Does the Salience of Climate-Related Risk Affect Asset Prices?

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Abstract

Using regression discontinuity and difference-in-discontinuities designs to compare prices of California homes across a new wildfire risk zone boundary, I identify a null local effect. In contrast, difference-in-differences panel estimates indicate that prices of homes newly assigned to a riskier zone drop by 2.5% on average. Both findings are consistent with actual wildfire risk, which is continuous at the boundary but higher on average inside a riskier zone. These findings suggest that households update their risk beliefs in response to re-zoning but do not respond to the increased salience of risk arising from the new risk zone.

JEL codes: D83, G1, G14, G18, Q54, R30

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1 Introduction

Climate-related risks are difficult to assess and process for non-experts, e.g., due to lack of information, limited attention, or the lack of a model. As a result, regulators may be concerned that households do not correctly account for such risks when choosing in which neighborhood to locate or how much to pay for a home. Risk zoning, e.g., for flood or wildfire, has become a commonly-used policy intervention to provide risk information to households and make the risk more salient for homes located inside the risk zone. Risk zoning has the potential to affect the location of housing developments, and thus in turn the economic costs of natural disasters (Rappaport and Sachs, 2003; Kahn, 2005). For example, an estimated 46 million homes and $9.2 trillion in property value are currently located in the wildland-urban interface and are exposed to wildfire risk in the United States (International Association of Wildland Fire, 2013; Radeloff et al., 2018).

One key question is whether risk zoning regulations are effective and how they affect residential real estate prices. Perhaps more importantly, risk re-zoning events offer a laboratory allowing economists to examine the fundamental economic question of which factors drive households' risk-taking behavior and asset prices.

This paper is the first to estimate both a local effect and an average effect of a new climate-related risk zone on residential real estate prices, thereby, distinguishing between the salience of risk and the risk information effect. Specifically, I use the 2007 change in the existing wildfire risk zone in California, which makes the wildfire risk more salient for homes located inside the new risk zone than for homes located just outside – because by law sellers are mandated to disclose their home's risk zone assignment to prospective buyers. While some homes are newly assigned to the risk zone, others experience a change in their

pre-2007 risk zone level. Using real estate sales transactions in southern California, I exploit this policy shift combined with the spatial discontinuity in the salience of risk at the new risk zone boundary to identify the effect of risk salience on residential real estate prices.[1]

To identify the effect of the risk zone on residential real estate prices, I rely on three empirical designs. First, I implement a spatial regression discontinuity (RD) design comparing homes that experience a one-level increase in risk zone relative to neighboring homes that do not change risk zone status. I find an estimated null local average treatment effect (LATE) on prices. Second, I implement a difference-in-discontinuities (hereafter RD-DiD) design that compares the prices of homes on each side of the new risk zone boundary both before and after the 2007 policy change. This design also yields an estimated null LATE. I interpret these null LATEs as evidence that households do not respond to the increased salience of risk arising from assignment to a one-level riskier zone. Both LATE estimates are robust to alternative choices of bandwidth, polynomial order, sample selection, and to the inclusion of covariates. Third, it is conceivable that the new risk zone does not make risk more salient, and thus affect home prices locally, because households are simply inattentive to wildfire risk in general. To test this hypothesis, and similar to the extant literature, I exploit a difference-in-differences (DiD) design in the vicinity of the new risk zone boundary. In contrast to the LATE estimates, the average treatment effect on the treated (ATT) is significant and negative (-2.5%). It suggests that households are in fact attentive to wildfire risk and update their risk beliefs in response to the new risk zone. The ATT estimate is robust to a series of alternative model specifications, including to a large choice of distance bins, covariates, and fixed effects. Placebo tests using a different date for the policy imple-

[1] I use the term salience as defined by: "the phenomenon that when one's attention is differentially directed to one portion of the environment rather than others, the information contained in that portion will receive disproportionate weighting in subsequent judgments" (Taylor and Thompson, 1982).

mentation or defining treatment homes as those that sold before experiencing a change in risk zone rule out that the estimates pick up a local effect that coincides with the timing of the policy change or differential trends for the treatment homes.

I explore several mechanisms that could explain the coexistence of null LATEs and significantly negative ATT on home prices. Contrasting these price estimates with high-resolution, objective wildfire risk measures that were not available to households at the time, I find that risk is continuous at the new risk zone boundary, consistent with the LATEs, and increases on average inside a riskier zone, consistent with the ATT. Therefore, households seem to make their asset pricing decisions consistent with a rational decision-making model.[2]

These findings on whether the salience of risk affects real estate prices contribute to our understanding of belief formation and asset prices, see for example Brunnermeier et al. (2007, 2021), as well as to the literature on salience effects. In particular, multiple theories exist through which salience may affect choices (Chetty et al., 2009; Bordalo et al., 2012, 2013; Gabaix, 2014). This paper provides evidence suggesting that, in the context of large, risky assets, households do not respond to the increased salience of risk generated by a policy intervention. This is in contrast to documented effects of the salience of prices (e.g., Chetty et al. (2009) and Finkelstein (2009)) and risk (Célérier and Vallée, 2017; Frydman and Wang, 2020) involving smaller purchases, as well as a prior literature examining whether salience of risk affects real estate prices.

My comparison of LATE and ATT contrasts with the quasi-experimental literature that examines how climate-related risk salience affects residential real estate prices using ATTs. Giglio et al. (2021) examine the effect of future sea-level-rise risk salience on home prices

[2]I do not find evidence supporting other mechanisms. In particular, I do not find evidence that the new risk zone leads to changes in the sales transactions volume, in the insurance or mortgage market, or in sorting based on risk preferences.

using variation in a "climate attention index" accounting for the frequency of climate-related language in for-sale listings. This setting does not lend itself to a regression discontinuity design because there is no natural boundary where the salience of risk might be discontinuous, in contrast to my setting with a spatial risk salience discontinuity at the new risk zone boundary. A related strand of literature examines the effect of future sea-level-rise risk on home prices, e.g., Bernstein et al. (2019); Baldauf et al. (2020); Murfin and Spiegel (2020). In contrast to these studies exploiting variation in risk, my paper focuses on variation in the *salience* of risk at the new risk zone boundary, holding risk constant. Other studies use changes in risk maps to estimate ATTs, such as flood zone maps (e.g., Gibson and Mullins (2020); Hino and Burke (2021))[3] or wildfire risk ratings (Donovan et al., 2007).[4]

The paper relates to the literature examining how risk salience from a recent natural disaster affects decision-makers' choices. For example, recent natural disasters have been shown to affect real estate prices in high-risk areas not directly hit by the event, e.g., for flooding and hurricanes (e.g., Hallstrom and Smith (2005); Eichholtz et al. (2019); Muller and Hopkins (2019))[5] and wildfires (e.g., McCoy and Walsh (2018)). Dessaint and Matray (2017) find that corporate managers increase their cash holdings after a recent hurricane. Gallagher (2014) shows that households buy temporarily more flood insurance after a flood event is reported in their television media market. Although a recent natural disaster does not change the risk per se, it may affect decision-makers' risk beliefs, for example due to

[3]In addition, flood risk map updates differ from my setting in several key dimensions. First, location inside the flood zone introduces a mandatory, although not well enforced, flood insurance requirement for buyers – which thus affects their total financial costs. Also, insurance prices change dramatically at the floodplain boundary, even if the underlying flood risk does not. Second, the state-wide implementation of the California wildfire risk zone contrasts with the often staggered risk zone implementation and multiple map revisions in the context of flood zones.

[4]In contrast to my setting, a home's risk rating is endogenous in Donovan et al. (2007) as households can take risk mitigating actions to affect the risk rating.

[5]In contrast, Baldauf et al. (2020) find that recent hurricanes in nearby, unaffected states have a negligible effect on the prices of homes predicted to be affected by future sea level rise.

recency effects (Agarwal et al., 2008; Malmendier, 2021).

The remainder of the paper is structured as follows. The next section provides institutional background on the risk zone and wildfire risk. Section 3 describes the data. Section 4 motivates the identification strategy. Section 5 presents the results. Section 6 explores potential mechanisms. The final section concludes.

2 Background on the fire risk zones and wildfire risk

2.1 Policy motivation

While an earlier risk zone was in place since 1985, a new risk zone was adopted state-wide in November 2007 under Title 14 ordinance to incorporate improved fire science, data and mapping techniques (CAL FIRE, 2022). (The next and latest risk zone map was released in November 2022 and is beyond the scope of the present study.) The objective of the 2007 risk zone is two-fold: it is to inform residents about fire hazard in their area and to implement fire-safe practices and building standards for new construction.

2.2 Risk zone design

The wildfire risk zones, referred to by the State of California as Fire Hazard Severity Zones or FHSZs, are produced by the California Department of Forestry and Fire Protection (CAL FIRE) – see CAL FIRE (2022) for details. The risk zones identify areas based on the severity of fire hazard that is expected to prevail. They are determined using what CAL FIRE (2022) describes as "the best available science and data at the time" to develop a model that predicts potential fire behavior and the probability of an area burning. The model assigns every area

with a hazard score. The variables entering the model include continuous variables such as existing and potential fuel (natural vegetation), terrain characteristics, and typical fire weather. There exist three types of zones based on increasing fire hazard: moderate, high and very high.

2.3 Risk zone implementation

The 2007 risk zone revises and, in most places, marginally expands the pre-existing 1985 risk zone – with small contractions in some areas. In most places, the 2007 change in the zone boundary does not exceed a couple of kilometers, as illustrated in online Appendices A.2 and A.3. Importantly, because the zone represents overall hazard rates, homeowners can not take private risk mitigating actions to affect their assignment to a particular risk zone. Sellers are mandated by law to disclose to prospective buyers at the time of sale whether/which risk zone their home belongs to. In practice, after January 1st 2008, being located inside a risk zone (no matter the level) comes with permit requirements for new buildings, or extensions/remodeling of the exterior made to existing buildings, that must comply with California building code Chapter 7a. The implication, in a nutshell, is that roofs, exterior walls, and decks should use ignition-resistant materials and attic vents should be designed to resist the intrusion of flames or burning embers.

The risk zone implementation was not meant to affect the insurance or mortgage markets. It is because insurance companies have access to fine-resolution risk probabilities that supersede the coarse, hazard information contained in the risk zone.[6] Nevertheless, I test

[6]Insurance rates are in addition heavily regulated in California and are prohibited by law to be determined by the wildfire risk zones. Based on personal communications with bankers and mortgage brokers conducting business both inside and outside the risk zones and underwriting mortgages to a large number of lenders in my study area, the new risk zone does not influence lending practices. See online Appendix A.1 for additional background.

empirically in online Appendix E and fail to find an effect of the new risk zone on insurance premium quotes or on mortgages as measured by rate spread, loan-to-value, and mortgage terms.

2.4 Wildfire risk measures

The first publicly available fine-scale resolution wildfire risk measures for California are published in 2020 by the U.S. Forest Service (Scott et al., 2020). They reflect the wildfire risk that prevails circa 2014 for every 30mx30m pixel in the landscape. I assume that this wildfire risk approximates the overall wildfire risk in my 2000-2015 time period. The two risk measures of interest are (1) the burn probability (BP) or wildfire probability, which represents the annual probability of a wildfire burning in a specific location, and (2) the risk to potential structures (RPS) or fire risk to homes, which "integrates wildfire likelihood and intensity with generalized consequences to a home on every pixel. For every place on the landscape, it poses the hypothetical question: What would be the relative risk to a house if one existed here?" (Scott et al., 2020). I convert each annual risk measure into the probability of at least one risky event occurring in the next 30 years to better match the time-horizon associated with real estate purchases.

3 Data

The data include home sales transactions, the wildfire risk zone, high-resolution fire risk measures, and neighborhood characteristics. This section describes the main variables, while online Appendix A contains details of the data cleaning, additional data sources to test for sorting and alternative mechanisms, the summary statistics, and illustrations of the spatial

distribution of the homes, risk zones, and fire risk measures.

3.1 Home sales transactions

The home sales transactions were purchased from CoreLogic and cover all sales between January 2000 and December 2015 in zipcodes most likely to be affected by wildfire risk across seven counties in the Los Angeles and San Diego Basins, namely, Santa Barbara, Los Angeles, Orange, Ventura, Riverside, San Bernardino, and San Diego. The key variables are the sale price and sale date, address, and home characteristics such as size, age, number of bedrooms and bathrooms, and presence of a swimming pool. Every home is geocoded and matched to a series of spatial layers, including wildfire perimeters, topography, and fire risk measures. Homes are also linked to the American Community Survey (ACS) to obtain demographics at the census tract level.

Starting with a dataset of 2,187,007 unique properties, I focus on single family residences (excluding mobile homes) and arms-length transactions of owner-occupied properties (i.e., primary homes). All prices are deflated using the Consumer Price Index from the U.S. Bureau of Labor Statistics. In addition, to focus on the sole effect of the new risk zone absent any realization of wildfire risk in the vicinity, I drop homes located within 10km of a wildfire perimeter that burned within three years prior to a sale.

3.2 Location inside the fire risk zone

The geocoded homes are mapped into both the old (pre-2007) and new (post-2007) fire risk zones obtained from CAL FIRE. For each risk zone, there exist three levels: moderate, high, and very high. For each home inside the new risk zone, I calculate its distance to the new risk zone boundaries. For example, if a home is located inside the high risk zone, I calculate

the distance to the moderate and to the very high risk zone boundaries. For each home outside the new risk zone, I calculate its distance to the moderate risk zone. The moderate and high risk zones are relatively thin, while the very high risk zone is vast as it extends into the wilderness. In my sample, the median (max) width for the new moderate zone is 1.1km (5.8km), and for the new high risk zone it is 540m (4.1km).

3.3 Definition of the treatment and control homes

Throughout the paper, I define as control homes those that do not change risk zone level in 2007, while I define as treatment homes those that experience a one-level increase in their risk zone.[7] For example, a treatment home is located inside the moderate risk zone prior to 2007 and inside the high risk zone after 2007. I observe its sale either before or after 2007, or in some cases both before and after 2007. In addition, to improve the comparability of treated and control homes, I restrict observations (1) to come from census tracts that feature both control homes and treatment homes (this restriction is relaxed in online Appendix C and results are quantitatively similar), and (2) to be located within 1km of the new risk zone boundary.

