and high-risk zones. I define low-risk areas as those classified as very low or low WHP zones, and high-risk areas as those classified as moderate, high, or very high. Combining observations into two broader groups allows for greater statistical power in modeling, particularly given the sparse transaction data in the higher-risk categories. The model is updated to reflect zone-specific treatment effects:

$$ln(Price_{i,f,t}) = \beta_{0,z} + \beta_{1,z}(\text{NearFire}_{i,f} \times \text{Post}_{f,t}) + \delta_{i,f} + \lambda_{f,m,y} + \varepsilon_{i,f,t}$$

where z indexes the WHP zone. The coefficient $\beta_{1,z}$ captures the average treatment on

the treated within each zone category. Estimation is conducted separately by zone, so identification is based on within-zone variation in pre- and post-fire sales between treated and control homes.

I extend the model to an event study specification to examine dynamic treatment effects over time within each wildfire zone using the following model:

$$\ln(Price_{i,f,t}) = \sum_{k \neq -1} \beta_{k,z} \cdot 1\{\text{EventTime}_{i,f,t} = k\} \cdot \text{NearFire}_{i,f} + \delta_{i,f} + \lambda_{f,m,y} + \varepsilon_{i,f,t}$$

where $\text{EventTime}_{i,f,t}$ denotes the sale time relative to the time of wildfire exposure, with $k = 0$ as the year of the fire and $k = -1$ omitted as the baseline. Similarly to above, the indicator $\text{NearFire}_{i,f}$ equals one if property i is within 30km of wildfire f. The coefficients $\beta_{k,z}$ capture zone-specific dynamic treatment effects in the years surrounding the fire.

I run two additional regressions for heterogeneity by distance to the fire and size of the fire, measured by acres burned. These are estimated using the stacked difference-in-differences model. Both regressions are estimated for the full sample and separately for homes in low and high hazard potential zones. I run robustness checks by clustering standard errors at the house level, selecting alternative treatment lags, testing different post-treatment windows, using an alternative control group, and re-estimating the model with alternative WHP subgroup definitions. The former three robustness checks are implemented using the stacked difference-in-differences model for the full sample and by risk zone, while the latter two use an event study specification estimated separately for low- and high-risk zones.

RESULTS

Main Results

I begin by estimating the average treatment effect on the treated (ATT) of wildfires on single-residence sale prices. Table 6 reports the ATT estimates using the main stacked difference-in-differences model estimated on all available transactions, as well as transactions that fall in low-risk and high-risk WHP classifications.

Table 5: Estimated Effects of Wildfire Exposure on Home Prices

	Dependent Variable: Log Sale Price		
	(1) Full Sample	(2) Low Risk	(3) High Risk
NearFire × *Post*	0.0099*	0.0145**	0.0043
	(0.0056)	(0.0065)	(0.0106)
Observations	237,702	142,293	95,409
Adjusted R^2	0.915	0.924	0.904
Mean Dep. Var.	12.963	12.947	12.986

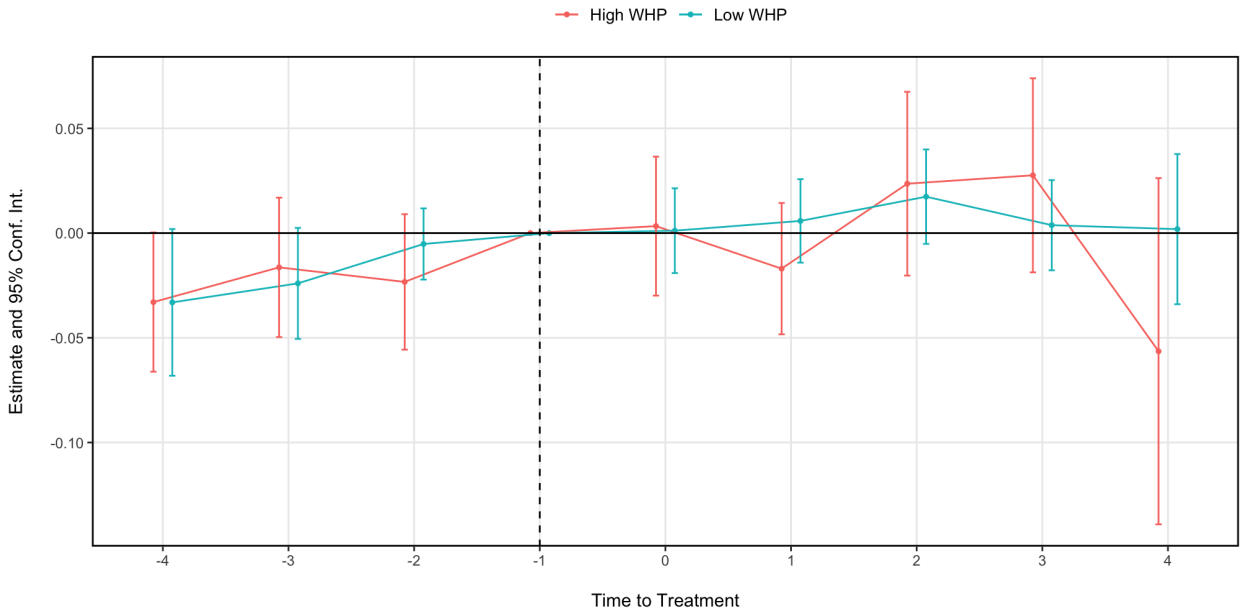
Note: Each column reports estimates from the main stacked difference-in-differences specification, separately estimated on (1) all transactions, (2) transactions in low-risk wildfire hazard zones, and (3) transactions in high-risk zones. All models include house-by-fire fixed effects and month-by-year-by-fire interacted fixed effects. Standard errors, shown in parentheses, are clustered at the wildfire level.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

