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W.U.I. ON FIRE: RISK, SALIENCE & HOUSING DEMAND

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ABSTRACT

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Abstract. We investigate the effects of wildfires on risk perceptions by quantifying the impact of severe wildfires on housing price and transaction dynamics. Our empirical results are interpreted through the lens of a parsimonious model of sorting between locations that vary in their perceived level of fire risk. The model allows us to infer the evolution of risk perceptions among potential sellers and buyers of properties located in the proximity of large wildfire events. Our empirical analysis is based on a multi-dimensional characterization of the potential linkages between fire events and risk perceptions which incorporates measures of both proximity and burn scar views as well as a properties latent wildfire risk. Our analysis provides a connection between changes in underlying risk perceptions and the observed differences in housing price and quantity dynamics across properties that differ in both their spatial relationship to wild fire events (views vs. proximity) and their latent risk for wildfire.

1. Introduction

Both the frequency and severity of natural disasters is increasing. Half of the ten most costly disasters in history occurred in the last decade alone.[1] This trend is particularly strong in the case of wildfires which have seen a four-fold increase in their frequency and a six-fold increase in the average size of their burn scars since 1986. (Westerling et al., 2006). Currently, the United States experiences over 100,000 wildland forest fires each year.[2] In 2012, a single Colorado fire destroyed more than 87,000 acres. Nationwide, wildfires cost federal agencies $2.9 billion annually. (GAO, 2013).

While part of this trend may be attributed to changes in global climate, other factors include household location and risk mitigation decisions. For example, as a result of population deconcentration, urban areas are increasingly interdigitating with wild and rural lands creating what has been called the Wildland-Urban Interface (WUI) which, as of 2005, contained 39% of the stock of residential housing across the United States. (Travis et al., 2002, Conroy

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[1]Natural disasters: Counting the cost of calamities. *The Economist*, (2012). http://www.economist.com/node/21542755.

[2]Wildfires: Dry, hot, and windy. *National Geographic*, (2013). http://environment.nationalgeographic.com/environment/natural-disasters/wildfires/

et al., 2003, Radeloff et al., 2005). The sprawling configurations of WUI developments have modified the interactions between environmental and socio-economic dynamics leading to a sharp increase in the likelihood of severe wildfires impacting inhabited spaces. (Radeloff et al., 2005, Spyratos et al., 2007). Property-specific risks as well as the overall risk of fire in forested lands may be partially offset by investing in fire-resistant building materials and in reducing the fuel load around ones property. (Shafran, 2008). However, due to information asymmetries and spillovers these mitigation behaviors appear to occur at much lower levels than would be socially optimal. (Shafran, 2008, Steelman, 2008).

With the risk and impact of natural disasters on the rise, an important question is, "To what extent do wildfires impact the salience of wildfire risk?" The degree to which disasters affect risk perceptions and the pattern by which they evolve over time speak to the types of policies and market interventions that may be effective at aligning risk perceptions with risk realities, and hence, mitigation behavior. Our approach to this question is to quantify the impact of wildfires on housing price *and* transaction dynamics utilizing a series of wildfires that occurred throughout the Colorado Front Range (COFR) between 2002 and 2012. Exploring the impact on transaction rates is a unique feature of our analysis which is often overlooked in papers implementing hedonic methods.

We center our analysis on 18 wildfires which occurred in 8 counties spanning the COFR and utilize the universe of housing transactions data for 358,823 unique residential properties between the years 2000-2012. Using geo-spatial data on wildfire burn scars and latitude and longitude co-ordinates for each property in our sample, we implement GIS routines to produce multiple measures reflecting potential saliency. These include *proximity* to wildfire and *view* of wildfire burn scars – which may also capture the dis-amenity effects of fire – in addition to property-specific indexes of *latent wildfire risk*. Our measures for latent risk represent the probability of a wildfire occurring or burning into an area based on the physical attributes of the terrain surrounding each property such as slope, aspect, elevation and vegetation fuel type. Comparing market dynamics, in terms of both price and transaction rates, across each saliency dimension allows us to draw inferences into the process through which individuals update risk perceptions in the wake of natural disasters.

To better understand the link between price-capitalization, the probability of transacting and risk-salience, we formulate a simple theoretical model of preference-based sorting in response to changing risk perceptions. Using this theoretical framework we can interpret our price and quantity results in terms of differential saliency between extant residents and potential buyers. Specifically, our model provides distinct predictions regarding the evolution of risk perceptions, prices and quantities. Namely, if risk-saliency following a disaster doesn't vary across extant residents and potential buyers our model predicts a decrease in prices but no change in the probability of transacting; all agents discount treated locations, but the relative preference ordering of agents living in the fire prone area (as opposed to zero risk locations) remains unchanged. In contrast, negative price shocks coincide with positive quantity shocks when post-disaster saliency varies by the initial allocation of individuals. These observations, which we explore formally below, allow us to draw inferences regarding the saliency dynamics of wildfire by investigating the evolution of prices and quantities across various treatment dimensions (proximity, view and latent risk).

There is an extant literature evaluating the effects of wildfires on house prices including Loomis (2004), Troy and Romm (2004), Donovan et al. (2007), Mueller and Loomis (2008), Huggett Jr et al. (2008), Mueller et al. (2009), Champ et al. (2009), Stetler et al. (2010) and Mueller and Loomis (2014). Loomis (2004), for instance, finds that housing values in an unburned town two miles from a major wildfire dropped on the order of 15% based on housing transactions data five years after the fire. Mueller et al. (2009) analyze housing market responses to repeated wildfires in Southern California which occurred at different points in time but within a small geographic area and finds that repeated events lead to increasingly negative effects on home prices. Donovan et al. (2007) evaluates the role of information shocks on risk perceptions by analyzing the relationship between housing prices and wildfire risk after a website was made available which enabled residents in the city of Colorado Springs to view their risk-rating. They found that households generally placed a premium on higher risk properties (largely due to positive amenity effects associated with drivers of risk) before the website was available but not after. This finding is consistent with the notion we advance in our paper that the provision of information may elevate risk perceptions. These papers differ from ours in that they do not have an explicit focus on the impact of a wildfire on risk-salience, generally study a limited geographic area with a small number of fires, and fail to consider the connection between risk perceptions and transaction rates.