Online Appendix A.3 provides the number of observations for each individual risk zone increase. Because of the small number of treatment homes outside the risk zone prior to 2007 and now located inside the moderate risk zone after 2007, I drop this individual risk increase treatment and focus instead on homes experiencing an increase in risk zone from moderate to high and from high to very high. Furthermore, for conciseness, I will focus the analysis

[7]There exist places where the risk zone "jumps" risk levels, for example from moderate to very high. Throughout the paper, I focus on the sales of homes that experience a one-level increase in risk zone and exclude homes that jump risk levels. Furthermore, I restrict the sample to treated (control) homes that are located inside a risk zone that is one level higher (lower) than the adjacent risk zone, i.e., treated and control homes differ in their risk level by exactly one level.

on a generic one-level increase in risk zone, i.e., I pool individual one-level increases together (from moderate to high risk and from high to very high risk). I relegate the analysis of particular individual level increases to online Appendix D. (Results are similar for individual level increases.)

4 Empirical strategy

The paper exploits the change in a wildfire risk zone, implemented state-wide in November 2007, and the spatial discontinuity in the salience of risk that is generated at the new risk zone boundary. In the rest of the section, I lay out the three empirical models for estimating the effect of a one-level increase in risk zone on home prices. The first two models identify the effect of risk salience at the new risk zone boundary on home prices, while the third identify the effect of the risk information contained in the new risk zone on home prices.

4.1 Regression discontinuity design

First, I implement a spatial regression discontinuity (RD) design to estimate the local average treatment effect (LATE) of being located inside a riskier wildfire zone on home prices. The spatial RD model is shown in equation (1):

$$\ln p_i = \beta_0 + g_0(x_i) + Z(\beta_{RD} + g_1(x_i)) + \varepsilon_i, \tag{1}$$

where the dependent variable is the natural log of home i's sale price. The running variable x_i measures the distance of home i to the new risk zone boundary, with cutoff $\bar{x} = 0$. The dummy variable Z takes value 1 for treated homes ($x_i \geq 0$) and 0 for control homes ($x_i < 0$).

Treated homes are always located inside a zone that is one level higher after the 2007 policy change than the control homes which do not change risk zone level. $g_0(x_i)$ and $g_1(x_i)$ are two continuous polynomials of order p. The coefficient β_{RD} is the treatment effect, i.e., the change in $\ln p_i$ at the cutoff. The bandwidth is selected optimally using a data-driven procedure following Calonico et al. (2014a,b), which minimizes the mean square error (MSE) of the bias-variance trade-off given the data. In all specifications, a triangular kernel function is used to construct the local polynomial estimator $g_j(x_i)$, where $j \in [0, 1]$. In the main specification, the polynomial $g_j(x_i)$ is of degree one, following Gelman and Imbens (2019). Following Cattaneo et al. (2020b), throughout the paper I report conventional point estimates, robust bias-corrected standard errors and confidence intervals, and robust p-values. Standard errors are computed using the heteroskedasticity-robust nearest neighbor variance estimator with a minimum of three neighbors.[8] I estimate equation (1) for homes that sell after the new risk zone implementation, both without and with covariates. Including covariates can improve the estimation efficiency (with smaller standard errors).

The strength of the RD design is to compare homes that are located as close to the new risk zone boundary as possible to ensure the treated and control homes are as similar as possible and only differ with respect to their risk zone assignment. A requirement for the validity of the RD design is thus that home characteristics (observed and unobserved) do not change discontinuously at the cutoff. Online Appendix B.1 provides visual evidence that the distribution of covariates, which include age, size, number of bedrooms, number of bathrooms, and presence of a swimming pool, is continuous around the threshold. Furthermore, re-estimating equation (1) with each covariate as the dependent variable suggests that there

[8]Results are quantitatively similar when clustering standard errors at the census tract level. However, because the new risk zone boundary crosses through census tracts and other administrative jurisdictions, I do not report spatially clustered standard errors.

is no discontinuity in these observables at the cutoff.

Another requirement for the RD design to be valid is that homeowners should not be able to manipulate their assignment at the cutoff. The risk zones are designed to reflect hazard rate over broad areas such that a particular homeowner cannot take risk mitigating actions, e.g., clearing vegetation around the home, to affect their assignment to the risk zone. Still, I formally test for risk zone manipulation assignment at the cutoff in online Appendix B.1. Using the testing procedure from Cattaneo et al. (2020a), I fail to reject the null hypothesis of discontinuity of the running variable (p-value>0.1).

Figure 1 panels (a) and (c) depict the local log price means of the treated (right) and control (left) homes, while panels (b) and (d) show the residuals of log prices on covariates in the pre-treatment period (panels (a) and (b)) and post-treatment period (panels (c) and (d)). Fitting a polynomial of order 4 does not indicate evidence of a discontinuity at the new risk zone boundary in either the pre- or post-treatment period. Panels (e) and (f) illustrate the fire risk to homes and wildfire probability over 30 years, respectively. The risk increases smoothly from left (control) to right (treated homes).

Because one cannot test formally that no unobservables are changing discontinuously at the new risk zone threshold, this motivates the use of a second design leveraging homes that sold both before and after the new 2007 risk zone implementation.[9]

4.2 Difference-in-discontinuities design

The difference-in-discontinuities (RD-DiD) model consists in estimating a continuous polynomial on each side of the cutoff ($\bar{x} = 0$) both before and after the policy change. It is

[9]This design follows that presented in Grembi et al. (2016). In their context, one of the observables changes discontinuously at the cutoff.

depicted in equation (2):

$$\begin{aligned}\ln p_{it} = \beta_0 + g_0(x_{it}) + Z(\beta_1 + g_1(x_{it})) \\ + Post_t \left[\delta_0 + g_2(x_{it}) + Z(\delta_{RDDiD} + g_3(x_{it})\right] + \varepsilon_{it},\end{aligned} \tag{2}$$

where t denotes the time t and $Post_t$ is a dummy taking value 1 in the period following the 2007 change in risk zoning. The treatment effect, β_{RDDiD}, captures the change in $\ln p_{it}$ at the cutoff comparing before and after the policy change. In the main specification, the polynomial $g_j(x_{it})$, where $j \in [0, 3]$, is of degree one.

4.3 Difference-in-differences design

I estimate an average treatment effect on the treated (ATT) comparing the prices of homes that experience an increase in their risk zone level with those of homes that remain in the same risk zone. The DiD model is depicted in equation (3):

$$\ln p_{it} = \beta_0 + \beta_{DiD} Treat_i \times Post_t + \beta_1 Post_t + \mathbf{X}_i' \beta_X + \lambda_i + \mu_{gt} + \varepsilon_{it} \tag{3}$$

The dependent variable is the natural log of home i's sale price at time t. The treatment group, $Treat_i$, is defined as all homes that are located inside a zone that is one level higher than that prior to the 2007 risk zone implementation. The control group is defined as homes that remain inside the same risk zone after the new 2007 risk zone implementation. $Post_t$ is a dummy variable taking value 1 following the 2007 change in risk zoning. The coefficient β_{DiD} is the ATT. In the simplest specification, $\mathbf{X}_i$ denotes home and neighborhood covariates, while the preferred specification features home fixed effects λ_i to most flexibly

control for time-invariant unobservables, such as home and neighborhood quality. To control for temporal shocks, e.g., macro-level housing shocks, and possible heterogeneity in temporal shocks across the region, μ_{gt} denotes year and quarter fixed effects or, more flexibly, county-by-year and quarter fixed effects.

To examine whether the parallel trends assumption holds, I estimate equation (3) only with home, county-by-year, and quarter fixed effects and plot the residuals separately for the treated and control groups and for the pre- and post-treatment periods using daily variation in prices. Online Appendix B.2 provides visual evidence in support of the common trends assumption for pre-2007 prices in the treated and control groups (for the sample of homes within 600m of the new risk zone boundary, as well as for finer distance bins).

5 Results

5.1 Regression discontinuity and difference-in-discontinuities designs

Table 1 contains the RD and RD-DiD estimation results. Using a spatial RD design, the effect of a one-level increase in risk zone on home prices is negative, -4.9%, without covariates, and -0.4% (columns (1) and (2), respectively), but not significant at the 10%-level. Following Calonico et al. (2015), the MSE-optimal bandwidth is 193m and 170m, without and with covariates, respectively. Running a placebo test for the homes that changed risk zone in 2007 but sold prior to 2007 (denoted hereafter 'RD - post=0') also yields insignificant estimates (-4.9% without covariates and -0.9% with covariates (columns (3) and (4), respectively). The MSE-optimal bandwidth in this case is 198m and 235m, without and with covariates, respectively.

The RD-DiD design accounts for any pre-existing differences across homes on different

sides of the new risk zone boundary. Table 1 indicates RD-DiD estimates of 0.3% without covariates and -0.07% with covariates (columns (5) and (6), respectively). The MSE-optimal bandwidth in this case is 184m and 168m, without and with covariates, respectively. The RD-DiD estimates are robust to a large choice of bandwidths (ranging from 50m to 1000m with 50m intervals) as depicted in Panel (a), Figure 2.

Additional robustness checks for the RD and RD-DiD are provided in online Appendix C. In particular, estimates are robust to the choice of the polynomial order and to different sample selections, including relaxing the sample restriction that homes come from census tracts featuring both treatment and control homes. Estimates are robust to different boundary cutoffs. This concern may arise if, for example, there is a systematic bias in the implementation of the risk zone. In addition, because households may respond differently to the salience of risk in housing booms versus busts, I re-estimate equations (1) and (2) separately during periods of housing booms and busts. The findings are qualitatively similar. Last, RD estimates are not significant in any given year.

5.2 Difference-in-differences design

Panel A in Table 2 shows the main DiD estimates of the effect of being located inside a one-level riskier zone relative to neighboring control homes that do not change risk zone. All homes are located within 600m of the new 2007 risk zone boundary. Columns (1) through (4) represent specifications with increasingly more flexible fixed effects, with estimates ranging from a -5.5% to -2.5%. Column (1) features census tract, year, and quarter fixed effects, while covariates are added in column (2). Columns (3) and (4) feature home fixed effects. The preferred model specification (column (4)), which includes county-by-year fixed effects to most flexibly control for regional shocks across the study region, yields a price penalty

estimate of 2.5%.

Estimates are robust to a large choice of bandwidths (ranging from 200m to 1000m with 50m intervals) as depicted in Panel (b), Figure 2. In online Appendix C, I also show that estimates are robust to dropping every year in the 2000-2015 time period, one year at a time, or to estimating the model separately during periods of housing booms and busts.

To understand how the ATT estimates vary spatially and attempt to reconcile them with the LATE estimates, I split the 600m-bandwidth into smaller distance bins. The DiD estimates for these finer bins are shown in Panel B, Table 2. The ATT estimated within 200m of the new risk zone boundary is -1.8% with covariates and census tract fixed effects (significant at p-value=0.05; column (1)) and -0.2% with home and county-by-year fixed effects (insignificant at p-value=0.1; column (2)). These ATT estimates are consistent with the LATE estimates in Table 1 – obtained for a similar bandwidth. The ATT estimates increase considerably and become significant at the 1%-level further away from the new risk zone boundary, with price penalties between 8.4% and 6.9% (columns (3) and (4)).

To test the validity of the DiD design, I ran two placebo tests in online Appendix B.2. The first placebo test alters the date of the policy implementation, while the second tampers with the definition of the treatment group. In both cases, I focus on model specifications with home fixed effects. First, considering homes with repeat sales after the 2007 risk zone implementation, I now redefine *Post* in equation (3) as the year 2011 (the middle of the 2008-2015 time period). For both sales, treated and control homes are located inside the same risk zone. However, prior to the implementation of the 2007 new risk zone, treated homes were located inside a lower risk zone than control homes. None of the estimates are significant at p-value=0.1. Second, to rule out that the estimates capture a local effect affecting other, non-treated homes in the area at the time of the 2007 zone implementation,

the second placebo test redefines treated and control homes such that they remain inside the same risk zone after the implementation of the 2007 new risk zone. Treated homes differ from control homes in that they are always located inside a higher risk zone than control homes. Estimates are generally not significant, in particular for the preferred specification with county-by-year fixed effects. This placebo test is reassuring because the new risk zone coincides with the beginning of the housing crisis.

6 Potential mechanisms

In this section, I explore possible mechanisms that could explain the null LATEs and ATT price penalty on homes that face a one-level increase in their risk zone assignment. The primary mechanism that appears to explain the findings is that households do not respond to the increased salience of risk generated from the new risk zone but, rather, leverage the risk information contained in the new risk zone to update their risk beliefs about the average risk prevailing in their neighborhood. In online Appendix E, I explore alternative mechanisms that could influence home prices, but fail to find that they drive the effects I observe. In particular, I examine whether the new risk zone has an effect on sorting, home sales volume, or on the insurance and mortgage markets.

To test the plausibility of this mechanism, I investigate how wildfire risk varies over space. I leverage high-resolution (30mx30m) wildfire risk measures (not available to households during my sample period), which I map into each home. Then, I run an RD and OLS design with each risk measure as the dependent variable. Table 3 depicts the effect of being located inside a one-level higher risk zone on the fire risk to homes and the wildfire probability within 30 years. The RD design, Panel A, yields null LATEs on fire risk to homes and

wildfire probability over 30 years (at p-value=0.1). In contrast, the OLS approach, Panel B, indicates a 2% to 1.8% increase in fire risk to homes over 30 years (p-value=0.01; columns (1) and (2)) and a 2.7% to 2.5% increase in wildfire probability over 30 years for homes located within 600m of the new 2007 risk zone boundary (p-value=0.01; columns (1) and (2)).