These results show a small but statistically significant increase in log sale prices in the full sample and low-risk subsample. For the full sample of transactions, the results suggest that home prices increase by 0.99% following a wildfire, compared to homes 50 to 70 kilometers from the fire. This effect is significant at the 10% level. However, the effect varies by risk classification. In low-risk zones, sale prices increase by 1.45% after a wildfire, significant at the 5% level. In contrast, the estimated effect in high-risk zones is 0.43% and not statistically significant. Overall, these findings do not support the hypothesis that home prices decline after a wildfire. The larger and statistically significant effect in low-risk zones suggests that price changes are more pronounced in areas with lower perceived wildfire risk.

However, the lack of a significant effect in high-risk zones limits strong conclusions about heterogeneity.

To examine how wildfire exposure affects home prices over time, I estimate an event study specification separately for low- and high-risk zones. Figure 5 plots dynamic treatment effects relative to the year of wildfire exposure for each risk zone.

Figure 5: Event Study Estimates by WHP Zone



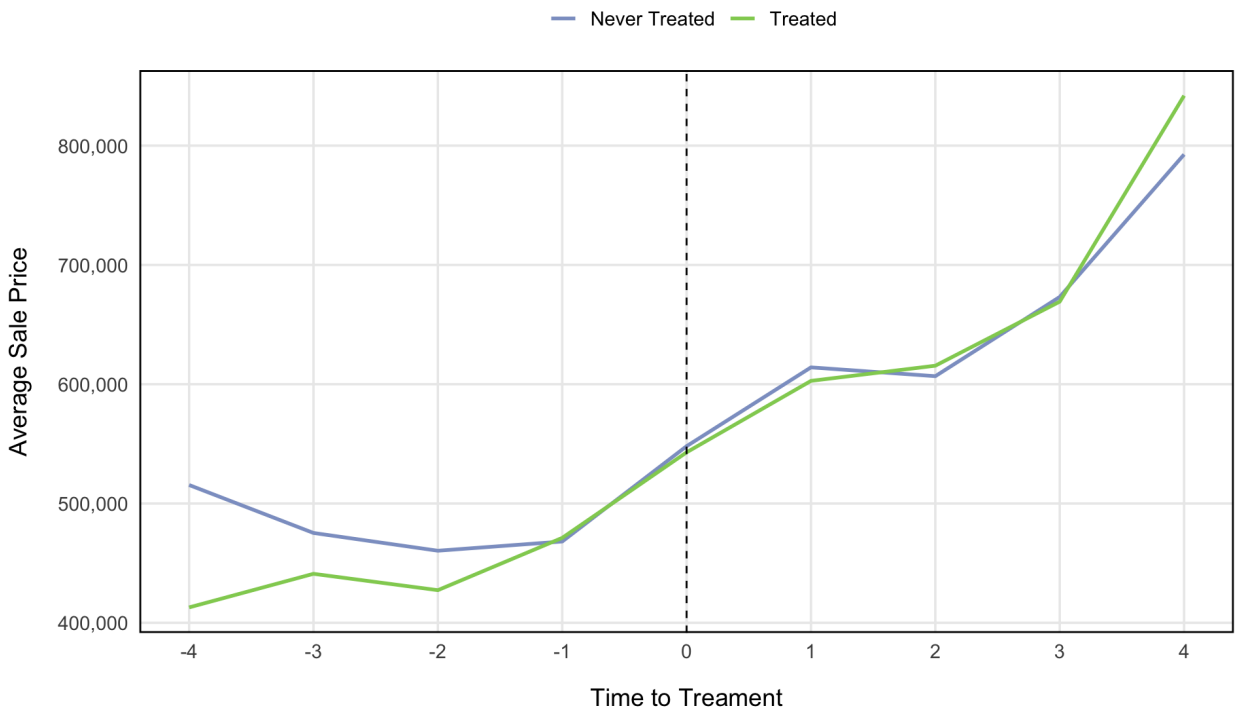
Note: Each point reflects the estimated treatment effect relative to the year of wildfire exposure, year 0, for houses in low and high wildfire hazard potential (WHP) zones. The model controls for house-by-fire fixed effects and month-by-year-by-fire interacted fixed effects. Standard errors are clustered at the wildfire level and vertical bars represent 95% confidence intervals.

Figure 5 illustrates the event study estimates of treatment effects relative to the time of wildfire exposure for both low-risk and high-risk zones, with year 0 corresponding to the wildfire event. For both zones, point estimates fluctuate after treatment. However, the confidence intervals in the treated period consistently include zero. This indicates that none of the post-treatment estimates are statistically significant at the 95% confidence level. Confidence intervals for the high-risk and low-risk zones overlap, suggesting that the estimated zone-specific effects are not different from each other. The low-risk zone exhibits

an upward trend in the pre-treatment period. This raises concerns about the validity of the parallel trends assumption. As a result, while there is no evidence of heterogeneity in treatment effects over time, pre-treatment trends in the low-risk zone caution against a causal interpretation.