In terms of the price side of our analysis, our empirical work is in some ways closer to that of Kousky (2010), Bin and Landry (2012) and Atreya et al. (2013) who analyze the effects of major floods on flood risk perceptions using price data. Bin and Landry (2012) compare residential housing prices for properties located in FEMA designated flood zones to those properties located outside of flood zones before and after two major hurricanes in Pitt County, North Carolina. The authors report a 5.7% to 8.8% hurricane-induced flood-risk discount which lasts for 5 to 6 years. Atreya et al. (2013) perform a similar analysis after a major flood in Dougherty County, Georgia and report a post-hurricane flood-risk discount of 32% which lasts for 7 to 9 years. Kousky (2010) finds no significant change in property prices in the 100-year floodplain but does report a 2% - 5% reduction in property prices in the 500-year floodplain following the 1993 flood on the Missouri and Mississippi rivers. Each of these studies is limited, however, by a lack of precise, geo-spatial information delineating damaged areas. Flood damage is typically concentrated within designated risk areas. This may obscure the interpretation of their results as evidence of heightened risk salience due to potentially correlated dis-amenity effects associated with flooding.

Hallstrom and Smith (2005) attempt to discern the degree to which hurricanes convey risk information to homeowners net of storm damage by comparing price differentials between properties in and out of the 100-year flood plain following Hurricane Andrew in 1992. They base their analysis on price data from Lee County, Florida which did not experience any damage from the storm. These authors find a 19% decline in housing prices in Special Flood Hazard Areas suggesting that home buyers and sellers do act on the information conveyed by a severe storm.

In other works, the relationship between natural disasters and risk salience has been addressed in the context of additional environmental hazards using housing price data associated with the rupture and explosion of a major pipeline (Hansen et al., 2006), hazardous waste (McCluskey and Rausser, 2001), levee breaks (Tobin and Montz, 1988, 1997), and earthquakes (Naoi et al., 2009). Collectively, existing work suggests that major disasters may heighten risk perceptions as measured through price changes, but in the absence of recurring events, these effects diminish, sometimes quickly, to pre-disaster levels. Overall, the findings in the existing literature are consistent with Tversky and Kahneman's *Availability Heuristic* in which households form subjective beliefs over the likelihood of an event based on readily available information such as experiencing the effects of a natural disaster or hearing about catastrophic events in the news. (Tversky and Kahneman, 1974).

As we allude to above, four distinct features of our analysis distinguish our work from the extant literature. First, we consider the effects of multiple disasters which occurred at different points in time over a large geographic area. Second, we utilize precise, geo-spatial data on wildfire burn scars to account for several potential mechanisms through which forest fires may impact risk perceptions and attempt to tease out the dis-amenity effects associated with fire that are potentially correlated with our saliency dimensions. Third, to the best of our knowledge, our work is the first to consider both price and quantity dynamics. Finally, we provide a simple theoretical framework that links price and transaction changes to underlying changes in risk perceptions.

In our empirical work, the three specific saliency dimensions we consider are: 1) properties located within a 2km ring of a wildfire burn scar (with properties in the immediately adjacent area used as controls); 2) properties with a view of a burn scar (with proximate homes without a view used as controls); and, 3) properties located in high latent-risk zones (with proximate properties in low latent-risk areas used as controls). Using hedonic property and duration models, we then compare housing prices and transaction rates between each treatment and control group before and after wildfires accounting for fire-specific fixed effects and underlying regional trends in housing values.

We find that home prices in the 2km rings fall by 8.3%, 7.8% and 6.8% in the first, second and third years following a significant wildfire. Our duration analysis predicts a lagged increase in transaction rates in the magnitude of 21% in the third year following a wildfire (with no significant increase predicted in years one and two). Properties with a view of a wildfire burn scar incur an immediate loss in the range of 3% - 4%, relative to properties without a view, which remains persistent even after three years. We find no relative change in property turnover along this dimension. Restricting attention to properties located further than 5km from a fire and without a view of a wildfire burn scar, we find that housing values in high-risk zones, relative to housing values in low-risk zones, incur a loss in the range of 6% - 9% in the year immediately following a wildfire which is associated with a 19% increase in the likelihood of transacting. These price effects become statistically insignificant and decay in magnitude towards the range of 1% - 5% after two years. There is no significant effect on transaction rates after the first year. After three-years, price differentials and turnover rates are restored to pre-fire levels. As we discuss below, interpreted in the context of our theoretical model, these results suggest that the evolution of risk perceptions following a major fire depends both on the characteristics of the property itself (relationship to the fire and latent risk) and the location of the individual whose risk perception we are considering (potential seller, potential buyer).

We proceed as follows. We summarize our theoretical model of price-capitalization and preference-based sorting in response to changing risk perceptions in Section (2). We then characterize our study area and the details behind the construction of our geo-spatial data in Section (3). We present our empirical methodology in Section (4) and our findings in Section (5).

2. A Simple Model of Price-Capitalization, Risk-Salience and Preference-Based Sorting

We consider an economy comprised of a continuum of individuals of measure 1 who choose to live in one of two locations $j \in \{t, c\}$. We conceptualize t as a treated area and c as a control area in order to distinguish between communities who's residents differ in either their experience with or their perceived likelihood of wildfire. For example, t may be an area providing amenity values to some, but with heightened wildfire risk. Conditional on choosing location j, each individual consumes a fixed quantity of housing at a price p_j. We fix the price level in c at $\bar{p}_c$ such that the price level in the treated area (p_t) adjusts endogenously to clear both housing markets. All individuals are endowed with the identical income level y and have an exogenously determined taste (ω) for living in t whose distribution in the population can be described by a strictly increasing continuous distribution function $F_0(\cdot)$.

Individuals choosing to live in the control region receive utility given by:

$$u_c = y - \bar{p}_c,$$

while those choosing to live in the treated area have their utility augmented by their level of ω,

$$u_t = y - p_t + \omega.$$

Thus, in equilibrium, individuals sort based on their value of ω, choosing location t if,

$$\omega \geq p_t - \bar{p}_c = \omega_0^\star.$$

We assume that a unit measure of housing supply q is split across the two communities so that $q_t + q_c = 1$ with $q_t,\ q_c > 0$. Since any individual with type $\omega < p_t - \bar{p}_c$ prefers the control region, in equilibrium the price level in the treated area adjusts endogenously to satisfy the equilibrium condition:

$$F_0\left(p_t - \bar{p}_c\right) = q_c.$$

That is, p_t adjusts such that the proportion of individuals satisfying $\omega < \omega_0^\star$ exactly equals the proportion of the housing supply in c. We denote by p_t^0 the market clearing price in the baseline case before any risk saliency shock.

To conceptualize the salience-effects of a natural disaster, we assume that when a forest fire happens in or near the treated area, due to heightened risk perceptions, utility realized from living in t shifts downward by some amount, s. Assuming that the salience-effect may be stronger for those living in t at the time of the fire, we allow for heterogeneity in the shift across individuals based on their location in the baseline equilibrium:

$$s_t \geq s_c \geq 0,\ \ s_t > 0.$$

Thus, after a fire, utility associated with living in t may vary by initial location:

$$\begin{aligned} u_{t|c} &= y - p_t - s_c + \omega \\ u_{t|t} &= y - p_t - s_t + \omega. \end{aligned}$$

With this framework in place, we make several observations regarding how the baseline equilibrium changes following a fire.