7 Conclusions

This paper addresses the question of whether the salience of climate-related risk affects households' large asset pricing decisions. Specifically, I examine how the increased salience of risk triggered by a new wildfire risk zoning policy in California affects residential real estate prices. The new risk zone generates a spatial discontinuity in the salience of risk at the new risk zone boundary because each home's risk zone assignment must be disclosed by law in the sales prospectus. Using both regression discontinuity and a difference-in-discontinuities designs, I do not find evidence of local average treatment effects (LATEs) of being assigned to a riskier wildfire zone on home prices.

A difference-in-differences panel approach suggests a -2.5% average treatment effect on the treated (ATT) on home prices from being assigned to a riskier wildfire zone. Considering jointly the LATEs and ATT, the LATE findings suggest that the increased salience of risk at the new risk zone boundary does not affect residential real estate prices, while I interpret the ATT as evidence that households update their risk beliefs in response to the risk information contained in the new risk zone (rather than to a risk salience effect). Absent the regression discontinuity design, I may have incorrectly concluded that households respond to the salience of risk, highlighting the challenges with distinguishing salience from other effects.

Salience effects have undoubtedly been shown to affect decision-making. See DellaVigna (2009) and Bordalo et al. (2022) for reviews. Yet, my findings raise the question of whether salience is an important driver of decision-making for large assets. Perhaps my findings might motivate models of decision-making in which agents rationally trade off the mental cost of information acquisition and processing with the magnitude of economic mistakes.

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List of tables

Table 1 RD and RD-DiD estimates of being located inside a one-level higher risk zone on log of home prices

	RD (Post=1)		RD (Post=0)		RD-DiD	
	(1)	(2)	(3)	(4)	(5)	(6)
$Z = 1$	-0.0487	-0.0222	-0.0485	-0.0257		
	(0.0439)	(0.0275)	(0.0427)	(0.0321)		
$Z \times Post$					0.0025	0.0145
					(0.0450)	(0.0326)
Covariates		✓		✓		✓
Bandwidth (m)	193	210	198	209	184	191
N	2841	2842	2603	2593	5290	5183

Note: The spatial cutoff is the new 2007 risk zone boundary. Treated homes ($Z = 1$) are located inside a risk zone that is one-level higher than control homes. $Post = 1$ denotes the period after the new risk zone was implemented (Nov. 2007). The MSE-optimal bandwidth is derived using a local linear polynomial. (with covariates columns (2), (4), and (6)). The polynomial is of degree one. Observations are restricted to census tracts featuring both control and treatment homes. Covariates: age, house size, # bedrooms, swimming pool dummy, slope, distances to national forest and to primary road, and dummy for location inside the wildland-urban interface. Columns (1)-(4): RD in the period after (Post=1) or prior to (Post=0; placebo) the new risk zone implementation. Robust bias-corrected standard errors computed with the nearest neighbor variance estimator; Columns (5)-(6): Difference-in-discontinuities design leveraging both the post and pre-policy periods. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table 2 DiD estimates of a one-level increase in risk zone on log of home prices

	Panel A: 0-600m			
	(1)	(2)	(3)	(4)
$Treat \times Post$	-0.0421***	-0.0376***	-0.0548***	-0.0254***
	(0.0127)	(0.0080)	(0.0101)	(0.0093)
Quarter	✓	✓	✓	✓
Year FE	✓	✓	✓	
County×Year				✓
Census tract FE	✓	✓		
Covariates		✓		
Home FE			✓	✓
N	8036	7768	5424	5424
R^2_{adj}	0.67	0.87	0.78	0.82
	Panel B: Finer distance bins			
	0-200m		200m-600m	
	(1)	(2)	(3)	(4)
$Treat \times Post$	-0.0183*	-0.0017	-0.0843***	-0.0693***
	(0.0096)	(0.0107)	(0.0142)	(0.0192)
Quarter	✓	✓	✓	✓
Year FE	✓		✓	
County×Year		✓		✓
Census tract FE	✓		✓	
Covariates	✓		✓	
Home FE		✓		✓
N	5316	3760	2452	1664
R^2_{adj}	0.87	0.82	0.87	0.82

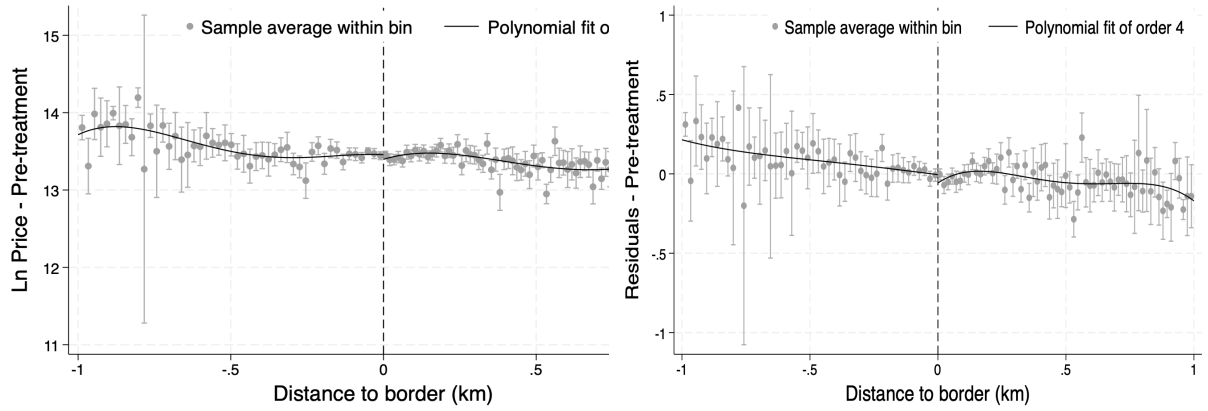
Note: Panels A and B feature homes located at different distances from the new 2007 risk zone boundary. Covariates: age and age squared, home size and home size squared, # bedrooms, # baths, swimming pool dummy, elevation, slope, dummy for location inside the wildland-urban interface, distances to nearest primary road, national forest, state or local park. Observations are restricted to census tracts featuring both control and treatment homes. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Table 3 RD and OLS estimates of being located inside a one-level higher risk zone on fire risk to homes and wildfire probability over 30 years

	Fire risk to homes		Wildfire probability	
	(1)	(2)	(3)	(4)
	Panel A: RD estimates			
$Z = 1$	0.0119	0.0144	0.0127	0.0166
	(0.0094)	(0.0096)	(0.0157)	(0.0159)
Covariates		✓		✓
Bandwidth (m)	270	255	157	155
N	3939	3784	3085	2982
	Panel B: OLS estimates			
$Treat$	0.0197***	0.0197***	0.0270***	0.0270***
	(0.0020)	(0.0019)	(0.0027)	(0.0027)
Census tract FE	✓	✓	✓	✓
Covariates		✓		✓
N	5156	5034	5156	5034
R^2_{adj}	0.78	0.84	0.81	0.85

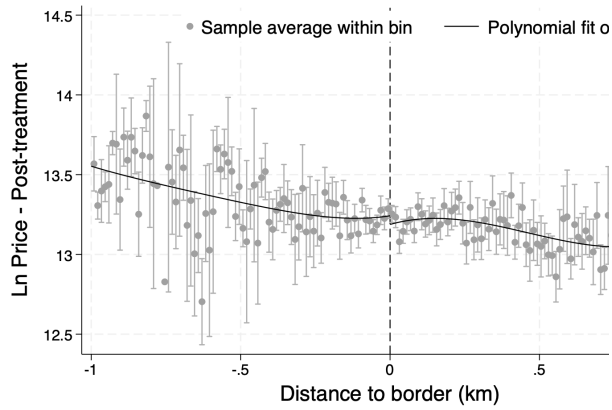
Note: The spatial cutoff is the new 2007 risk zone boundary. Treated homes ($Z = 1$) are located inside a risk zone that is one-level higher than control homes. Observations are restricted to census tracts featuring both control and treatment homes. When homes sell multiple times, only one risk measure per home sale is used. Covariates in Panels A and B: slope, distances to nearest primary road and national forest, and dummy for location inside the wildland-urban interface. Panel A: RD estimates. MSE-optimal bandwidth derived using a local linear polynomial (including covariates in columns (2) and (4)). The polynomial is of degree one. Robust standard errors computed with the nearest neighbor variance estimator. Panel B: OLS estimates for the model: $Risk_i = \beta_0 + \beta_{OLS} Treat_i + \mathbf{X}_i' \beta_X + \varepsilon_i$, with census tract fixed effects and covariates $\mathbf{X}$. Homes are restricted to being located within 600m from the new 2007 risk zone boundary. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

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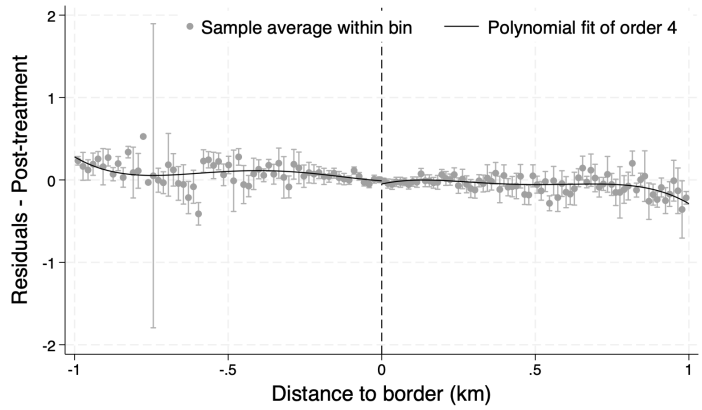


(a) Local means of log home prices (pre-2007)

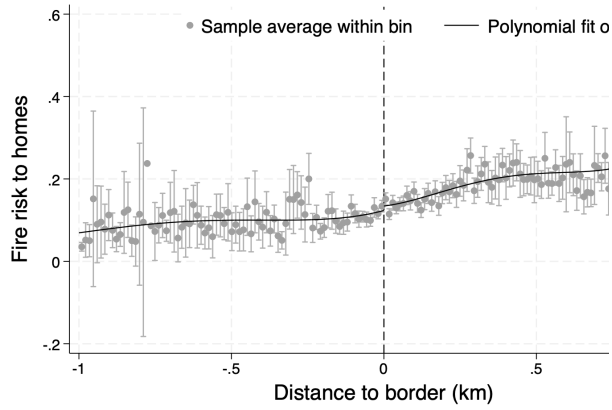
(b) Log home price residuals (pre-2007)



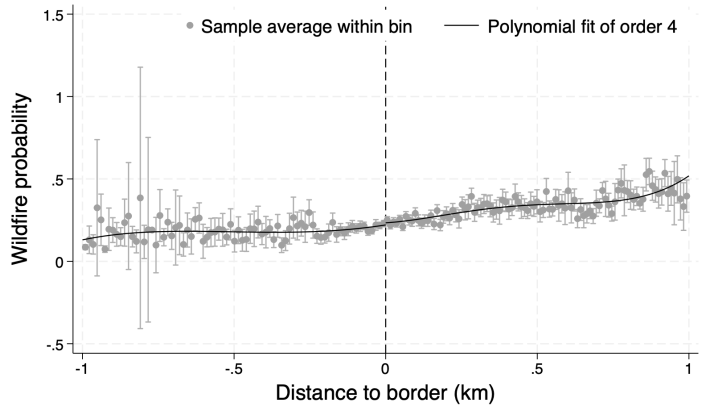
(c) Local means of log home prices (post-2007)



(d) Log home price residuals (post-2007)



(e) Fire risk to homes



(f) Wildfire probability

Figure 1 Panels (a)-(d): Log prices of homes being located inside a one-level higher risk zone before (Panels (a)-(b)) or after (Panels (c)-(d)) the 2007 change in risk zoning over distance from the cutoff. Panels (a) and (c) depict the local means of log home prices. Panels (b) and (d) depict the residuals of log home prices on covariates: age, house size, # bedrooms, # baths, and swimming pool dummy. Panel (e): Fire risk to homes. Panel (f): Wildfire probability. In all panels, the cutoff is the 2007 risk zone boundary. Homes located on the right hand-side of the cutoff are located inside a risk zone that is one-level higher than homes located on the left hand-side of the cutoff. Number of bins data-driven such that bins sample means mimick underlying variability of the data (Calonico et al., 2015). Vertical bars denote 90%-CIs. Polynomials of degree four fitted over the data. Observations restricted to census tracts featuring both control and treatment homes.