While not intended to validate the parallel trends assumption, Figure 6 offers a descriptive look at how average prices evolve across treated and untreated homes over time. The figure plots average home prices relative to treatment in raw dollars. Trends diverge before treatment, with the treated group exhibiting higher average prices before treatment. Home sale prices in the treated and untreated groups increase similarly following the fire.

Figure 6: Average Home Prices Relative to Treatment

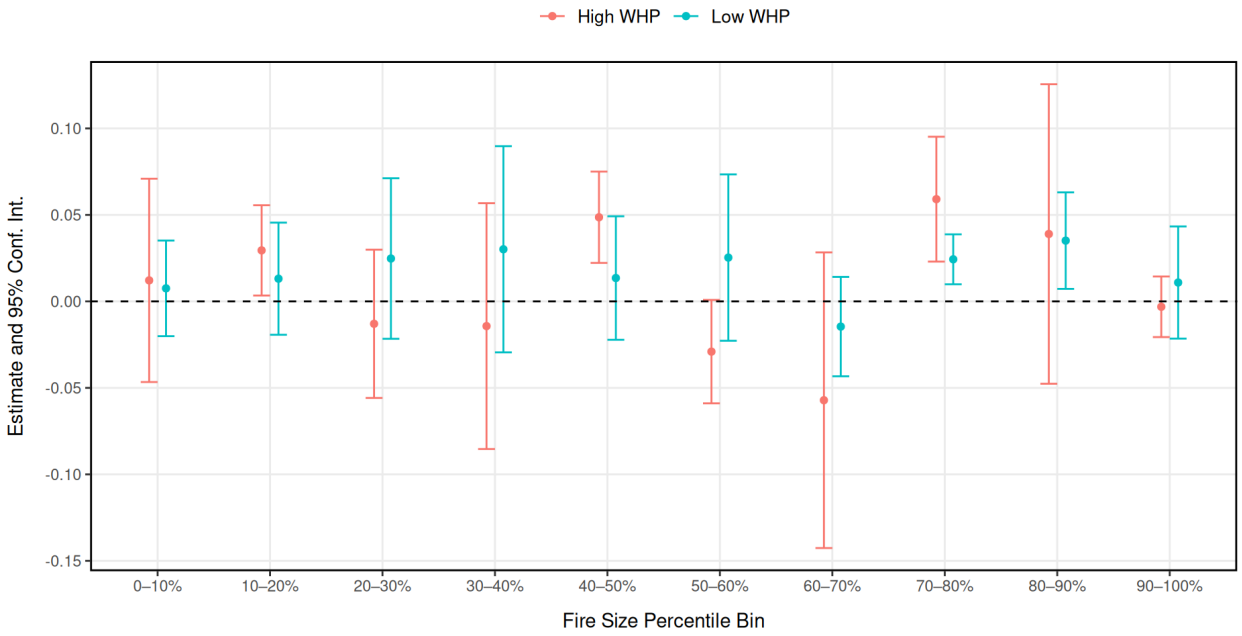


Note: Figure plots the average sale prices (in dollars) relative to the time of treatment for treated and untreated homes. Year 0 corresponds to the wildfire event. The figure shows raw averages and does not adjust for differences across homes or time.

In addition to variation over time, I test for heterogeneous treatment effects by two dimensions of exposure: the size of the wildfire and the distance between properties and

the fire perimeter. To examine variation by fire size, I construct percentile bins based on the distribution of acres burned at the fire level. Specifically, I group fires into ten 10% bins according to their percentile rank in total acres burned. Each home is then assigned to the fire size percentile bin corresponding to the fire it is associated with. Percentile bins are ordered such that the 0–10% bin contains the smallest 10% of fires by acres burned, while the 90–100% bin includes the largest 10%. Figure 7 plots treatment effects and 95% confidence intervals by fire size percentile bins, estimated separately for homes in low and high wildfire hazard potential (WHP) zones.

Figure 7: Heterogeneous Effects by Fire Size Percentile and WHP Zone



Note: Each point reflects the average treatment effect for treated homes within a given percentile bin of the fire size distribution, relative to the control group for each fire. Each model is estimated separately by WHP zone and includes house-by-fire fixed effects and month-by-year-by-fire interacted fixed effects. Standard errors are clustered at the wildfire level and vertical bars represent 95% confidence intervals.