OBSERVATION 1: Positive Saliency Shock Reduces p_t.
The post-fire equilibrium price in t is strictly less than the pre-fire equilibrium price: $p_t^1 < p_t^0$.

Observation 1 follows directly from the following. First, because s_t is greater than zero, for any $p_t \geq p_t^0$, there exists $\delta > 0$ such that for any $\omega \in [\omega_0^\star,\ \omega_0^\star + \delta)$, $y - p_t + \omega - s_t < y - \bar{p}_c$.

Because $F_0(\cdot)$ is strictly increasing, the set of $\omega \in [\omega_0^\star,\ \omega_0^\star + \delta)$ has positive measure. Thus, post-fire if $p_t \geq p_t^0$ the set of individuals with $\omega \geq \omega_0^\star$ who prefer t over c will be strictly smaller than prior to the fire. Second, it follows immediately from the baseline equilibrium condition that, because $s_c \geq 0$, any individual with $\omega < \omega_0^\star$ will strictly prefer community c if $p_t \geq p_t^0$. Since there will be excess supply in t if $p_t \geq p_t^0$, under the new equilibrium it must be the case that $p_t^1 < p_t^0$.

OBSERVATION 2: No Resorting Under Equal Shocks to Risk Salience.
If the fire saliency doesn't vary with baseline equilibrium location choice ($s_t = s_c = s$) then the post-fire equilibrium sorting of individuals is identical to that of the baseline equilibrium. Further, the size of the fire-driven price drop identified in Observation 1 is increasing in s. Specifically: $\partial p_t^1 / \partial s = -1$.

The first half of Observation 2 stems from the fact that when $s_t = s_c$ all individual preferences for locating in t have shifted by an identical distance. We can simply re-cast the problem in terms of a newly defined distribution of types $F_1(\omega_1) = F_0(\omega_1 + s)$ where each individual's value of ω has essentially been shifted down by s. Thus, in equilibrium, the sorting of individuals across the two locations must be preserved. The second part of Observation 2 follows from totally differentiating the post-fire equilibrium condition:

$$F_0\left(p_t^1 - \bar{p}_c + s\right) = q_c.$$

OBSERVATION 3: Unequal Shocks to Risk Salience Lead to Resorting.
If fire saliency is higher for individuals initially located in t ($s_t > s_c$) then there will exist $\delta_t,\ \delta_c > 0$ such that following the fire the new equilibrium reallocates individuals with $\omega_0^\star \leq \omega < \delta_t$ from t to c and all individuals with $\delta_c \leq \omega < \omega_0^\star$ from c to t.

The logic behind Observation 3 is as follows. First, note that because $s_t > s_c$ if it is optimal for all individuals with $\omega \geq \omega_0^\star$ to choose t post-fire then there exists $\delta > 0$ such that for any $\omega \in [\omega_0^\star - \delta,\ \omega_0^\star)$,

$$y - p_t^1 - s_c + \omega > y - p_t^1 - s_t + \omega_0^\star \geq y - \bar{p}_c.$$

In other words, if p_t^1 is such that all individuals who were initially located in t choose to remain in t post-fire, then for some values of $\omega < \omega_0^\star$ it will now be optimal to locate in t post-fire as well. However, by construction, the measure of $\{\omega | \omega \geq \omega_0^\star - \delta\}$ is greater than q_t and this can't be an equilibrium because there would be excess demand in t. Thus, to clear the housing market in the post-fire equilibrium it must be the case that over some positive measure set of $\omega \geq \omega_0^\star$ it must hold that $y - p_t^1 - s_t + \omega < y - \bar{p}_c$. Further, it is straightforward to demonstrate that this set must be continuous and include $\omega_0^\star$ as its lower bound. The complimentary result can be derived by similar logic.

The bounds of these two sets $(\delta_t,\ \delta_c)$ are identified by the optimality conditions. The range of $\omega \geq \omega_0^\star$ values for which region c is optimal in the post-fire equilibrium must satisfy:

$$y - p_t^1 - s_t + \omega < y - \bar{p}_c.$$

Thus, the relevant range for ω is:

$$\omega_0^\star \leq \omega < p_t^1 - \bar{p}_c + s_t = \delta_t.$$

Similarly, the set of $\omega < \omega_0^\star$ value for which t is optimal post-fire must satisfy:

$$y - p_t^1 - s_c + \omega > y - \bar{p}_c.$$

And the relevant range for ω is:

$$\delta_c = p_t^1 - \bar{p}_c + s_c \leq \omega < \omega_0^\star.$$

The new market clearing price is determined by the requirement that for housing market equilibrium to hold, it must be the case that the measure of these two sets be equal:

$$F_0\left(p_t^1 - \bar{p}_c + s_t\right) - F_0\left(\omega_0^\star\right) = F_0\left(\omega_0^\star\right) - F_0\left(p_t^1 - \bar{p}_c + s_c\right). \tag{1}$$

Recalling that $F_0\left(\omega_0^\star\right) = q_c$, the new market clearing price is implicitly defined by:

$$\frac{F_0\left(p_t^1 - \bar{p}_c + s_t\right) + F_0\left(p_t^1 - \bar{p}_c + s_c\right)}{2} = q_c. \tag{2}$$

Total differentiation of the market clearing condition in (2) and equation (1) indicates that the magnitude of the price adjustment and the measure of residents who sort between t and c vary proportionally to the magnitude of each locations salience shock. We summarize these formally in Observations (4) and (5).

OBSERVATION 4: Characterizing Price Effects.

The post-fire price drop in t is increasing in both location's risk-saliency. Specifically:

$$\frac{\partial p_t^1}{\partial s_t} = \frac{-F_0'\left(p_t^1 - \bar{p}_c + s_t\right)}{F_0'\left(p_t^1 - \bar{p}_c + s_t\right) + F_0'\left(p_t^1 - \bar{p}_c + s_c\right)},$$

and

$$\frac{\partial p_t^1}{\partial s_c} = \frac{-F_0'\left(p_t^1 - \bar{p}_c + s_c\right)}{F_0'\left(p_t^1 - \bar{p}_c + s_t\right) + F_0'\left(p_t^1 - \bar{p}_c + s_c\right)}.$$

OBSERVATION 5: Characterizing Quantity Effects.