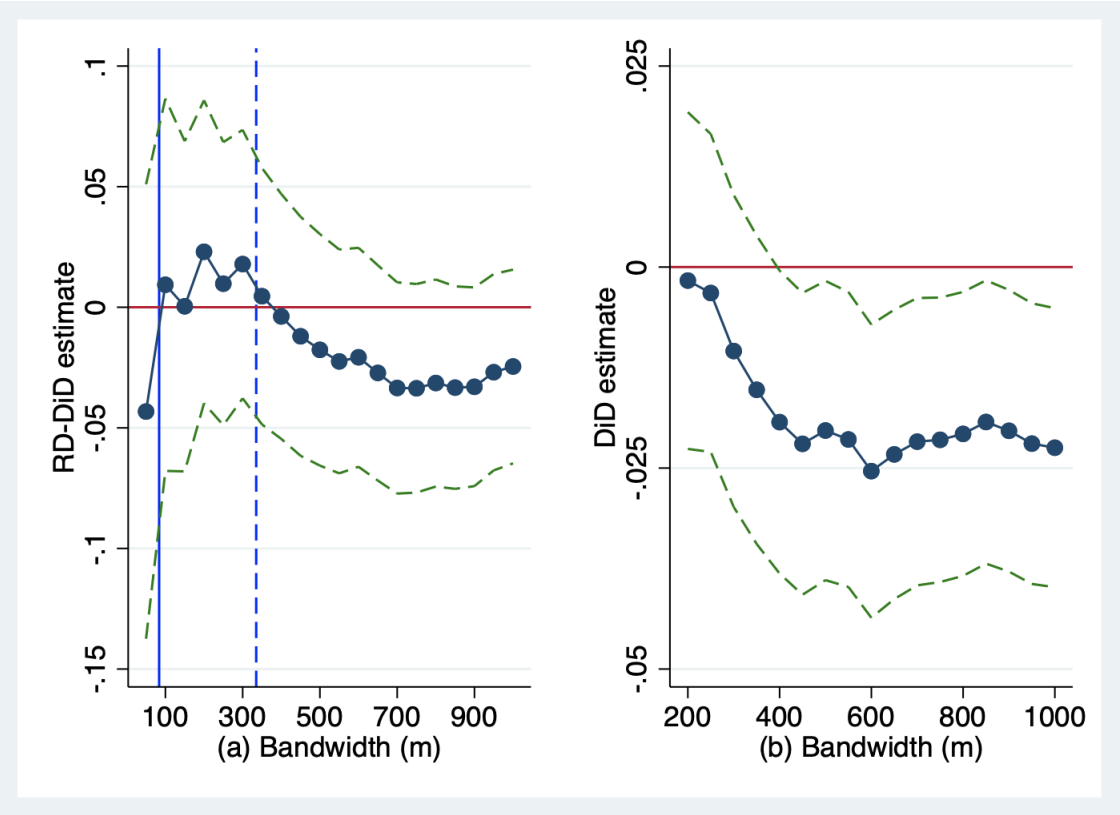


Figure 2 Difference-in-discontinuities (RD-DiD) and difference-in-differences (DiD) estimates of the effect on log home prices of being located inside a one-level higher risk zone. Panel (a): RD-DiD estimates with bandwidth ranging from 200m to 1000m with 50m intervals. Regressions include covariates (age, size, number of bedrooms, presence of a swimming pool, distances to the nearest primary road and to the nearest national forest, and dummy for location inside the wildland-urban interface). Panel (b): DiD estimates with bandwidth ranging from 200m to 1000m with 50m intervals. Regressions include home, county-by-year, and quarter fixed effects, and robust standard errors. In both panels, the central line depicts the point estimates; the dashed green lines depict the 95 percent confidence interval. Observations are restricted to census tracts featuring both control and treatment homes.

Online Appendix

A Background and Data

A.1 Data sources and description

A.1.1 Home sales transactions and additional data cleaning

Restricting the CoreLogic sales transactions to single family residences (no mobile homes) and arms-length transactions of owner-occupied properties (i.e., primary homes) accounts for 1,215,523 homes. Transactions with missing sale price are omitted, as well as homes sold more than once within the same year to eliminate potential house flippers (1,070,639 remaining homes).[10] In addition, homes with sale prices in the bottom and top 1% are dropped from the sample to eliminate potential outliers. To further clean the repeat-sales sample, homes whose price change between sales is in the top and bottom 1% are dropped to reduce the likelihood that a home experiences significant renovation or unusual damages in-between sales. The CoreLogic dataset only contains information up to the prior sale. Therefore, I do not observe more than two sales. Linking the CoreLogic transactions data (truncated to two sales) with the untruncated Zillow dataset (ZTRAX), I do not find that the distribution of homes with more than two sales differs significantly across treatment and control groups based on observables. Furthermore, homes located inside national forests are excluded due to concerns of belonging to different housing markets. Homes inside a wildfire perimeter or within a 50m buffer outside a wildfire perimeter are further discarded to ensure that homes potentially damaged by wildfires are excluded.

A.1.2 Data sources for the wildfire and neighborhood characteristics

CAL FIRE (fire.ca.gov) provides spatial data on wildfire perimeters, the wildland-urban interface (WUI), and the fire risk zones or Fire Hazard Severity Zones (FHSZ). The wildfire data contain spatial information on burn perimeters and start and containment dates.[11] National forests spatial layers come from the National Datasets maintained by the US Forest Service (data.fs.usda.gov). State and local parks layers come from the California Protected Areas Data Portal (calands.org/cpad). Spatial data on primary roads come from the US Data Catalog (catalog.data.gov). The 2000 census tract boundaries and census characteristics, including median household income, race, and ethnicity come from the American Community Survey. In ArcGIS, I calculate slope, elevation, and distances to the risk zone boundaries,

[10] I discard second homes as preferences for such homes may differ from those for primary homes. I discard homes that are flipped because they are often renovated before going back on the market.

[11] The study area and time period include some of California's largest wildfires, including the 2003 Cedar Fire (271k acres), the 2007 Witch Fire (162k acres), and the 2009 Station Fire (161k acres).

nearest burn scar, nearest national forest, nearest state or local park, and nearest primary road.

A.1.3 Buyer demographics and Home Mortgage Disclosure Act (HMDA)

To learn about buyer demographics, I link the mortgage information contained in the CoreLogic sales transaction data with the Home Mortgage Disclosure Act (HMDA) data, as in Bayer et al. (2016). HMDA includes data on household income, race, ethnicity, and loan information. (I do not use the gender of the loan applicant as it contains many missing values.) HMDA observations with no mortgage year, no loan amount, no lendername, or indications that the lender was a private lender, are dropped. The sales transaction data contain loan information only for the most recent sale and, thus, for each home the demographics information corresponds to that of the most recent buyer. Matching on mortgage year, lender name, loan amount and type, county, and census tract, and keeping properties with unique matches, I obtain a matching success rate of 40.4%. This rate compares favorably with that reported in Bayer et al. (2016).

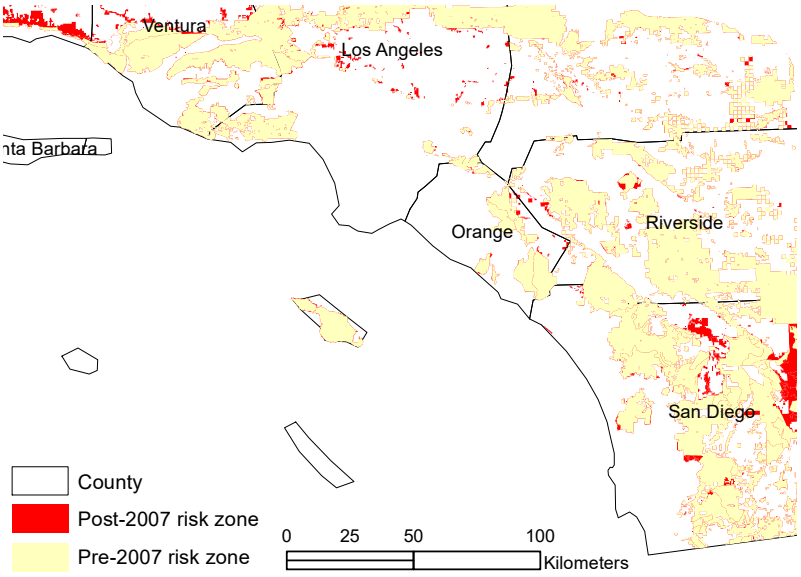
A.1.4 The 2007 change in fire risk zone

The fire risk zones reflect fire hazard rather than risk. As such, they do not account for private risk mitigating actions on a given property, and households do not have the ability to influence the assignment of their home to the risk zone. The risk zones are managed either by the State of California (state responsibility area; SRA) or local governments of California (local responsibility area; LRA), depending on which jurisdiction is primarily responsible for fire protection and suppression efforts in that area. Although CAL FIRE worked with 117 local governments in the seven counties encompassing my study area to develop and recommend very high fire-hazard zones in local responsibility areas, adoption decisions across the different local governments have been on a case-by-case basis. Because of the endogeneity of such decisions, I discard sales post-2007 in the new recommended local risk zones (LRA) and restrict the analysis to homes assigned to the new state risk zone (SRA), as depicted in Figure A1, Panel (a). (Figure A1, Panel (b) depicts the new recommended, but not mandatory, risk zones in local responsibility areas that are excluded from the analysis.)

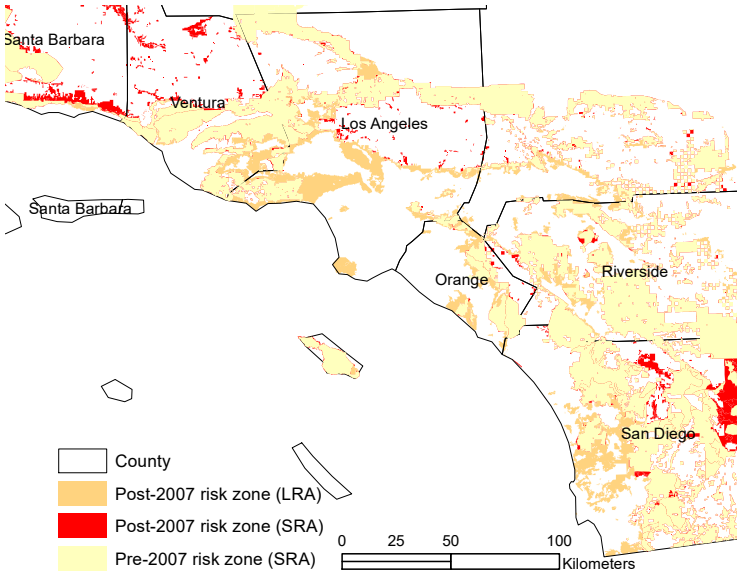
A.1.5 Insurance markets

Fire damages are covered as part of regular home insurance policies, which is mandatory for all homes with a federally-backed mortgage (virtually all homes in my sample) and is heavily regulated in California.

Insurers in California are highly aware of wildfire risk to homes, but are unlikely to rely on the state risk zone to underwrite policies to homeowners. First, because the state



(a)



(b)

Figure A1 California wildfire risk zones pre- and post-2007. Panel (a): the new risk zones were adopted in 2007 state-wide in the state responsibility areas (SRA; the focus of the present study). Panel (b): in addition to the state-wide adoption of the new risk zones in the SRA, risk zones in the local responsibility areas (LRA) were adopted on a voluntary basis, and at times adopted with modifications. Those new risk zones in the LRA and excluded from the study.

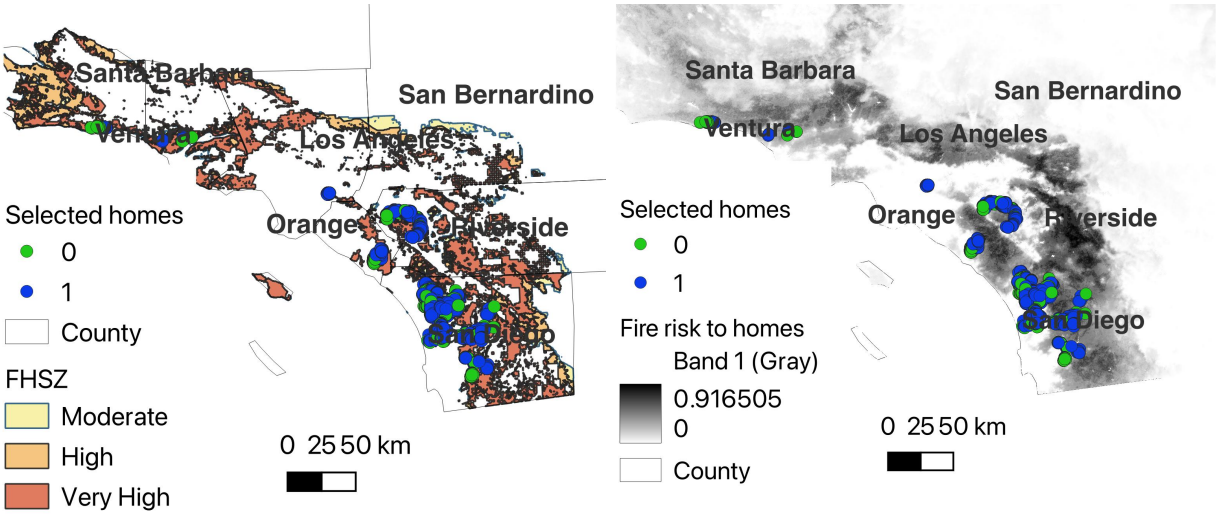
risk zone represents fire hazard rather than risk. The latter is affected by a home's roof material and brush and vegetation clearance to the property line – which insurers take into account (Dixon et al., 2018). Second, because insurers already rely on fine-scale (30-meter resolution) probabilistic wildfire risk models to determine each home's propensity to burn – contrasting with the coarse information provided in the risk zone.[12] The California Department of Insurance (CDI) strictly regulates which variables can be used as inputs into insurers' probabilistic models. They include continuous variables such as the amount of fuel, terrain characteristics, distance to high-risk wilderness areas, and a measure of access for fire suppression (Cignarale et al., 2017). CDI explicitly prohibits the use of risk zones in those models or for setting insurance premiums. This rule was publicized in the media and on state agencies' websites through a Memorandum of Understanding signed on October 2007 between CDI, CAL FIRE, and the insurance industry, announcing that the new risk zone would not affect insurance premiums. The memorandum was published at the time on the CDI website (http://www.insurance.ca.gov/0400-news/0100-press-releases/0060-2007/...), the CALFIRE website (http://www.fire.ca.gov/...), and in the Insurance Journal (https://www.insurancejournal.com/news/west/2007/10/16/84317.htm), among others.[13] In addition, even though the California Department of Insurance (CDI) allows insurers to use probabilistic models to determine how to vary rates across homes by wildfire risk, CDI does not allow the use of such probabilistic models to project expected future losses and determine the average rate level for an insurer's overall book of business. Rather, to vary rates, insurers are required to use past loss history to set the so-called catastrophe load for wildfire risk (Dixon et al., 2018; Issler et al., 2019).

Homeowners who cannot get access to home insurance in the private market can purchase fire insurance via CDI's FAIR Plan. FAIR guarantees that all properties in California, regardless of wildfire risk, are eligible for coverage from the FAIR Plan (Cignarale et al., 2017; Dixon et al., 2018).

[12] Risk Management Solutions (https://www.rms.com/software/risk-modeler) and Corelogic (Jeffrey et al., 2019) are examples of commercial probabilistic wildfire risk models used by the insurance industry.