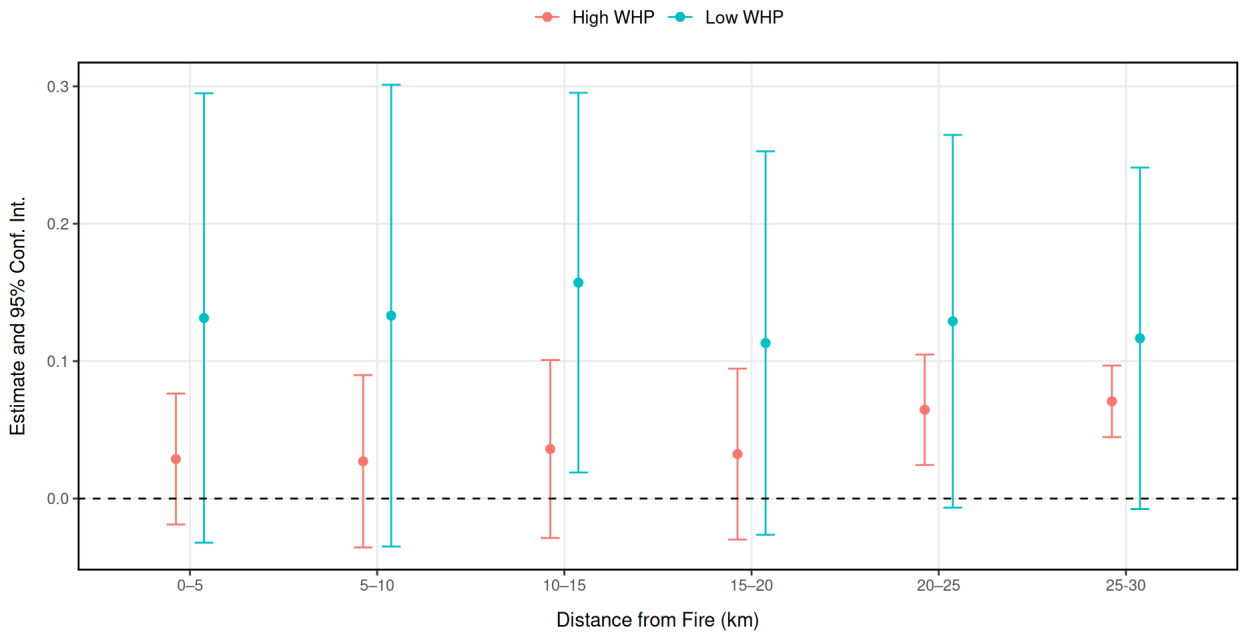
In low-risk zones, estimated treatment effects are generally positive across most fire sizes, with point estimates ranging from roughly 1% to 4%, and one estimate near -2%. Estimates are positive and statistically significant at the 95% confidence level in the low-risk zone for fires in the 70th to 90th percentile. In high-risk zones, both positive and negative

effects are observed, with some statistically significant estimates and no observable pattern.

At all fire sizes, high- and low-risk zone estimates have overlapping confidence intervals. However, high-risk zone estimates from the 50th to the 80th percentile fall outside the confidence intervals of the corresponding low-risk zone estimates. Within the 70th to 80th percentile, significantly positive effects are observed in both high-risk and low-risk zones. For fires in the 50th to 60th percentile bin, both the high-risk and low-risk estimates fall outside of each others confidence intervals. These differences suggest potential heterogeneity in price responses across fire size and risk classification. However, for the smallest and largest fires, no differences are observed between zones. Overall, there is some evidence suggesting heterogeneity in treatment effects by fire size across zones, though no clear pattern emerges.

To test for heterogeneity in price responses by proximity to fire, Figure 8 plots treatment effects across risk zones for homes located between 0 and 30 kilometers from the wildfire.

Figure 8: Heterogeneous Effects by Distance to Fire and WHP Zone



Note: Each point reflects the average treatment effect for treated homes in 5-kilometer bins between 0 and 30 kilometers of a wildfire, relative to never-treated homes. Each model is estimated separately by WHP zone and includes house-by-fire fixed effects and month-by-year-by-fire interacted fixed effects. Standard errors are clustered at the wildfire level and vertical bars represent 95% confidence intervals.

Point estimates suggest that homes in high-risk zones experience positive price effects at all distances up to 30 kilometers from the fire. Estimates for the high-risk zone are statistically insignificant at closer distances and become positive and significant for fires occurring 20 to 30 kilometers away. In low-risk zones, estimated effects are positive but generally insignificant across all distance bins. Confidence intervals for high- and low-risk zone estimates overlap at all distances, suggesting homogeneous price responses by distance to the wildfire.

Robustness Checks

I first test the sensitivity of standard errors to the level of clustering. The main specification clusters standard errors at the wildfire level, which is consistent with the common practice of clustering at the level of treatment in difference-in-differences models. As a robustness check, I also cluster at the house level, following the approach by Huang & Skidmore (2024). Table 6 reports the results.

Table 6: Robustness Check, Standard Errors Clustered at House Level

Dependent Variable: Log Sale Price			
	(1) Full Sample	(2) Low Risk	(3) High Risk
NearFire × *Post*	0.0099***	0.0145***	0.0043
	(0.0033)	(0.0040)	(0.0065)
Observations	237,702	142,293	95,409
Adjusted R^2	0.915	0.924	0.904
Mean Dep. Var.	12.963	12.947	12.986

Note: Each column reports estimates from the main stacked difference-in-differences specification, separately estimated on (1) all transactions, (2) transactions in low-risk wildfire hazard zones, and (3) transactions in high-risk zones. All models include house-by-fire fixed effects and month-by-year-by-fire interacted fixed effects. Standard errors, shown in parentheses, are clustered at the house level.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Clustering standard errors at the house produces tighter confidence intervals, particularly in the high-risk zone, where standard errors are 39% smaller. Estimates in the full

sample and the low-risk subsample become significant at the 1% level. Tighter confidence intervals are expected, as clustering at the house level involves a larger number of clusters than clustering at the wildfire level.

I test the sensitivity of the results to alternative treatment timing by introducing lags between the wildfire event and the home transaction. Specifically, I redefine the post-treatment period as beginning 3 months, 6 months, and one year after the wildfire. This accounts for delayed market responses or transaction lags following a wildfire. Table 7 reports the results.