The size of the post-fire relocation – measure of $\{\omega | \delta_c \leq \omega < \omega_0^\star\}$ = measure of $\{\omega | \omega_0^\star \leq \omega < \delta_t\}$ – is increasing in s_t and decreasing in s_c. Specifically, this change is given by:

$$\frac{F_0'\left(p_t^1 - \bar{p}_c + s_t\right) \cdot F_0'\left(p_t^1 - \bar{p}_c + s_c\right)}{F_0'\left(p_t^1 - \bar{p}_c + s_t\right) + F_0'\left(p_t^1 - \bar{p}_c + s_c\right)}.$$

To summarize our theoretical results, the treated and control regions in our model delineate locations based on resident's experience with or their perceived likelihood of wildfire. The predictions of our theoretical model allow us to interpret price and quantity responses in terms of differential saliency between extant residents and potential buyers. If risk-saliency changes following a disaster don't vary across extant residents and potential buyers our model predicts a decrease in prices but no change in the probability of transacting. Negative price shocks coincide with positive quantity shocks only when post-disaster saliency varies between potential sellers located in the treated area and potential buyers located outside the treated area; that is, when one group experiences a stronger shock than the other. As such, we can approach the task of discerning saliency dynamics by investigating the evolution of prices and quantities through the lens of our theoretical framework.

3. Study Area and Data

The Colorado Front Range forms a barrier between the easternmost range of the Rocky Mountains and the Great Plains regions of eastern Colorado. Its population increased by 30% from 1990 - 2000 with the growth predominantly concentrated in the interface and intermix communities of the WUI. (Travis et al. 2002). As depicted in Figure (1), we conduct our analysis across 8 counties spanning the COFR: Boulder, Douglas, Larimer, Pueblo, El Paso, Jefferson, Teller and Fremont. We identify WUI properties in these locations based on GIS data provided by the Silvis Lab[3]. (Radeloff et al., 2005). The WUI is composed of interface and intermix regions. In both types of WUI regions, housing density must exceed one structure per 40 acres while intermix areas must also be at least 50% vegetated and lie within 1.5 miles of an area at least 1,325 acres large that is at least 75% vegetated.

We obtained a list of wildfire incidents from FEMA's disaster declaration web-page[4]. We use FEMA as a reference point for distinguishing severe wildfires from less significant ground or brush fires. FEMA records each fire's start-date, end-date and the total dollars obligated in public assistance grants. We cross-check these dates with the information contained in each fire's Incident Status Summary (ICS-209) report which we obtained from the National Fire and Aviation Management Web Application[5] maintained by the National Inter-agency Fire Center[6].

Spatial data-sets for each fire's burn scar were acquired from the Geospatial Multi-Agency Coordination Group (GeoMAC)[7] and Monitoring Trends in Burn Severity (MTBS)[8]. We include in our analysis any fire with a burn area exceeding 500 acres which appears in either the GeoMAC or MTBS data-sets, regardless of whether or not it received a FEMA declaration or not. We summarize the set of fires included in our empirical work in Table (1)[9]. The spatial distribution of the wildfires in our sample are depicted in Figure (1). Their

[3]http://silvis.forest.wisc.edu/
[4]http://www.fema.gov/disasters
[5]https://fam.nwcg.gov/fam-web/
[6]http://www.nifc.gov/. A sample ICS-209 report for the Fourmile Canyon Fire of 2010 may be found here: ICS-209 Fourmile Canyon
[7]http://www.geomac.gov/index.shtml
[8]http://www.mtbs.gov/
[9]Other notable fires which occurred in the COFR but whose burn areas which extend beyond either the spatial or temporal coverage of our housing price data are the Hayman Fire of 2002, the Mason Fire of 2005 and the Wetmore fire of 2012.

size varies from 606 to 87,505 acres and the costs of suppressing them range from $250 thousand to $38 million.

Our housing transactions data is provided by DataQuick Information Systems, used under a license agreement with the Social Science Research Institute at Duke University. In the 8 counties of interest to our study, we observe repeated transaction histories for 358,823 unique residential properties between the years 2000 and 2012. The data records information on: the type of sale (newly constructed, re-sale, refinance or equity dealings, timeshare, or subdivision sale); the relevant transaction-level information including sale price and sale date; building characteristics from the most recent tax assessment including square footage, lot size, number of bedrooms, number of bathrooms and the number of stories; and the site address. In order to obtain precise Geo-referenced locations for each property, we ran a batch geo-coding routine[10] in ArcMap10 which returns the latitude and longitude coordinates for each properties roof-top or parcel-centroid.

We limit transactions to arms length sales of owner occupied, residential single family residences. Properties lying in the 1$^{\text{st}}$ or 99$^{\text{th}}$ percentile with respect to square footage or sale price, or the 99$^{\text{th}}$ percentile with respect to the number stories, baths, beds, units or rooms were dropped. Houses with a negative age[11] were removed as well.

To determine the portion of the landscape visible from each property in our sample, we perform a Viewshed Analysis[12] in GIS. This method has been used in hedonic models to address the visual impacts of shale gas wells (Muehlenbachs et al. 2014) wind turbines (Sunak and Madlener, 2012), natural landscapes (Walls et al., 2013) and wildfire (Stetler et al., 2010). Given a Digital Elevation Model (DEM) of the terrain which we obtained from the National Map[13], we compute the visible area from each property as determined by the line-of-sight between each observer point and every cell in the DEM. To determine fire-visibility, we overlay and intersect each property's viewshed with each fire's burn scar. This process is depicted in Figure (2).

[10]The 10.0 North America Geocode Service Locator, updated as of June 2012, was used to generate latitude and longitude coordinates.
[11]We calculate age as year sold minus year built.
[12]To increase the computational speed of this algorithm, we limit the search over the DEM to a radius of 20km of each property.
[13]http://nationalmap.gov/

We measure latent wildfire risk with the Wildfire Threat Index (WTI) developed by the Colorado Wildfire Risk Assessment Project (CO-WRAP[14]) which represents the likelihood of a wildfire occurring or burning into an area. (CO-WRAP, 2013). The WTI takes as inputs: surface fuels, canopy characteristics, land cover, terrain, slope, and elevation. The threat index is compiled to a resolution of 30m and allows for consistent comparison of wildfire risk between different parts of the State. The WTI ranges from "Lowest Threat" to "Highest Threat" and is depicted in Figure (3).

4. Empirical Methodology

Our basic empirical approach entails hedonic models of residential housing prices and duration models of housing transaction rates estimated along multiple dimensions of potential salience. Contemporaneous shifts in local and macroeconomic housing markets complicate our task of identifying the causal effects of a natural disaster from housing transaction data. To overcome this empirical challenge, we implement a difference-in-differences estimation strategy which identifies treatment groups based upon multiple geo-spatial measures of saliency and compares market dynamics in each group to the outcomes of properties in control groups that do not receive said treatment, but that are otherwise influenced by the same contemporaneous factors. Our treatment groups include properties located within a 2km ring of a wildfire (with immediately adjacent properties used as controls), properties with a view of a burn scar (with neighboring properties without a view used as controls), and properties located in high latent risk-zones (with proximate homes located in low latent risk areas used as controls). We motivate our use of a 2km cutoff in sections (5.2.1).