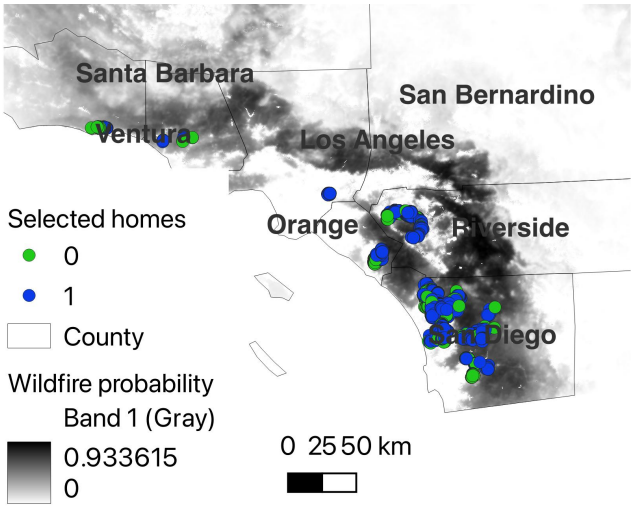
[13] An interview published in the Orange County Registar with Steve Inlow, who works in an insurance policy underwriting business representing about 20 insurance companies in Orange County, confirms that his business does not use the fire risk zones (https://www.ocregister.com/2012/03/05/could-fire-maps-hurt-property-values).

A.2 Spatial distribution of homes, risk zones, and wildfire risk



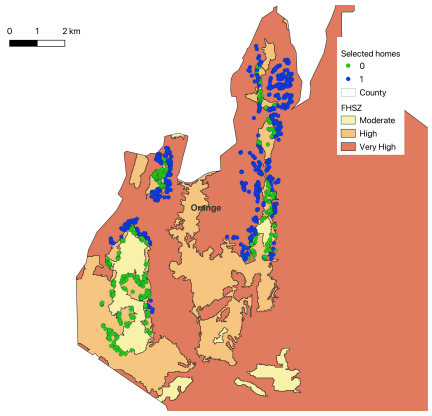
(a) Homes; Risk zones (FHZS)

(b) Homes; Fire risk to homes

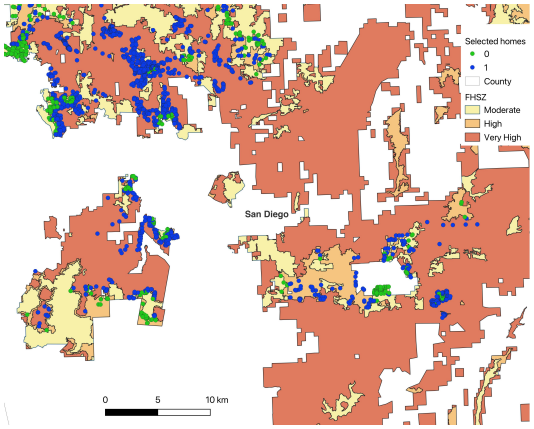


(c) Homes; Wildfire probability

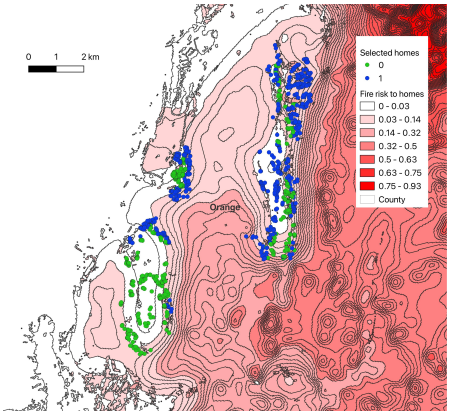
Figure A3 Spatial distribution of treatment and control homes, risk zone, and wildfire risk measures. Panel (a): New 2007 California wildfire risk zone. Panel (b): Fire risk to homes (RPS) over 30 years. Panel (c): Wildfire probability (BP) over 30 years. Treatment homes (denoted "1") are located inside a one-level higher risk zone relative to control homes (denoted "0"). Homes are restricted to being located within 1km of the new 2007 risk zone boundary. Only census tracts featuring both control and treatment homes are selected.



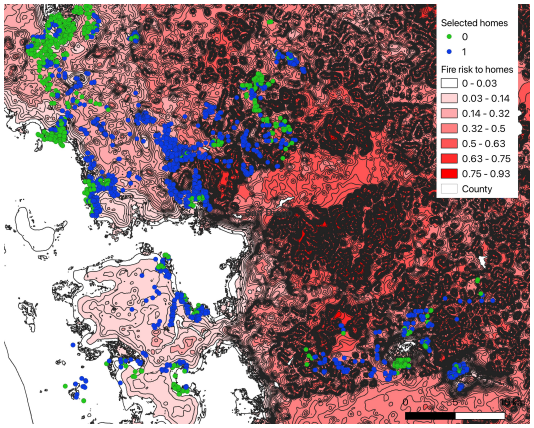
(a) Subsample 1; Wildfire risk zone



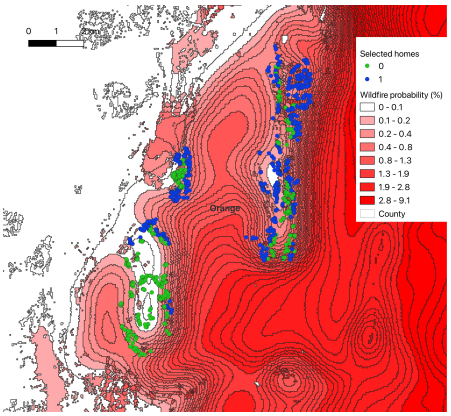
(b) Subsample 2; Wildfire risk zones



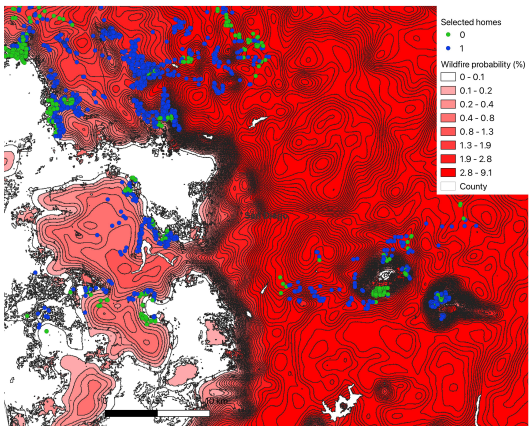
(c) Subsample 1; Fire risk to homes



(d) Subsample 2; Fire risk to homes



(e) Subsample 1; Wildfire probability



(f) Subsample 2; Wildfire probability

Figure A4 Illustrations of the spatial distribution of treatment and control homes in two subregions. Left panels: Orange County. Right panels: San Diego County. Panels (a)-(b): new 2007 California wildfire risk zones. Panels (c)-(d): Fire risk to homes (RPS) over 30 years. Panels (e)-(f): Wildfire probability (BP) over 30 years. The ranges of the bins in each map were chosen following Jenks' classification method. Treatment homes (blue; denoted "1") are located inside a one-level higher risk zone relative to control homes (green; denoted "0"). Homes are restricted to being located within 1km of the new 2007 risk zone boundary. Only census tracts featuring both control and treatment homes are selected.

A.3 Summary statistics

Table A1 Distribution of homes and wildfire risk across the new 2007 risk zones

	Risk zone level			
	Outside	Moderate	High	Very high
	(1)	(2)	(3)	(4)
All homes	974179	6476	6124	20654
Median fire risk to homes (RPS; %)	0.1	0.2	0.3	0.7

Table A2 Distribution of treatment and control homes across the individual one-level risk zone increases

	Risk zone increase in 2007		
	Outside→Moderate	Moderate→High	High→Very high
	(1)	(2)	(3)
Panel A: No sample restriction			
Number of control homes	166120	1814	1943
Number of treatment homes	400	2117	6162
Panel B: Homes within 1km of the new risk zone boundary & from census tracts featuring both control and treatment homes			
Number of control homes	4965	1714	1806
Number of treatment homes	311	1834	3244

Note: Treatment and control homes are defined depending on whether they become located inside a risk zone that is one level higher after 2007.

Table A3 Summary statistics in the pre-treatment period (Nov. 2007) for the regression discontinuity, difference-in-discontinuities, and difference-in-differences analyses.

	Treatment homes		Control homes		Difference
	Mean	SD	Mean	SD	with t-test
	(1)	(2)	(3)	(4)	(5)
	Panel A: Home and neighborhood characteristics				
Sale price (k$2015)	740.61	333.62	792.13	346.23	51.52***
Living area (k sqft)	2.53	0.99	2.56	0.98	0.03
Age	21.08	14.23	20.55	14.94	-0.53
# bedrooms	3.43	0.85	3.56	0.88	0.13***
# bathrooms	2.87	0.92	3.00	0.97	0.13***
Swimming pool (0/1)	0.30	0.46	0.26	0.44	-0.04**
Burn probability	0.27	0.18	0.18	0.17	-0.09***
Fire risk to homes	0.16	0.14	0.10	0.11	-0.06***
WUI (0/1)	1.00	0.05	0.99	0.09	-0.01*
Elevation (m)	282.97	143.85	227.98	133.49	-54.98***
Slope	5.39	4.04	4.26	3.40	-1.13***
Dist. national forest (km)	12.69	6.81	12.36	6.76	-0.34
Dist. state or local park (km)	1.22	1.12	1.18	1.10	-0.04
Dist. LA or San Diego (km)	62.89	28.08	69.98	30.74	7.08***
Dist. main road (km)	2.30	2.06	2.31	1.95	0.01
Unemployment rate (ACS)	6.42	3.05	6.28	3.25	-0.14
Median hh. income (k$) (ACS)	102.92	38.56	104.47	36.49	1.55
% White (ACS)	83.42	10.47	82.86	11.15	-0.55
% Black (ACS)	2.41	2.62	2.53	2.59	0.12
% Asian (ACS)	7.63	5.64	8.23	6.57	0.59**
% Hispanics (ACS)	19.69	12.74	18.80	12.70	-0.89*
Mortgage term (yrs)	26.09	9.98	26.32	9.81	0.23
LTV ratio	0.54	0.26	0.54	0.26	-0.00
Observations	2708		1582		4290
	Panel B: HMDA variables				
Income (k$)	149.61	102.27	164.99	130.16	15.38**
Share White	0.78	0.41	0.78	0.41	-0.00
Share Black	0.01	0.10	0.01	0.10	-0.00
Share Asian	0.06	0.23	0.06	0.24	0.00
Share Hispanics	0.11	0.32	0.08	0.28	-0.03*
LTV ratio	0.76	0.17	0.75	0.17	-0.00
Rate spread	3.24	1.81	2.75	1.38	-0.49
Observations	1037		728		1765

Note: HMDA variables are only available for the latest sale, and thus are shown for all latest sales (which mostly occur in the post-treatment period). Homes are located within a 1km bandwidth from the new 2007 risk zone boundary. Treatment homes are located inside a risk zone that is one-level higher than control homes. Column (5) shows the difference between the mean of the treatment homes and that of control homes and a t-test (* p<0.1, ** p<0.05, *** p<0.01). Observations are restricted to census tracts featuring both control homes and treatment homes.

Table A4 Summary statistics in the pre-treatment period (Nov. 2007) for the repeat sales sample used in the difference-in-differences analysis with home fixed effects.

	Treatment homes		Control homes		Difference
	Mean	SD	Mean	SD	with t-test
	(1)	(2)	(3)	(4)	(5)
	Panel A: Home and neighborhood characteristics				
Sale price (k$2015)	789.64	342.26	850.45	346.53	60.81***
Living area (k sqft)	2.64	1.05	2.68	1.01	0.04
Age	21.32	14.72	18.59	14.21	-2.74***
# bedrooms	3.51	0.86	3.68	0.89	0.17***
# bathrooms	2.98	0.96	3.18	0.98	0.20***
Swimming pool (0/1)	0.32	0.47	0.26	0.44	-0.07***
Burn probability	0.27	0.18	0.17	0.16	-0.10***
Fire risk to homes	0.16	0.13	0.09	0.10	-0.07***
WUI (0/1)	1.00	0.06	0.99	0.09	-0.00
Elevation (m)	282.93	143.10	229.67	128.37	-53.25***
Slope	5.46	4.14	4.13	3.46	-1.33***
Dist. national forest (km)	12.21	6.68	11.96	6.21	-0.24
Dist. state or local park (km)	1.21	1.13	1.13	1.13	-0.08
Dist. LA or San Diego (km)	63.35	27.54	71.75	28.73	8.41***
Dist. main road (km)	2.40	2.10	2.48	1.97	0.09
Unemployment rate (ACS)	6.70	3.31	6.27	3.42	-0.43**
Median hh. income (k$) (ACS)	105.85	41.47	110.63	38.52	4.79**
% White (ACS)	83.69	10.43	82.83	10.29	-0.87*
% Black (ACS)	2.48	2.67	2.52	2.51	0.04
% Asian (ACS)	7.47	5.71	9.26	7.13	1.79***
% Hispanics (ACS)	19.28	12.65	18.16	11.98	-1.13*
Mortgage term (yrs)	25.84	10.38	26.32	9.80	0.48
LTV ratio	0.55	0.29	0.55	0.29	0.00
Observations	1660		1057		2717
	Panel B: HMDA variables				
Income (k$)	141.01	87.21	162.40	133.23	21.40***
Share White	0.79	0.41	0.79	0.41	-0.00
Share Black	0.01	0.10	0.01	0.10	0.00
Share Asian	0.06	0.23	0.06	0.24	0.01
Share Hispanics	0.12	0.32	0.08	0.27	-0.04*
LTV ratio	0.79	0.16	0.78	0.16	-0.02
Rate spread	2.30	1.11	2.19	1.07	-0.11
Observations	860		639		1499

Note: HMDA variables are only available for the latest sale, and thus are shown for the post-treatment period instead of the pre-treatment period. Homes are located within a 1km bandwidth from the new 2007 risk zone boundary. Treatment homes are located inside a risk zone that is one-level higher than control homes. Column (5) shows the difference between the mean of the treatment homes and that of control homes and a t-test (* p<0.1, ** p<0.05, *** p<0.01). Observations are restricted to census tracts featuring both control homes and treatment homes.