Table 7: Robustness Check, Alternative Post-Treatment Lag Definitions

	Dependent Variable = Log Sale Price		
	(1) Full Sample	(2) Low Risk	(3) High Risk
3-Month Lag			
NearFire × *Post*	0.0095	0.0143**	0.0042
	(0.0059)	(0.0067)	(0.0105)
6-Month Lag			
NearFire × *Post*	0.0086	0.0113*	0.0084
	(0.0059)	(0.0067)	(0.0115)
1-Year Lag			
NearFire × *Post*	0.0082	0.0121	0.0096
	(0.0070)	(0.0082)	(0.0137)
Observations	237,702	142,293	95,409
Adjusted R^2	0.962	0.968	0.962
Mean Dep. Var.	12.963	12.947	12.986

Note: Each column reports estimates from the main stacked difference-in-differences specification, using alternative definitions of the post-treatment lag. The alternative post-treatment lags are applied to (1) all transactions, (2) transactions in low-risk wildfire hazard zones, and (3) transactions in high-risk zones. All models are estimated with house-by-fire, and month-by-year-by-fire interacted fixed effects. Standard errors, shown in parentheses, are clustered at the wildfire level.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Across all specifications, the estimated treatment effects remain positive. This suggests that wildfire exposure is associated with an increase in home prices, even when housing market responses are delayed. The effect of wildfire exposure on housing prices are most

significant for the low-risk subsample in the 3- and 6-month thresholds. Estimates are positive and insignificant for the full sample and the high-risk subsample across all post-treatment lag specifications.

McCoy & Walsh (2018) find that perceptions of wildfire risk tend to dissipate within two to three years following a wildfire event. Based on this finding, I restrict the observed post-period to two-year and three-year windows. Table 8 reports the results.

Table 8: Robustness Check, Alternative Post-Treatment Window

	Dependent Variable = Log Sale Price		
	(1) Full Sample	(2) Low Risk	(3) High Risk
2-Year Window			
NearFire × *Post*	0.0126*	0.0177**	0.0008
	(0.0065)	(0.0090)	(0.0132)
Observations	203,908	123,749	80,159
Adjusted R^2	0.912	0.942	0.938
Mean Dep. Var.	12.930	12.917	12.950
3-Year Window			
NearFire × *Post*	0.0134**	0.0160*	0.0042
	(0.0059)	(0.0082)	(0.0128)
Observations	224,800	135,530	89,270
Adjusted R^2	0.913	0.942	0.932
Mean Dep. Var.	12.946	12.933	12.966

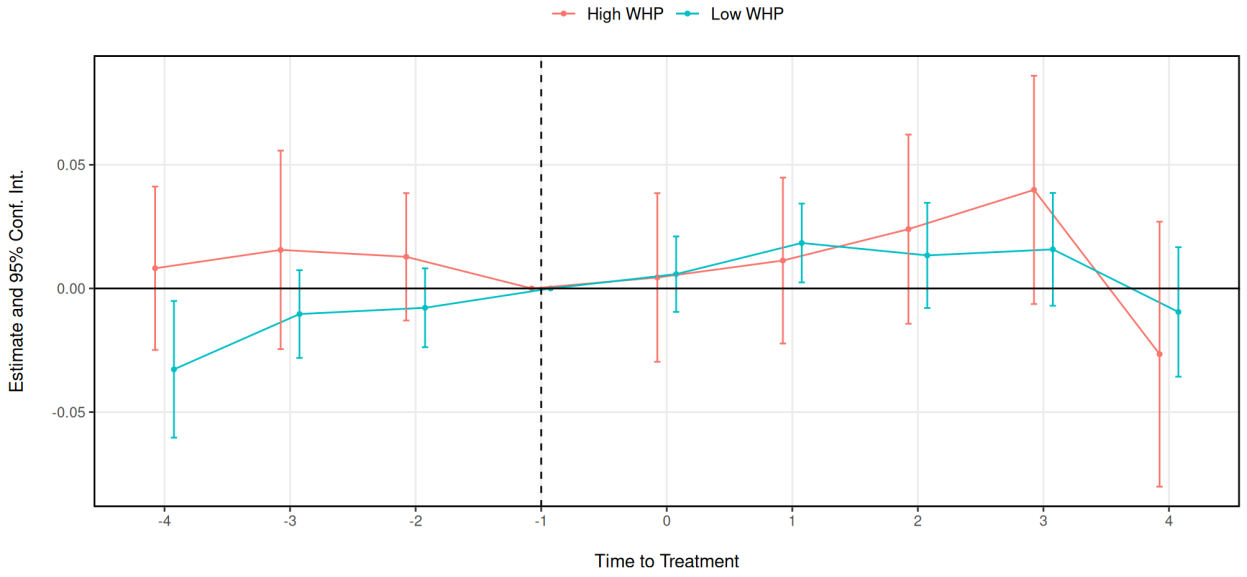
Note: Each column reports estimates from the main stacked difference-in-differences specification, using alternative definitions of the post-treatment window. The specifications are applied to (1) all transactions, (2) transactions in low-risk wildfire hazard zones, and (3) transactions in high-risk zones. All models include house-by-fire fixed effects and month-by-year-by-fire interacted fixed effects. Standard errors, shown in parentheses, are clustered at the wildfire level.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Across both post-treatment window specifications, estimated treatment effects remain consistent with the main specification. In the full sample, the estimated ATT increases slightly to 0.0126 for the two-year window and 0.0134 for the three-year window, compared to 0.0099 in the main specification. Effects in the low-risk zone are slightly larger and remain statistically significant. In the high-risk zone, effects remain small and statistically

insignificant across all specifications. The results indicate that price effects are slightly larger in the immediate post-treatment period for the full sample and low-risk group, while the effect in high-risk zones appears to be delayed or minimal. Overall, estimates are not largely different from the main results when using alternative post-treatment window specifications.