To implement our estimation procedure, we assign each property i to its nearest fire $m \in M$. To minimize the potential confounding effects of exposure to multiple fires we then drop from our sample any observations that lie within 7 km of multiple fires. For each treatment group, our hedonic models take the form:

$$\begin{aligned} \ln p_{itm} &= \alpha \cdot Post_{itm} + \beta \cdot Treat_{im} \times Post_{itm} + \gamma^m \cdot Treat_{im} \\ &\quad + \delta^m \cdot \tau_t + \pi^m \cdot Treat_{im} \times \tau_t + Z_i' \omega_1 \\ &\quad + G_{it}' \omega_2 + \epsilon_{itm}, \end{aligned} \tag{3}$$

[14] http://www.coloradowildfirerisk.com/

where $Post_{itm}$ is a post-fire dummy and $Treat_{im}$ is a treatment group indicator. For each treatment definition, we are interested in the estimate on the coefficient of the treatment-group by post-fire interaction term, β. Moreover, in order to understand how our estimate for β varies in each year following a wildfire, we replace $Post_{itm}$ with 1, 2 and 3-year post-fire indicator variables $\left\{Year_{itm}^k\right\}_{k=1}^3$. This transforms the baseline specification in (3) into:

$$\begin{aligned}\ln p_{itm} \quad = \quad & \sum_{k=1}^{3}\left(\alpha^k \cdot Year_{itm}^k + \beta^k \cdot Treat_{im} \times Year_{itm}^k\right) + \gamma^m \cdot Treat_{im} \\ & +\delta^m \cdot \tau_t + \pi^m \cdot Treat_{im} \times \tau_t + Z_i'\omega_1 \\ & +G_{it}'\omega_2 + \epsilon_{itm}, \qquad (4)\end{aligned}$$

Thus, the estimate of β_k may be interpreted as the difference-in-differences estimate of β restricting attention to post-fire transactions which occur between $k-1$ and k years of a wildfire. To control for composition effects, we allow our main effects to vary by fire by including a full-set of group by fire interaction terms, $\gamma^m \cdot Treat_{im}$. To account for trends in housing prices which may vary over time and space, we fit fire-specific trends which can vary by treatment group, $\delta^m \cdot \tau_t + \pi^m \cdot Treat_{im} \times \tau_t$. Our set of structural controls, Z_i', include: second-order polynomials in square footage and age; basement square footage; indicator variables for number of bathrooms and bedrooms; and a variable indicating if a property has a swimming pool. Our set of geographic characteristics, G_i', include second-order polynomials in viewshed size, slope, county fixed effects, year by quarter fixed effects, and, in our most robust specifications, year by quarter by fire fixed effects.

For transaction rates, the probability that a property sells at any given point in time is conditional on whether it sold in the previous period. Moreover, properties which fail to transact in the time-fame of our property data are censored. For these reasons, we model the conditional probability of a property transacting as a continuous time duration process and estimate the relative increase or decrease in the transaction-hazard between each treatment and control group following a wildfire. In addition to our data being censored from the right, which we account for in our maximum likelihood estimation, a second issue is left censoring which occurs whenever ownership of a property initiates prior to the window of our sample. Archer et al. (2010), who estimate a Cox model of ownership duration to understand the effects of household characteristics, neighborhood factors and tenure on housing turnover rates, are also restricted by left-censored data. They argue in their paper, as do we in ours, that to the extent that the window of our transactions data is random, left censoring should not lead to biased estimates.

Letting t denote the elapsed time since property i last sold and $\lambda_0(t)$ the non-parametric baseline hazard function at time t, we estimate the coefficients of:

$$\lambda\left(t|z_i(t)\right) = \lambda_0(t)e^{z_i(t)}. \tag{5}$$

where,

$$\begin{aligned} z_i(t) &= \sum_{k=1}^{3}\left(\alpha^k \cdot Year_{itm}^k + \beta^k \cdot Treat_{im} \times Year_{itm}^k\right) + \gamma^m \cdot Treat_{im} \\ &\quad + Z_i'\omega_1 + G_{it}' \cdot \omega_2 + \epsilon_{itm}. \end{aligned} \tag{6}$$

In this specification, $\lambda\left(t|z_i(t)\right)$ represents the probability a property turns over at t conditional on its time-varying co-variates $z_i(t)$ and the non-parametric baseline hazard rate $\lambda_0(t)$.

5. Results

5.1. **Visual Evidence and Identification.** The difference-in-differences estimates of equation (4) will represent the causal effects of wildfire if the average change in housing prices for treated properties would have been proportional to the average change in outcomes for the non-treated in the absence of treatment. In addition, wildfires must not coincide with any other shock differentially affecting each group. We are less concerned with the second of these assumptions since we consider the effects of multiple disasters which occur at different points in time and space; however, since we do not observe counter-factual outcomes, we cannot explicitly test for the first. Instead, we provide graphical evidence that the evolution of prices in the periods immediately preceding wildfire are similar between treated and non-treated properties. After limiting our analysis to the WUI, we regress log-prices on a set of year-by-quarter fixed effects, county fixed effects, and structural control variables. For each treatment definition outlined in Section (4), Figure (4) fits group-specific, kernel-weighted local polynomials on the residuals of these regressions[15].

[15]These regressions vary with respect to the sample definition for each model. The residual plot for proximity is limited to properties within 10km of a wildfire while the plots for visibility and latent risk are restricted

In the visibility and risk plots presented in Figure (4), the pre-fire trends of each treatment group are generally similar to each control group, but we do detect a slight upward price trend for properties located in 2km wildfire rings which we account for in our empirical analysis by fitting fire-specific trends which which vary by treatment group. The visibility plot suggests that homeowners pay a premium to have a view of fire-prone landscapes prior to a wildfire. The risk plots also suggest a pre-fire premium for properties located in fire-prone areas. These results suggest a positive amenity value for being situated in an area with or that has a view of ridge lines, dense vegetation and other determinants of wildfire threat. Donovan et al. (2007) report a similar finding. Their estimates of the hedonic valuation of property-specific risk and vegetation ratings are positive and significant. Moreover, in a related paper, Champ et al. (2009) surveyed 898 households throughout the WUI in Colorado Springs and found that 75% of homebuyers were not concerned about wildfire risk at the time of purchase and that only 27% of were even aware that their properties were in at-risk areas.