B Validity tests

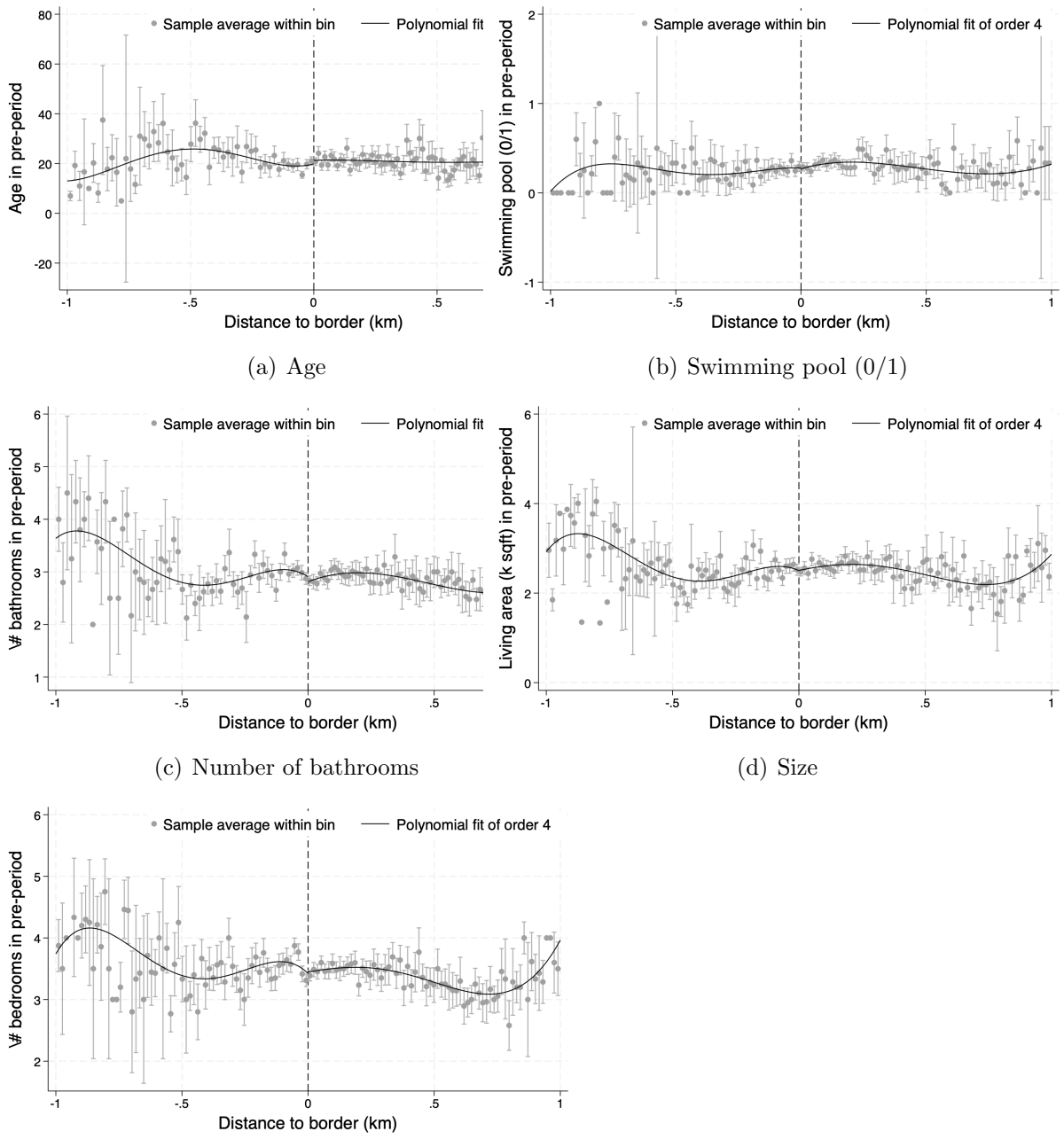
B.1 RD and RD-DiD designs

B.1.1 Covariates balance

Table B1 Tests of discontinuity of the covariates at the cutoff in the pretreatment period (prior to November 2007). Model (1) is run separately for each dependent variable.

	(1)	(2)	(3)	(4)	(5)
	Panel A: Home characteristics				
	Age	Size	#bedrooms	#totalbaths	Swimming pool
$Z = 1$	1.776	-0.058	-0.009	-0.125	-0.010
	(1.352)	(0.090)	(0.079)	(0.086)	(0.043)
N	2590	2603	2603	2603	2603
	Panel B: Environmental characteristics				
	Elevation	Slope	WUI	Dist. nat. forest	
$Z = 1$	-0.031	0.087	0.0002	-0.256	
	(11.670)	(0.311)	(0.009)	(0.643)	
N	2537	2537	2537	2537	
	Panel C: Location and neighborhood characteristics				
	Distance to primary road	Distance to park	Distance to LA or SD	Unemployment	Med.HH. income
$Z = 1$	-0.126	-0.071	-0.783	0.027	-2.424
	(0.126)	(0.081)	(2.506)	(0.270)	(4.310)
N	2537	2537	2537	2537	2537

Note: The cutoff is the 2007 risk zone boundary. Treated homes ($Z = 1$) are located inside a risk zone that is one-level higher than control homes. Bandwidth used, 198m, is the MSE-optimal bandwidth for Model (1) without covariates. The polynomial order is of degree one. Observations are restricted to census tracts featuring both control and treatment homes. Panel A: age in years, size (living area) in 1,000 sqft. Panel B: elevation in meters, slope in degree, distance to national forest in km. Panel C: all distances in km, unemployment rate from ACS, median household income (1,000$) from ACS. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.



(a) Age

(b) Swimming pool (0/1)

(c) Number of bathrooms

(d) Size

(e) Number of bedrooms

Figure B1 Visual evidence of covariates balance at the cutoff in the pretreatment period (prior to November 2007). The cutoff is the new 2007 risk zone boundary. Homes located on the right hand-side of the cutoff are located inside a risk zone that is one-level higher than homes located on the left hand-side of the cutoff. Plots with a 1km-bandwidth and polynomial of degree four fitted over the data. Number of bins is data-driven such that the bins sample means mimick the underlying variability of the data following Calonico et al. (2015). Vertical bars indicate 90% confidence intervals. Observations are restricted to census tracts featuring both control and treatment homes.

B.1.2 Threshold manipulation test

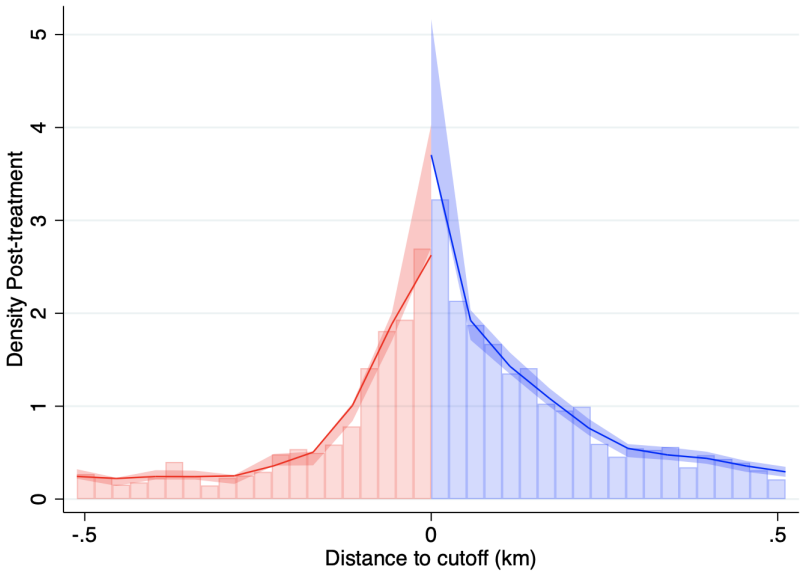
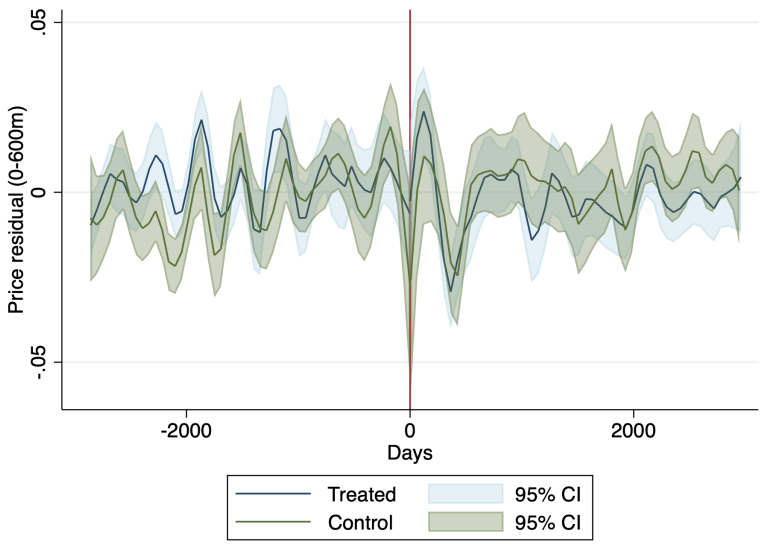


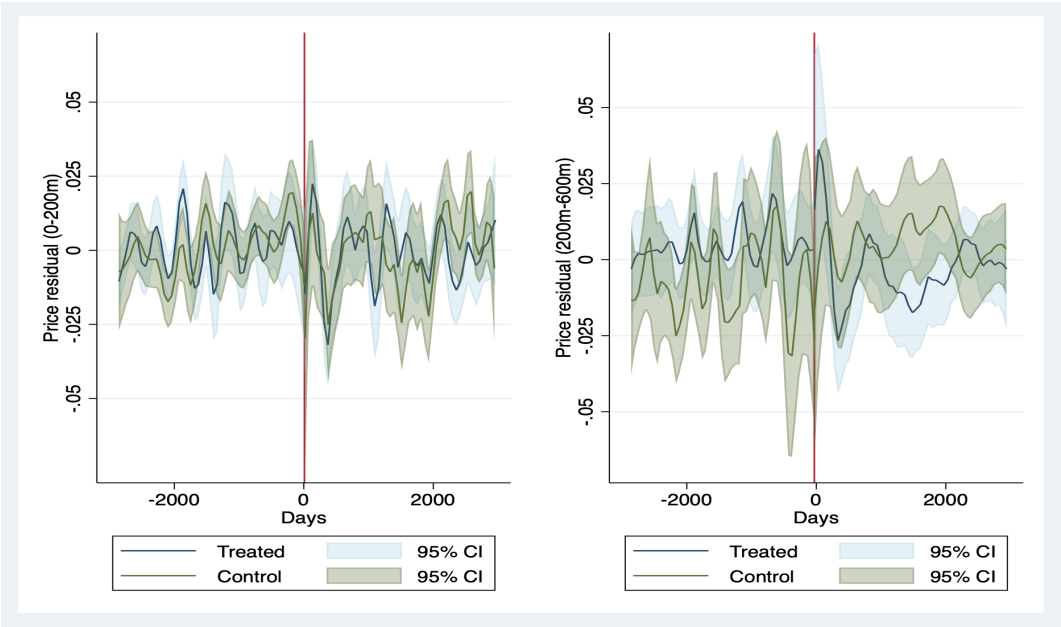
Figure B2 Manipulation test around the cutoff. Testing procedure using local polynomial density estimation and 95% confidence bands following Cattaneo et al. (2020a). The cutoff is the 2007 risk zone boundary. Homes located on the right hand-side of the cutoff are located inside a risk zone that is one-level higher than homes located on the left hand-side of the cutoff. The estimated difference in the density of the running variable at the cutoff is 1.08, and the robust p-value associated with the test of the null hypothesis that this difference is zero is 0.11. Observations are restricted to census tracts featuring both control and treatment homes.

B.2 DiD approach

B.2.1 Parallel trends



(a) Homes located within 600m of the new 2007 risk zone boundary



(b) Homes located within 200m (left) or between 200m and 600m (right)

Figure B4 Visual evidence of parallel trends for the effect of a one-level increase in risk zone on log home prices using a DiD design. Homes are located within 600m of the new 2007 risk zone boundary (Panel (a)), within 200m (Panel (b), left) or between 200m and 600m (Panel (b), right). Polynomial of degree 0 fitted through the residuals from regressing the effect of the 2007 change in risk zone on the log of home prices. The regressions include home, county-by-year, and quarter fixed effects. Observations are restricted to census tracts featuring both control and treatment homes.