I test the sensitivity of my event study results by using the area immediately outside the treatment boundary as the control group. This specification uses homes located 30 to 50 kilometers from the wildfire as controls and does not account for potential spillover effects. The event study estimates are presented in Figure 9.

Figure 9: Robustness Check, Alternative Control Group Event Study

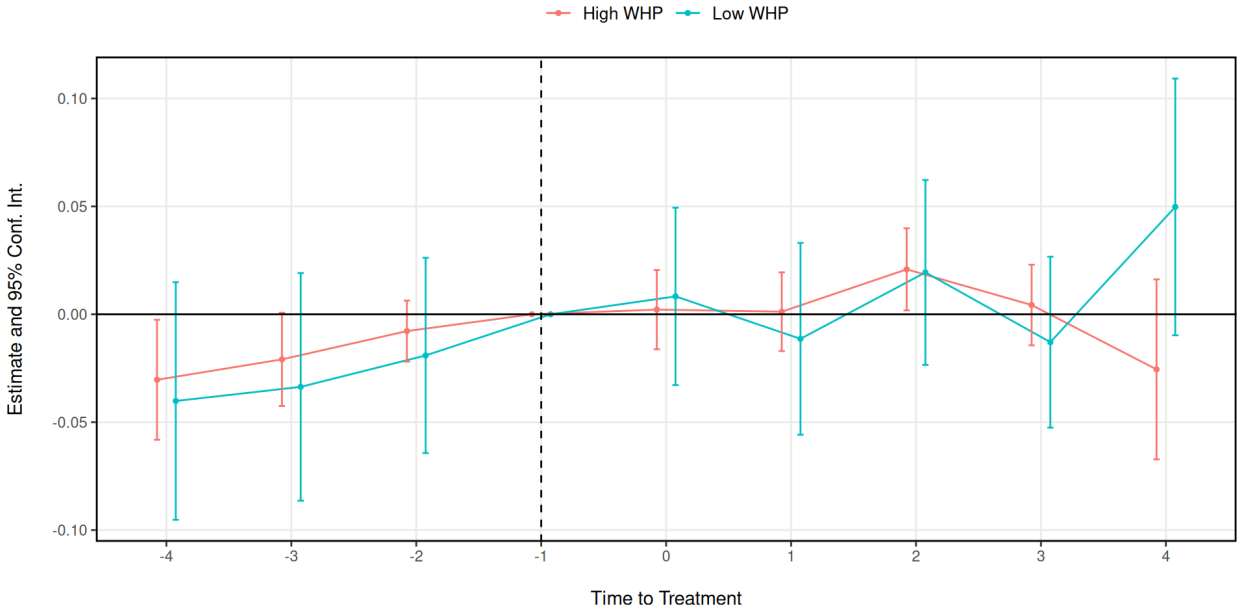


Note: Each point reflects the estimated treatment effect relative to the year of wildfire exposure, year 0, for houses in low and high wildfire hazard potential (WHP) zones. The control group is homes located within 30-50 kilometers from the wildfire boundary. The model controls for house-by-fire fixed effects and month-by-year-by-fire interacted fixed effects. Standard errors are clustered at the wildfire level and vertical bars represent 95% confidence intervals.

I test this alternative control group to assess whether it improves pre-trend balance in the low-risk zone. The pre-trend remains visible, and post-treatment estimates are largely statistically insignificant and similar in magnitude to those from the main event study specification.

As a final robustness check, I use an alternative WHP classification to assess whether it reveals greater heterogeneity in price effects over time between high- and low-risk zones. The low-risk group is redefined to include only the "very low" category, representing approximately the 0 to 0.44th percentile of fire risk among homes nationwide. The high-risk group is restricted to the "high" and "very high" categories, excluding "moderate," and now reflects the top one-sixth of wildfire risk in the U.S. This approach follows the practice of removing the middle of the distribution to assess heterogeneity in treatment effects (Gelman & Park, 2008). Figure 10 presents the event study results using this alternative classification.

Figure 10: Robustness Check, Alternative WHP Classification Event Study



Note: Each point reflects the estimated treatment effect relative to the year of wildfire exposure, year 0, for houses in low and high wildfire hazard potential (WHP) zones. The low WHP zone is redefined to include the "very low" group, and the high WHP zone is redefined to include the "high" and "very high" groups. The model controls for house-by-fire fixed effects and month-by-year-by-fire interacted fixed effects. Standard errors are clustered at the wildfire level and vertical bars represent 95% confidence intervals.

Robustness check results indicate that the alternative WHP classification does not reveal stronger heterogeneity in price responses between high- and low-risk zones. In both groups, pre-trends are visible, suggesting potential violations of the parallel trends assump-

tion. Post-treatment effects remain statistically insignificant and similar in magnitude to the main specification, indicating that refining the WHP classification does not meaningfully change the estimated impact of wildfire exposure on home prices.

Discussion

The results suggest that wildfire exposure is associated with slight increases in home prices, particularly in areas classified as low wildfire risk. In both low- and high-risk zones, house prices increase following exposure, but the magnitude and significance differ: prices rise by 1.45%, a statistically significant effect, in low-risk zones compared to a smaller, statistically insignificant 0.43% increase in high-risk zones. Event study estimates do not provide strong evidence of parallel trends in the pre-period, which cautions causal inference.