These graphs also provide visual evidence of the short and long term effects of wildfire on home values. In the years following a wildfire, we observe that each control group continues on their pre-existing trend while each treatment group experiences a sharp drop. Following the initial decline, prices of properties in high latent risk zones decay quickly toward their pre-fire level. Housing values in 2km rings are also initially discounted, but subsequently return to their pre-fire trend. In contrast, properties with a view of a burn scar incur immediate and persistent losses.

5.2. **Hedonic Property Models.** We begin our formal analysis by estimating equation (4) along two key dimensions*: Proximity* to wildfire and *view* of wildfire burn scars. These variables measure potential saliency effects as well as the dis-amenity effects of fire. We determine the extent to which our difference-in-differences estimates diminish towards zero along these scales. We then estimate our models of latent risk on the spatial extent where the potentially correlated amenity effects of wildfire are attenuated.

5.2.1. *Proximity* . Table (2) presents coefficient estimates of equation (4) comparing the outcomes of treated properties located within a 2km ring of a wildfire to control properties

properties within 5km and 30km, respectively. The graphical results using other sample definitions are qualitatively similar.

in the immediately adjacent area. Assuming that the set of adjacent properties represent a valid control group, the causal effect of wildfire is reflected in the coefficients on the 2km, post-fire interaction terms: (2km Ring)$\times$(Year k). The coefficient estimates in column 1 indicate an immediate and highly significant -8.7% post-fire discount one year out. This effect decreases in magnitude towards -7.5% in two years and to approximately -6.7% in year three. As reflected in columns (2) and (3), these results are robust to year by quarter by fire fixed effects and to a smaller set of control properties. They are also qualitatively similar to Mueller et al. (2009) who finds that house prices located within 1.75 wildfire buffers drop approximately -9.7% in the year immediately following a wildfire.

To test the sensitivity of our model to the cutoff delineating treated and non-treated areas, we limit our sample to properties within 30km of a wildfire burn scar and, starting with a 1km ring, estimate equation (4) as we increase the size of the treatment ring in 250m increments. Figure (5) plots the first-year coefficient estimates together with their 95% confidence intervals. We take note that the magnitudes of these effects are pronounced and increase into the range of -15% within 1km. Beyond 2km, our coefficient estimates and our confidence in them rapidly diminish to zero and beyond 5km they are zero.

5.2.2. *Visibility.* Table (3) presents the coefficient estimates of equation (4) comparing prices between properties with and without a view of a wildfire burn scar. By default, each property's Viewshed calculation will extend to the limits of our DEM. As shown in the first panel of Figure (2) which depicts a viewshed for a sample WUI property, visible areas may include portions of the terrain that are in the observers line-of-sight, but too distant for the observer to be able to discern temporal variations in the landscape. To account for this potential issue, we limit our analysis to properties located within 5km of each fires burn scar. Referring to the coefficient estimates for the view of fire, post-fire interaction terms in columns (1) and (2) of Table (3), (View of Fire)$\times$(Year k), we find that having a view of a burned area results in a highly significant 4% drop in price immediately following a wildfire. This effect remains unchanged even after three years have passed and is robust to year by quarter by fire fixed effects. Stetler et al. (2010) conduct a hedonic analysis of wildfire in northwest Montana between June 1996 and January 1997. In particular, they estimate the effect of having a view of a burned area after excluding wildfires that burned after the sale date of the homes in their sample. While not estimated in a difference-in-differences framework, the authors find that properties with a view of a wildfire sell for 2.5% less than homes without a view.

It is important to note that a property's view of a burn area may very well correlate with its distance to the fire. To address this concern, in column (3) we include second order polynomials in distance to fire. Including these variables reduces our coefficient estimates on view by approximately 1 percentage point in all three years; however, the effects of view still remain persistent over time. The linear terms for distance are positive and significant while the cubic terms are negative which suggests that prices for homes following a wildfire fall proportionally with their distance to the burn area. To see that these results are consistent with our findings in Table (2) in addition to our sensitivity analysis in Figure (5), note that the critical points of the first, second and third year effects all occur at approximately 3km.

Finally, to test the sensitivity of our model to the 5km cutoff we impose, we re-estimate Column (2) of Table (3) in 250m increments starting with a 1km cutoff and ending with a 14km cutoff. The coefficient estimates for each of these regressions together with their 95% confidence intervals are plotted in Figure (6). The figure shows that the effect of view diminishes gradually with distance but remains at approximately -4% between 1km and 5km.

5.2.3. *Latent Wildfire Risk.* The price adjustments with respect to proximity and visibility are only weak evidence that households update risk perceptions following a natural disaster; these estimates may be conflated with the dis-amenity effects of fire. We take a more direct approach to estimating the salience effects of a wildfire by estimating their impact on the price differential between properties in high and low risk areas that are not immediately proximate to a fire (i.e > 5km). We report the estimation results of our latent risk models, which are also based on equation (4), in Table (4). The coefficients of interest are the estimates of the latent risk, post-fire interaction terms, (High Latent Risk)$\times$(Year k).

We point out here that Atreya et al. (2013) use a similar framework and estimate the value for flood risk following a hurricane by comparing home values between properties in 100-year and 500-year flood zones to properties located outside of the floodplain. They find a sharp decline in prices in the 100-year flood zone but detect no significant effects in the 500-year zone which they argue is consistent with flood damages being localized in the 100-year floodplain. This is not surprising as their measure of latent risk strongly predicts flooding potential. However, with a lack of geo-spatial data on inundated areas, the authors had difficulty accounting for these contemporaneous dis-amenity effects. To account for this bias, as an additional control, we exclude any observation with a view of burn scar or located within 5km of a wildfire.

Column (1) in Table (4) presents our model estimates based on the entire sample. In columns (2) and (3) we drop any observation which lies within 5km of a wildfire; portions of the landscape where the price effects with respect to proximity and visibility are significant. We drop *any* observation with a view of a burn scar in columns (4) - (6). Referring to column (4), we find a -7.2% latent risk discount in the year immediately following a wildfire. This effect is significant at the 5% level and equates to an approximately $25,000 discount for an average-priced home in our sample. The magnitude of this effect remains significant and increases toward -9% when we limit our sample cutoff to 10-20km. However, in each case these coefficients decrease in magnitude towards zero and become insignificant in the second year.

5.3. **Duration Analysis.** The conceptual model presented in section (2) allows us to draw inferences regarding the saliency dynamics of wildfire by investigating the evolution of prices *and* quantities. We now turn to the quantity side of the market. As discussed above, we analyze transaction rates using a proportional hazards model. In what follows, we report hazard ratios corresponding to each of our three treatment definitions with p-values – relative to a no-effect level of one – reported in brackets.