B.2.2 Placebo tests

Table B2 Placebo tests for the DiD estimates of the effect of being located inside a one-level higher risk zone on log home prices

			Smaller distance bins			
	0-600m		0-200m		200m-600m	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Use 2011 as the policy implementation date						
$Treat \times Post$	-0.0002	-0.0067	-0.0108	-0.0189	0.0282	0.0225
	(0.0176)	(0.0186)	(0.0213)	(0.0225)	(0.0315)	(0.0337)
N	3007	3007	2057	2057	950	950
R^2_{adj}	0.457	0.478	0.440	0.484	0.507	0.523
Panel B: Treatment homes do not change risk zone						
$Treat \times Post$	0.0251*	-0.0016	0.0051	-0.0159	0.0743***	0.0279
	(0.0148)	(0.0145)	(0.0190)	(0.0197)	(0.0233)	(0.0227)
N	6946	6946	3014	3014	3932	3932
R^2_{adj}	0.860	0.875	0.861	0.874	0.863	0.879
Quarter FE	✓	✓	✓	✓	✓	✓
Year FE	✓		✓		✓	
County×Year FE		✓		✓		✓
Home FE	✓	✓	✓	✓	✓	✓

Note: Panel A: Only homes sold after the new 2007 risk zone are considered. *Post* is now redefined as post 2011. For both sales, treated and control homes are located inside the same risk zone. However, prior to the implementation of the 2007 new risk zone, treated homes were located inside a lower risk zone than control homes. Panel B: Treated and control homes remain on the same risk zone after the implementation of the 2007 new risk zone. Treated homes are always located inside a higher risk zone than control homes. In all specifications, observations are restricted to census tracts featuring both control and treatment homes. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

C Robustness tests

Table C1 Sensitivity of the RD and RD-DiD estimates to relaxing the sample restriction in the main analysis where observations come from census tracts featuring both control and treatment homes

	RD-Post		RD-Pre		RD-DiD	
	Trim C	No trim	Trim C	No trim	Trim C	No trim
	(1)	(2)	(3)	(4)	(5)	(6)
$Z = 1$	0.0052	0.0040	0.0139	0.0137		
	(0.0292)	(0.0293)	(0.0313)	(0.0311)		
$Z \times Post$					0.0044	0.0031
					(0.0335)	(0.0335)
N	2994	3000	3296	3305	5729	5743

Note: The cutoff is the 2007 risk zone boundary. Treated homes ($Z = 1$) are located inside a risk zone that is one-level higher than control homes. "Trim C" denotes a sample where only control homes are restricted to coming from census tracts with treatment homes. "No trim" denotes no sample restriction. MSE-optimal bandwidth derived using a local linear polynomial with covariates. All regressions include covariates. The polynomial order is of degree one. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

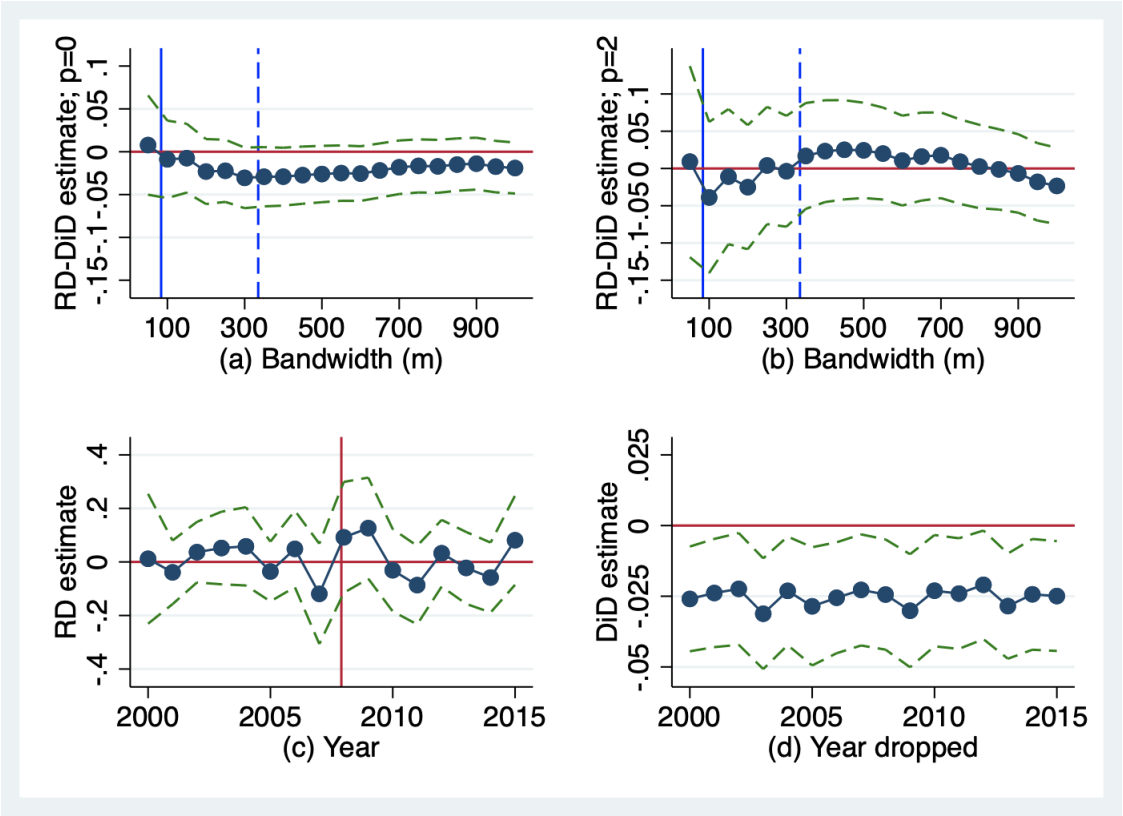


Figure C1 Panels (a) and (b): Sensitivity to polynomial order. Difference-in-discontinuities (RD-DiD) estimates of the effect of being located inside a one-level higher risk zone on log home prices. Panel (a): polynomial order $p = 0$. Panel (b): polynomial order $p = 2$. In panels (a)-(b), the bandwidth ranges from 50m to 1000m with 50m intervals. Half (solid blue line) and twice (dashed blue line) the MSE-optimal bandwidths depicted. Panel (c): Yearly RD point estimates of local linear regressions. Panels (a)-(c): All regressions include covariates. The MSE-optimal bandwidth is derived using a local linear polynomial with covariates. Panel (d): DiD estimates when dropping one year at a time. All regressions include home, county-by-year fixed effects, quarter fixed effects, and robust standard errors. In all panels, the central line depicts the point estimates; the dashed green lines depict the 95 percent confidence interval. Observations are restricted to census tracts featuring both control and treatment homes.

Table C2 Falsication tests: Cutoff set such that $Z = I(x \geq -A)$ or $Z = I(x \geq +A)$ where $A \in \{1/2bw, bw, 2bw\}$

	RD-Post			RD-Pre			RD-DiD		
	$1/2bw$	bw	$2bw$	$1/2bw$	bw	$2bw$	$1/2bw$	bw	$2bw$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					$Z = I(x \geq -A)$				
$Z = 1$	-0.086*	-0.051	-0.067	0.031	0.066	-0.026			
	(0.065)	(0.074)	(0.085)	(0.085)	(0.104)	(0.0860)			
$Z \times Post$							-0.0525	-0.0499	-0.382**
							(0.145)	(0.171)	(0.166)
N	1148	1207	1046	1056	766	855	2083	2221	1979
					$Z = I(x \geq +A)$				
$Z = 1$	-0.018	-0.035	0.002	-0.026	-0.048	0.003			
	(0.060)	(0.061)	(0.053)	(0.060)	(0.063)	(0.055)			
$Z \times Post$							0.030	-0.185*	0.105
							(0.120)	(0.112)	(0.112)
N	1793	2376	2614	2154	2533	2282	3554	4890	4988

Note: MSE-optimal bandwidth derived using a local linear polynomial with covariates. $1/2bw$ ($2bw$) denotes half (twice) the optimal bandwidth, respectively. All regressions include covariates. The polynomial order is of degree one. Observations are restricted to census tracts featuring both control and treatment homes. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table C3 RD and RD-DiD estimates of being located inside a one-level higher risk zone on log home prices during housing booms and busts

	Busts			Booms		
	RD (post=1)	RD (post=0)	RD-DiD	RD (post=1)	RD (post=0)	RD-DiD
	(1)	(2)	(3)	(4)	(5)	(6)
$Z = 1$	0.0154	0.0269		0.0021	-0.0108	
	(0.0451)	(0.0608)		(0.0370)	(0.0333)	
$Z \times Post$			-0.0762			0.0203
			(0.0589)			(0.0402)
N	1178	501	1597	1506	2299	3450

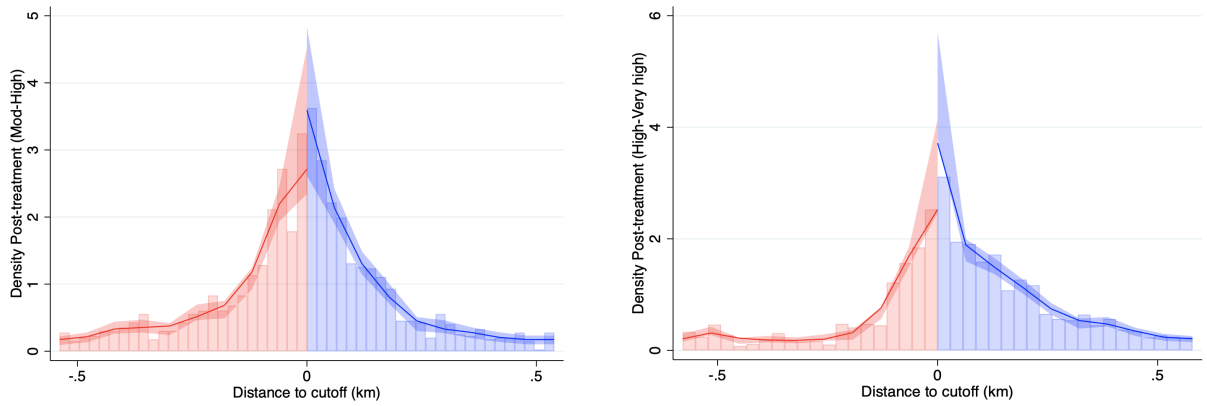
Note: Housing booms: until 2006Q1, from 2012Q2. Housing bust: from 2006Q2 to 2012Q1. Housing booms and busts are determined using California's house price index (FRED, 2023) and the methodology proposed in Bry and Boschan (1971) and Harding and Pagan (2002). The spatial cutoff is the new 2007 risk zone boundary. Treated homes ($Z = 1$) are located inside a risk zone that is one-level higher than control homes. $Post = 1$ denotes the period after the new risk zone was implemented. MSE-optimal bandwidth derived using a local linear polynomial with covariates. The polynomial is of degree one. All regressions include covariates. Observations are restricted to census tracts featuring both control and treatment homes. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table C4 DiD estimates of the effect of being located inside a one-level higher risk zone on log home prices during housing booms and busts

	Busts		Booms	
	(1)	(2)	(3)	(4)
$Treat \times Post$	-0.0325**	-0.0823***	-0.0439***	-0.0368**
	(0.0163)	(0.0310)	(0.0095)	(0.0166)
N	2435	1947	5333	3477
R^2_{adj}	0.88	0.84	0.86	0.76
Quarter FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Census FE	✓		✓	
Covariates	✓		✓	
Home FE		✓		✓

Note: Housing booms: until 2006Q1, from 2012Q2. Housing bust: from 2006Q2 to 2012Q1. Housing booms and busts are determined using California's house price index (FRED, 2023) and the methodology proposed in Bry and Boschan (1971) and Harding and Pagan (2002). Homes located within 600m from the new 2007 risk zone boundary. Covariates: age and age squared, home size and home size squared, # bedrooms, # baths, swimming pool dummy, elevation, slope, dummy for location inside the wildland-urban interface, distances to nearest primary road, national forest, state or local park. In all specifications, observations are restricted to census tracts featuring both control and treatment homes. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

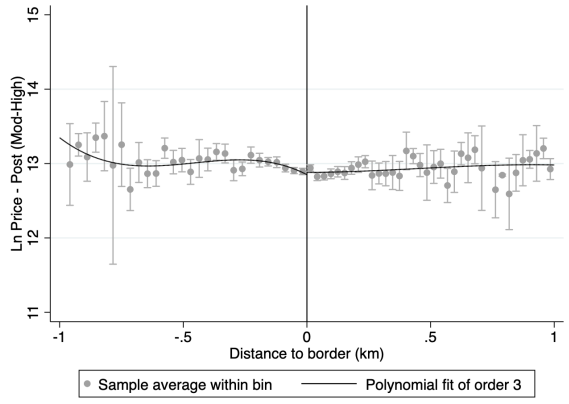
D Analysis for individual increases in risk zone levels



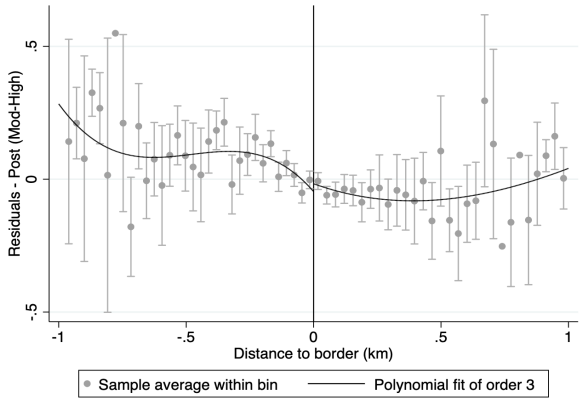
(a) Moderate → High

(b) High → Very high

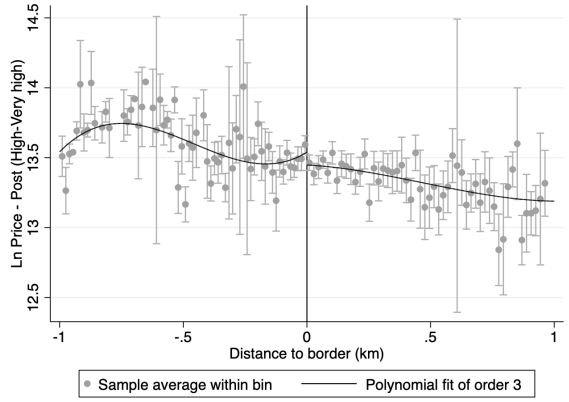
Figure C1 Manipulation tests around the cutoff for two individual level increases. Testing procedure using local polynomial density estimation and 95-% confidence bands following Cattaneo et al. (2020a). The cutoff is the 2007 risk zone boundary. Homes located on the right hand-side of the cutoff are located inside a risk zone that is one-level higher than homes located on the left hand-side of the cutoff. Panel (a): Moderate → High. Estimated difference in the density of the running variable at the cutoff is 0.88, and the robust p-value associated with the test of the null hypothesis that this difference is zero is 0.78. Panel (b): High → Very high. Estimated difference in the density of the running variable at the cutoff is 1.19, and the robust p-value associated with the test of the null hypothesis that this difference is zero is 0.09. Observations are restricted to census tracts featuring both control and treatment homes.