Heterogeneity tests by distance suggest little evidence of differences in housing market responses across risk zones. However, heterogeneity tests by fire size reveal some variation in responses to medium-to-large fires. Home prices in low-risk zones appear to react positively to wildfires, regardless of fire size. In high-risk zones, price responses are more variable, with both positive and negative effects observed.

There are a few possible explanations for the observed results. Since the pre-trends show evidence of violation of the parallel trends assumption, it is possible that I am not identifying a truly positive causal effect. Instead, the true effect may be closer to zero. This interpretation is consistent with homeowners having "complete information" and forming expectations based on predicted risk classifications, not actual fire events. Alternatively, a null result may be the result of buyers underestimating wildfire risk when damage is not visible from the property. This aligns with findings from Stetler et al. (2010), who find that buyer behavior is influenced if the wildfire burned area is visible from the property.

One possible explanation for the insignificant effects in high-risk zones is that homeowners already hold accurate beliefs about wildfire exposure. If homeowners value the

predicted wildfire risk classifications in their beliefs and view the wildfire event as reinforcing existing expectations, then home prices may not respond meaningfully. Alternatively, in low-risk zones, wildfires may be perceived as temporary benefits, reducing future fire risk, improving scenic views, or clearing excess vegetation, resulting in small positive price effects. Another possibility for the positive effect in low-risk areas is that the wildfire reinforces confidence in the risk classification itself. If a fire approaches homes in a low-risk zone but causes no damage, the event may reinforce the information provided by wildfire risk designations.

CONCLUSION

Wildfires are an increasingly frequent and destructive hazard in the Western United States. As residential development expands into fire-prone areas, both the risk of wildfire ignition and the potential number of homes affected increase significantly. The dynamic between increasing wildfire risk and expanding residential development motivates the need to better understand how homeowners react to wildfire events.

This paper examines how housing markets classified at different levels of predicted wildfire risk respond to wildfire exposure. Specifically, I asked: What is the impact of wildfires on house sale prices, and does the effect vary across predicted wildfire risk zones? To answer this, I estimated separate stacked difference-in-differences models by assigned wildfire risk classification. In doing so, my analysis attempted to understand whether homeowners incorporate available risk information, specifically Wildfire Hazard Potential maps, into their housing decisions.

The results found in this paper suggest that house prices increase slightly following wildfire exposure, with larger effects in low-risk zones and consistently insignificant responses in high-risk zones. Robustness checks yield similar results, lending support to the main findings. Heterogeneity in housing price responses are most apparent by wildfire size, where high-risk zones fluctuate between positive and negative effects, and low-risk zones show mostly positive effects. One key limitation of the analysis is the presence of pre-trends in the low-risk zone, which cautions causal interpretation.

Research on how housing markets respond to wildfires across risk zones remains limited at the regional level. This paper contributes to that gap by examining whether house price responses to wildfire exposure vary across wildfire risk zones in the Western United States. While this study focuses on price responses to wildfire exposure, future research should continue exploring how updates to official risk classifications affect homeowner behavior.

The literature on housing market responses to updates in wildfire risk classifications on a regional level is limited, but may offer a clearer lens into whether homeowners consider predicted wildfire risk classifications.

Policymakers should continue efforts to improve the visibility and usability of wildfire risk data. Although maps like the Wildfire Hazard Potential (WHP) series are publicly available, many homeowners may be unaware of them or may not fully understand their implications. Ongoing initiatives, such as the USDA Forest Service's Wildfire Risk to Communities platform, help expand public access to risk information. Additionally, recent state-level mandates for wildfire risk disclosures at the point of sale may increase awareness and preparedness among prospective buyers. Continued research on how homeowners perceive and respond to wildfire risk information is essential for designing effective communication strategies and policies aimed at reducing vulnerability in fire-prone areas.

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APPENDIX

DATA METHODOLOGY AND PROCESSING

Single Family Residential Transactions

The CoreLogic data are provided in three separate files: Owner Transfer, Property Basic, and Historical Property Basic. These datasets are available by state, with each file extracted individually for the eleven Western U.S. states: Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, and Wyoming. For California, the size of the files requires extraction by county. Once extracted, the data files for California are appended separately to create the three datasets. I implement all cleaning steps for the CoreLogic housing data by state due to the large size of the extracted files.

The Owner Transfer file contains transaction-level information, including sale dates and prices. The Property Basic and Historical Property Basic files contain structural characteristics of the property. These latter two are first reduced to include only properties that appear in the Owner Transfer data for the corresponding state. Only variables relevant to the analysis are retained.

Property Basic and Historical Property Basic are appended. Because properties can be assessed multiple times per year, duplicates are resolved by keeping only one observation per unique combination of the assessed year and property-level unique identifier (CLIP). When multiple values exist for a given variable, non-missing values are prioritized, and if multiple non-missing values remain, the first is kept.

The Owner Transfer data are appended across all states and cleaned to retain only valid single-family residential transactions. I restrict the sample to transactions occurring in or after 2000. Non-arm's length transactions are excluded, including bank foreclosures, short sales, inter-family transfers, quit-claim deeds, and foreclosure deeds. Small numbers of observations with undefined values for these indicators (16 in the arm's length variable and 185 in deed type) are dropped. Mobile homes are excluded, and observations with missing values for this indicator (0.5%) are also removed. Only properties identified as single-family residences are retained. Properties with missing values on the single-family indicator (0.06%) are temporarily kept and later filtered using the same classification in the Owner Transfer data. Transactions involving multiple or split parcels are also removed, resulting in a data set of only unique transactions.