Results for proximity are reported in Table (5). The estimated hazard ratios for (2km Ring)×(Year 1) and (2km Ring)×(Year 2) are insignificant despite corresponding to years which experienced negative price shocks. However, we find that a 21% increase in transaction probability occurs in year three after price effects are to be attenuated. Our theoretical analysis (Observation 2) predicts that prices fall with quantities remaining unchanged when sellers and buyers both experience the same shift in risk perceptions. Through this lens, our empirical results suggest that the spatial effects of wildfire – which may ultimately incorporate amenity changes – are highly salient to both extant residents in close proximity to a wildfire *and* to potential buyers in the control regions; but only in the first few years. Further, the model (Observation 3) predicts price decreases in association with transaction rate increases when negative saliency shocks are greater for those located in the treated area. Thus, the subsequent increase in housing transaction probabilities in the third year provides evidence that the spatial effects of fire become relatively less pronounced for individuals not living in immediate proximity of the fire after two years have elapsed.

Turning our attention to the effect of view as presented in Table (6), the estimated hazard ratios (View of Fire)$\times$(Year k) are insignificant in all years suggesting that view of wildfire has no measurable effect on transaction probabilities. However, we do find persistent price effects over this time frame. From the perspective of the model, this finding suggests that the visual-effects of wildfire are as relevant for a potential buyer as they are for an existing homeowner even after three years have passed.

The price and quantity results for proximity to a wildfire suggest that, immediately following a fire, both potential sellers and potential buyers experience a similar negative shock to their perception of the risk associated with owning a home close to the burn scar. The fact that price decreases attenuate over time and that transaction rates are at first unaffected and then accelerate over time suggest that the saliency of the recent fire recedes more quickly for potential buyers than for potential sellers. In contrast, for homes that have a view of the burn scar, the constant price decline and complete lack of a transaction effect suggest no decay in saliency for either buyers or sellers – perhaps because the view of the burn scar provides a consistent information signal regarding fire risk.

One confounding issue that may partially explain the failure of prices to return quickly to their pre-fire levels is the potential dis-amenity associated with close proximity to, or view of, a burn scar. By focusing on the effect of fire on high-risk and low-risk properties located between 5 and 30 km our final treatment dimension seeks to estimate a pure saliency effect. To the extent that dis-amenity effects exist, both control and treatment groups in this final set of analyses should experience identical amenity impacts. Table (7) presents transaction rate results for high latent risk properties relative to low latent risk properties.

The estimated hazard ratio for (High Latent Risk)$\times$(Year 1) shows a significant, 19% increase in transaction probabilities one year out. However, the coefficient estimates for year 2 and 3 are substantially lower in magnitude and are statistically insignificant. Recall that we detect no measurable effects on prices after the first year. This short –run price decline which is associated with a similarly short-lived increase in transaction rates suggests that, following a wildfire, potential buyers located on high risk lots that are in the general area of the fire but not so close as to be directly affected by the fire experience an increase in their perception of the fire risk associated with their house which exceeds that experienced by potential buyers. Without immediate proximity to, or view of, the burn scar to re-enforce this shock the increase in fire saliency attenuates quickly.

5.4. **Discussion and Summary of Findings.** In this paper we develop a parsimonious model that links underlying changes in location-specific risk perceptions to housing market dynamics. In particular, given estimates of both the price and quantity effects associated with significant wildfire events the model allows us to draw inferences about the underlying changes in risk perceptions that gave rise to the observed housing market impacts. This approach is an advance over the existing literature which has focused almost exclusively on the price effects of natural disasters and is thus limited in terms of the inferences it can draw regarding the impact of these events on underlying risk perceptions. Further, by considering several different dimensions along which the saliency effects of wildfire may vary, we are able to more clearly identify a pure saliency effect which in most previous work has been confounded with potentially co-varying dis-amenity effects associated with the destructive impacts of natural hazards.

Our empirical results suggest that, for properties located very close to a fire, both potential buyers and sellers experienced increases in the perceived fire risks associated with these locations. For close locations with no view of a burn scar we find evidence that after two years have elapsed, these heightened risk perceptions attenuate for potential buyers – relative to those of potential sellers. However, for locations with a burn scar view, no such relative attenuation in risk perception occurs, even 3 years out – perhaps because the presence of a burn scar serves to reinforce an initial saliency shock. Of course, in this case, we can't rule out the possibility that agents are responding to a dis-amenity effect as well. Finally, by focusing on differences in housing dynamics that are driven by variation in a given locations underlying latent fire risk, we are able to identify a pure saliency effect. Here our empirical results suggest that potential sellers in high risk locations experience an increase in perceived risk that is not shared by potential buyers. This short-lived (one year) increase in relative risk saliency experienced by households living in the general vicinity of, but not immediately proximate to, a wildfire suggests that households in high risk areas may be particularly sensitive to information shocks about fire risk.

These results provide insight into the potential for information treatments to impact risk perceptions and market behavior in the context of risks associated with natural hazards. Our work provides evidence suggesting that households update their risk beliefs and market behavior in response to information shocks – with households living in high risk areas being more responsive than those in low risk areas. However, the impact of these information treatments may be short lived. For the Colorado wildfires considered in our study, the saliency effects appear to attenuate over the course of a single year in locations that aren't located in immediate proximity to a burn scar. Unexplored in this study, and a fruitful avenue for future work, is the impact of large natural disasters on individual mitigation behaviors that have the potential to reduce the impact of these events when they do occur.