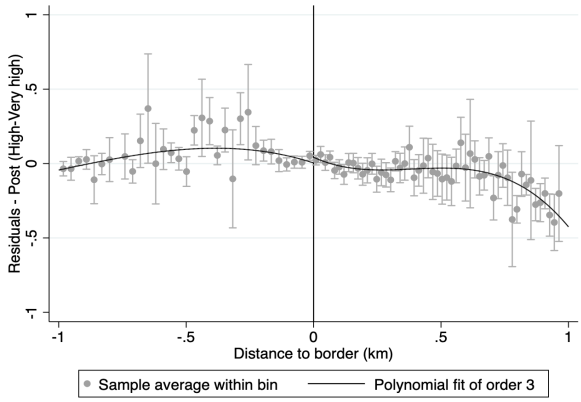
(a) Local means; Moderate → High



(b) Residuals; Moderate → High



(c) Local means; High → Very high



(d) Residuals; High → Very high

Figure D2 Visual evidence of the effect of being located inside a moderate relative to a high risk zone on log home prices (Moderate → High; Panels (a)-(b)) or inside a high relative to a very high risk zone on log home prices (High → Very high; Panels (c)-(d)) after the 2007 change in risk zoning (RD - Post=1). Left panels: local means of log home prices over distance from the cutoff. Right panels: residuals of log home prices on covariates over distance from the cutoff. The cutoff is the new 2007 risk zone boundary. Homes on the right hand-side of the cutoff are located inside the moderate risk zone while homes on the left hand-side of the cutoff are located inside the high risk zone. The number of bins is data-driven such that the bins sample means mimick the underlying variability of the data following Calonico et al. (2015). Vertical bars indicate 90% confidence intervals. Polynomials of degree $p = 3$ fitted over the data. Observations are restricted to census tracts featuring both control and treatment homes.

Table D1 RD and RD-DiD estimates of being located inside a one-level higher risk zone on log home prices for two individual level increases: Moderate → High and High → Very high

	Moderate→High			High→Very High		
	1/2 bw	bw	2 bw	1/2 bw	bw	2 bw
	(1)	(2)	(3)	(4)	(5)	(6)
			RD-Post=1			
$Z = 1$	0.0239	0.0167	0.0065	-0.0418	-0.0143	0.0067
	(0.0418)	(0.0338)	(0.0282)	(0.0377)	(0.0302)	(0.0261)
N	830	1192	1482	877	1395	1886
			RD-Post=0			
$Z = 1$	0.0181	-0.0081	-0.0072	0.0008	-0.0077	0.0042
	(0.0558)	(0.0453)	(0.0361)	(0.0457)	(0.0381)	(0.0315)
N	863	1174	1458	971	1488	1870
			RD-DiD			
$Z \times Post$	0.0139	0.0283	0.0007	-0.0505	-0.0050	0.0105
	(0.0515)	(0.0411)	(0.0338)	(0.0490)	(0.0396)	(0.0332)
N	1756	2430	2996	1641	2633	3597

Note: The cutoff is the 2007 risk zone boundary. Homes located on the right hand-side of the cutoff are located inside a risk zone that is one-level higher than homes located on the left hand-side of the cutoff. MSE-optimal bandwidth bw is derived using a local linear polynomial with covariates. $1/2bw$ ($2bw$) denotes half (twice) the optimal bandwidth, respectively. All regressions include covariates. The polynomial order is of degree one. Observations are restricted to census tracts featuring both control and treatment homes. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table D2 DiD estimates of being located inside a one-level higher risk zone on log home prices for two individual level increases: Moderate → High and High → Very high

	Moderate→High			High→Very High		
	(1)	(2)	(3)	(4)	(5)	(6)
$Treat \times Post$	-0.0239*	-0.0374**	-0.0349**	-0.0696***	-0.0728***	-0.0344***
	(0.0128)	(0.0154)	(0.0151)	(0.0102)	(0.0122)	(0.0124)
Quarter	✓	✓	✓	✓	✓	✓
Year FE	✓	✓		✓	✓	
County×Year			✓			✓
Census tract FE	✓			✓		
Covariates	✓			✓		
Home FE		✓	✓		✓	✓
N	3156	2130	2130	4293	3040	3040
R^2_{adj}	0.82	0.82	0.83	0.86	0.77	0.80

Note: Homes are located within 600m from the new 2007 risk zone boundary. Covariates: age and age squared, home size and home size squared, # bedrooms, # baths, swimming pool dummy, elevation, slope, dummy for location inside the wildland-urban interface, distances to nearest primary road, national forest, state or local park. Observations are restricted to census tracts featuring both control and treatment homes. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

E Examination of potential mechanisms

E.1 No evidence of changes in insurance premiums

To investigate whether insurance premiums are affected by the new 2007 risk zone, I examine the effect of the new risk zone on insurance premium quotes using DiD regressions. The annual insurance premium quotes come from California Department of Insurance for the median home in my sample based on price, size, and age characteristics. The quotes are at the zipcode level for the years 2004 to 2011 and come from admitted insurers in the seven counties in the study region. I assign zipcodes as treated if they are predominantly located inside the new risk zone, and as control otherwise. None of the estimates shown in Table E1 indicate that the new risk zone affected insurance premium quotes. The result holds when including county-by-year, zipcode, and insurance company level fixed effects.[14]

Table E1 DiD estimates of the effect of an increase in risk zone on zipcode-level insurance premium quotes

	(1)	(2)	(3)
Treat×Post	-8.353	-2.504	-2.594
	(17.74)	(17.47)	(17.53)
County×Year FE	✓	✓	✓
Zipcode FE		✓	✓
Insurance company FE			✓
N	14122	14122	14122
R^2_{adj}	0.05	0.05	0.84

Note: The quotes come from the California Department of Insurance for the median home in my sample based on price, size, and age characteristics. Quotes come from admitted insurers in the Los Angeles, San Bernardino, Riverside, Orange, San Diego, Ventura, and Santa Barbara counties. Quotes come from 76 insurance companies and cover the years 2004 to 2011. Zipcodes are assigned as treated if they are predominantly located inside the new risk zone, and as control otherwise. *Post* is defined as post 2007. Robust standard errors clustered at the insurance company level in parentheses. * p<0.1, ** p<0.05, *** p<0.01

[14] To put the magnitude of insurance premiums in perspective, in May 2007 (prior to the new policy implementation), mean (median) quotes in zipcodes predominantly located inside the future new risk zone zone amounted to $1363 ($1471) per year, with standard deviation of $448 (based on over 150 quotes). According to Dixon et al. (2018), average premium per policy in 2014 was $1160 in the 24 high-risk zipcodes of the Western part of San Bernardino County (and $780 and $930 in the 16 low-risk and 13 medium-risk zipcodes, respectively) based on insurance contracts from five admitted insurers.

E.2 No evidence of changes in mortgage markets

Another factor that may vary with the new risk zone and affect home prices is access to external financing. For example, lending agencies may perceive treated homes as having different default risk or potential for price growth relative to control homes (all else equal). Using the loan to value ratio and mortgage terms for the most recent buyer contained in the sales transactions data and the rate spread variable from matching the dataset to the HMDA, I run DiD regressions to examine the effect of the new 2007 risk zone on these outcome variables (columns (3)-(8) in Table E2). None of the estimates are significant.

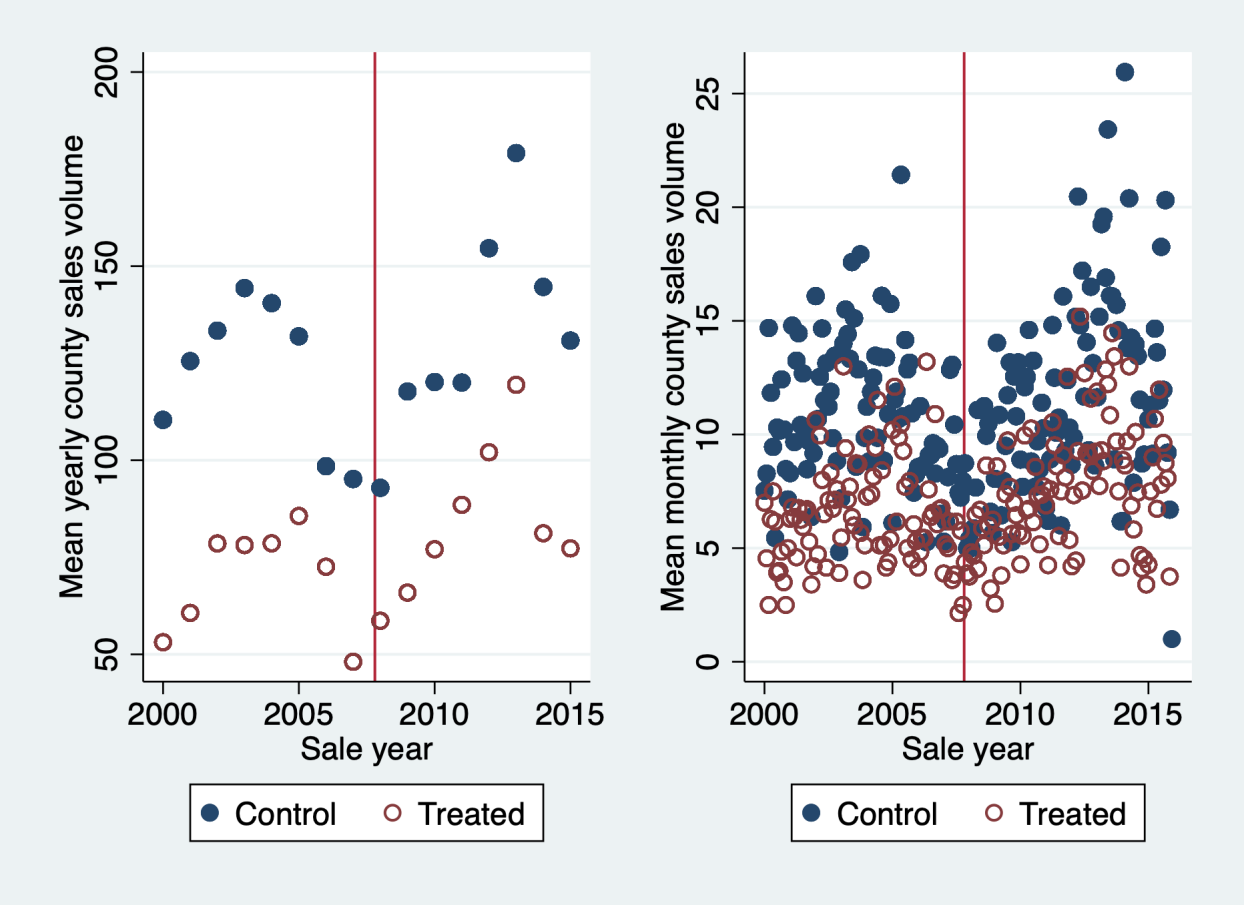


Figure E1 Number of sales at the county level for treatment and control homes located within 600m of the new 2007 risk zone boundary. Observations are restricted to census tracts featuring both control homes and treatment homes. The vertical line marks the new risk zone implementation date (November 2007). Panel (a): averages at the yearly level. Panel (b): averages at the monthly level.

Table E2 DiD estimates of effect of a one-level increase in risk zone on outcome variables: sales volume, LTV, mortgage terms, and spread rate

	Log monthly county sales volume		Loan-to-value ratio (LTV)		Mortgage term (in years)		Spread rate	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat×Post	-0.171	-0.184*	0.0177	0.00979	-0.304	-0.230	0.383	0.390
	(0.199)	(0.0959)	(0.0134)	(0.0115)	(0.420)	(0.439)	(0.401)	(0.694)
Quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓		✓		✓		✓	
County FE	✓							
Census tract FE			✓	✓	✓	✓	✓	
Cty×Year FE		✓		✓		✓		✓
Covariates			✓	✓	✓	✓	✓	✓
N	435	435	7981	7981	8014	8014	106	106
R^2_{adj}	0.15	0.75	0.11	0.12	0.01	0.01	0.57	0.68

Note: Covariates: age, house size, # bedrooms, # baths, and swimming pool dummy. In all specifications, homes are located within 600m of the new 2007 risk zone boundary. Observations are restricted to census tracts featuring both control and treatment homes. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

E.3 No evidence of sorting

One may be concerned that the type of households sorting into treated or control homes may change before and after the new 2007 risk zone. For example, changes in the risk belief priors of the buyers may vary if a greater share of households move in from regions with different wildfire risk experience. To investigate such potential shifts in neighborhood composition I examine whether the demographics and state origin of the buyers change in response to the treatment. I link the sales transactions data to the HMDA dataset containing buyers' income, race, and ethnicity, and to the Zillow ZTRAX dataset containing the buyer's address of origin. For each of these variables, I run DiD regressions to examine correlations between the effect of a one-level increase in risk zone on buyer characteristics. I do not find evidence that the share of California buyers changes in response to the treatment (columns (1)-(2) in Table E3). These results provide suggestive evidence that households' wildfire risk belief priors, as proxied by state of origin, do not change dramatically. In addition, I do not find evidence that neighborhood composition, as measured by income, race, and ethnicity, correlates with changes in risk zone (columns (3)-(8) in Table E3). To the extent that risk preferences are influenced by these demographic characteristics, the results suggest that risk preferences do not substantially change in response to the treatment.

Table E3 DiD estimates of the effect of a one-level increase in risk zone on the demographics of buyers. (1)-(2): Buyer's state of origin, (3)-(4): Gross household income, (5)-(6): Buyer identifies as white, (7)-(8): Buyer identifies as hispanic.

	Buyer origin		Income		White		Hispanic	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat×Post	-0.0387	-0.0502	-11.92	-12.31	-0.0513	-0.0617	0.0065	0.0061
	(0.0424)	(0.0461)	(19.16)	(19.72)	(0.0367)	(0.0386)	(0.0137)	(0.0155)
Quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓		✓		✓		✓	
Census tr FE	✓	✓	✓	✓	✓	✓	✓	
Cty×Year FE		✓		✓		✓		✓
N	931	931	3010	3010	7516	7516	7516	7516
R^2_{adj}	-0.01	-0.03	0.03	0.04	0.05	0.06	0.01	0.02

Note: (1)-(2): The state of origin is available for about 10% of buyers. It is coded as 1 if California, 0 otherwise. About 90% of buyers report coming from California. The source of this variable is the Zillow ZTRAX data. (3)-(8): Buyer demographics come from the Home Mortgage Disclosure Act (HMDA). In all specifications, homes are located within 600m of the new 2007 risk zone boundary. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.