To merge transaction records with property characteristics, each sale is assigned a unique identifier. I first attempt a direct join between the transaction and assessment data, matching sale year to assessed year. For sales that do not have an exact match, a crosswalk is constructed by joining each sale to all assessments for that property. The difference between the sale year and each assessed year is calculated, and the closest match is kept. When ties occur (there exists assessments equally distant before and after the sale), the assessment occurring before the sale is prioritized. Sales without any corresponding assessment are excluded.

Wildfire Hazard Potential Maps

The Wildfire Hazard Potential (WHP) maps are national raster datasets published in 2015, 2018, and 2020. Although the first map in the WHP series is considered the 2014 version, it was released in November 2015. For clarity and consistency, I refer to this version as the 2015 version throughout the paper. For each home in my dataset, I overlay block-level centroids with the WHP raster classifications and use the version of the WHP map that was publicly available at the time of the post-fire sale. Specifically, I define version use by publication date: homes sold between November 9, 2015 and October 9, 2018 are assigned 2015 values; sales from October 10, 2018 to November 19, 2020 are assigned 2018 values; and sales from November 20, 2020 through the end of my sample period in 2021 are assigned 2020 values.

I exclude properties located in areas marked as non-burnable land. I also resolve edge cases involving raster cells labeled as water. Since the raster resolution is 270-meters, I construct a 300-meter buffer around each water-classified cell and re-assign its classification based on the highest WHP category within the surrounding buffer. This ensures that homes near water bodies are not excluded from hazard classifications due to data gaps in the raster surface.

Although the maps follow a consistent conceptual framework, there are methodological differences across versions. All three editions use updated LANDFIRE data and fire simulation outputs available at the time. The 2018 version, as compared to the 2015 version, incorporates significant improvements to the fire simulation model (FSim), particularly in how it represents crown fire behavior. Specifically, "after the 2014 WHP was released, analysts working on FSim modeling realized an internal problem... [and] implemented significant improvements to both the modeling methods and the process of calibrating outputs to historical observations" (U.S. Forest Service (2018), as part of data supplements). These updates resulted in more reliable hazard estimates, especially in forested areas.

The 2020 WHP map involved further updates, both in data and modeling. It used updated LANDFIRE vegetation and fuel data and a new set of national fire simulations produced in 2020. The modeling process was revised to improve spatial consistency and better reflect historical fire occurrence. In particular, "a more objective model calibration process was implemented that aligned burn probability targets more tightly to historical fire occurrence statistics" (U.S. Forest Service (2020), as part of data supplements). The classification thresholds for "very low," "low," "moderate," "high," and "very high" wildfire hazard potential remain unchanged across the 2015, 2018, and 2020 editions of the WHP maps.

Wildfire Boundaries

I spatially join wildfire perimeter data to CoreLogic single-family housing transactions. I begin by appending all state-level, cleaned CoreLogic data into a single file and convert block-level latitude and longitude to spatial points. Homes with missing or invalid centroid

coordinates (centroid at (0,0) or NA) are removed from the dataset. All geometries, both house centroids and wildfire perimeters, are then projected to a common projected coordinate system (EPSG:5070 – NAD83 / Conus Albers). This projection is well suited for spatial analysis in the continental U.S. because it preserves area and distance.

Using this common projection, I run a loop through each wildfire individually. For every fire, I generate a 100-kilometer buffer and identify all homes that fall within this boundary. I retain only the intersecting homes and calculate the Euclidean distance between each home and the nearest edge of the fire perimeter. I include wildfires dating back to 2000 in case I run robustness checks that require longer pre-treatment windows.

After completing the matching process for each fire, I stack the resulting datasets into a single file. Homes within 30 kilometers of a wildfire are classified as treated, while homes located between 50 and 70 kilometers serve as the control group.

Final Datasets

To avoid including homes that may have been exposed to fire prior to the sample window, I look back three years to identify and exclude any homes that may have already been treated. Thus, I begin by filtering to sales and fires occurring on or after November 9, 2012. From this window, I retain only homes with at least one sale pre-treatment and assign each home to its first observed wildfire. Homes in the comparison group can be linked to multiple wildfires if they remain in the control group. For each home, I retain all sales leading up to the first post-fire sale and drop all later transactions. I then restrict the data to sales and fires beginning in November 9, 2015 and again include only homes that have at least one transaction before the fire and one post-fire.

From the final panel dataset, I construct two additional panels: low-risk and high-risk. Homes are classified as low-risk if the WHP category at the post-fire sale is "very low" or "low," and as high-risk if the WHP category is "moderate," "high," or "very high."

Additional Data Considered

Existing literature is limited in regional-level measures of wildfire severity that may influence perceived wildfire risk among homeowners. I attempted to construct a proxy for wildfire severity based on structural damage. I used the USA Structures dataset, developed by FEMA's Response Geospatial Office in collaboration with Oak Ridge National Laboratory and the U.S. Geological Survey, which provides "the nation's first comprehensive inventory of all structures larger than 450 square feet" in the U.S. (FEMA Geospatial Resource Center, nd). I retained the centroids of all structures located in the Western U.S. and, for each wildfire in my dataset, conducted a spatial join to identify structure centroids that intersected with the fire perimeter. I looped through each wildfire individually and counted the total number of structures located within the burn area of each fire. However, due to the large size of the USA Structures dataset and the intensive processing time required for these spatial operations, I ultimately excluded this measure from my analysis.