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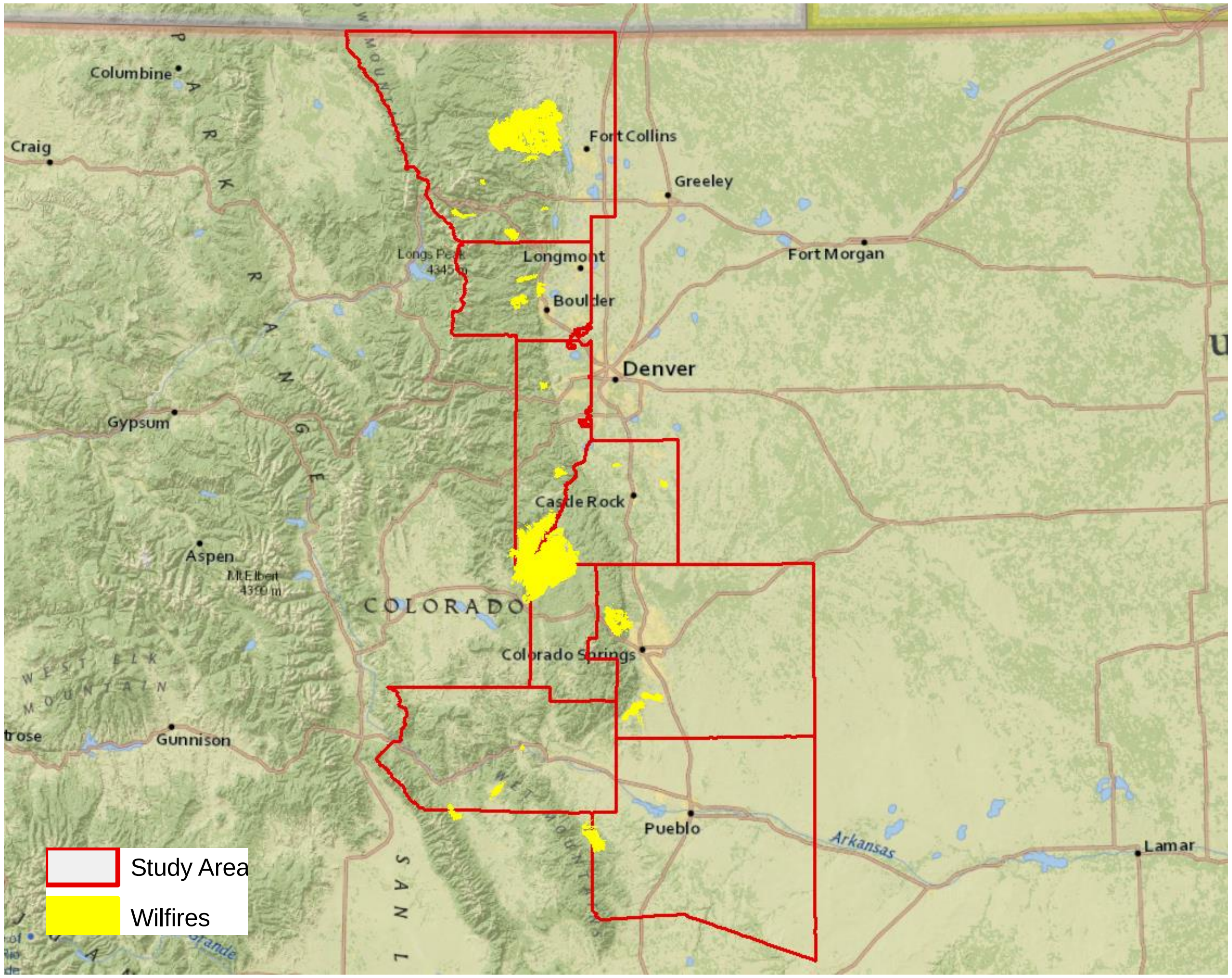

FIGURE 1. Study Area and Wildfire Burn Scars

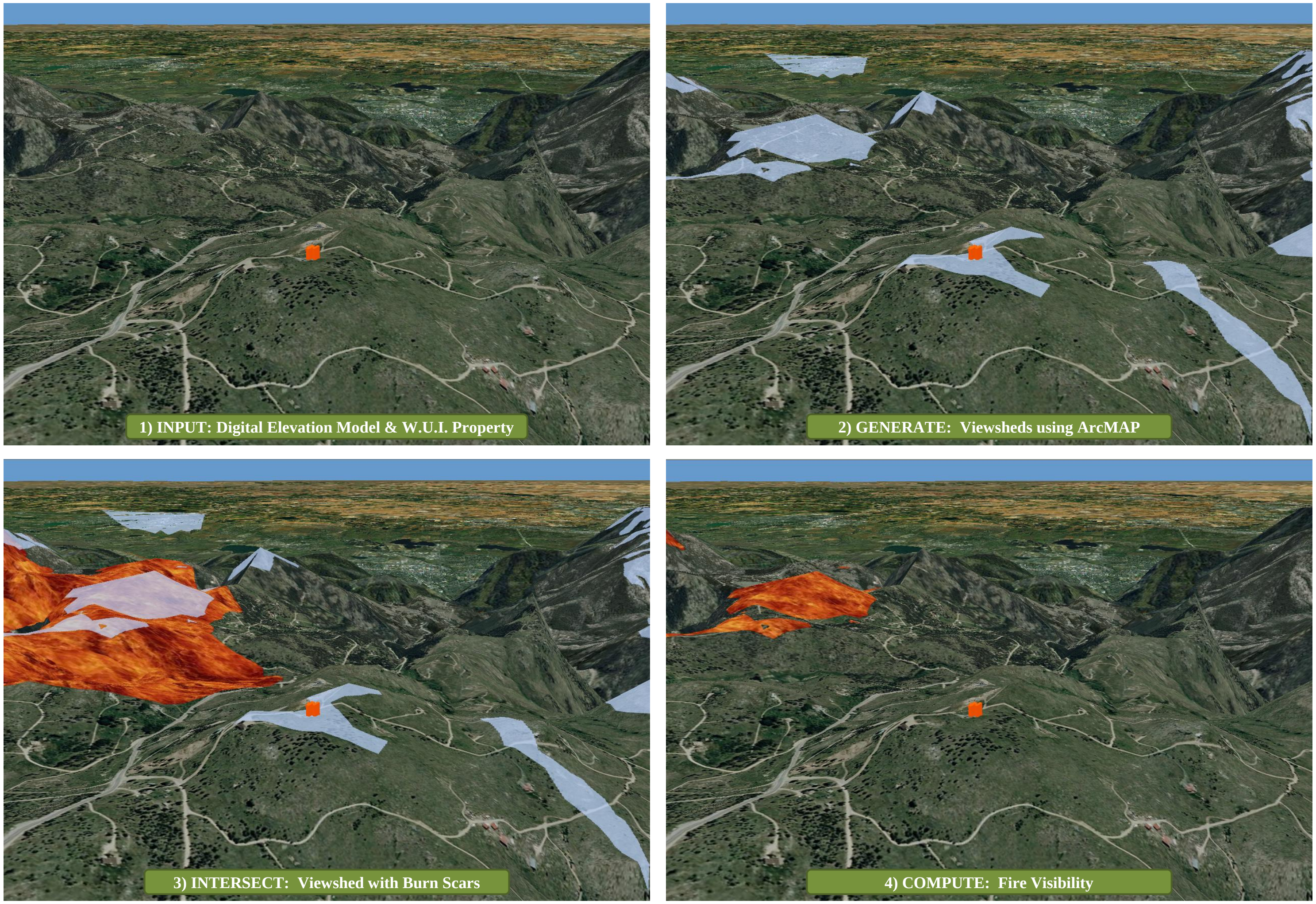

FIGURE 2. Viewshed Analysis

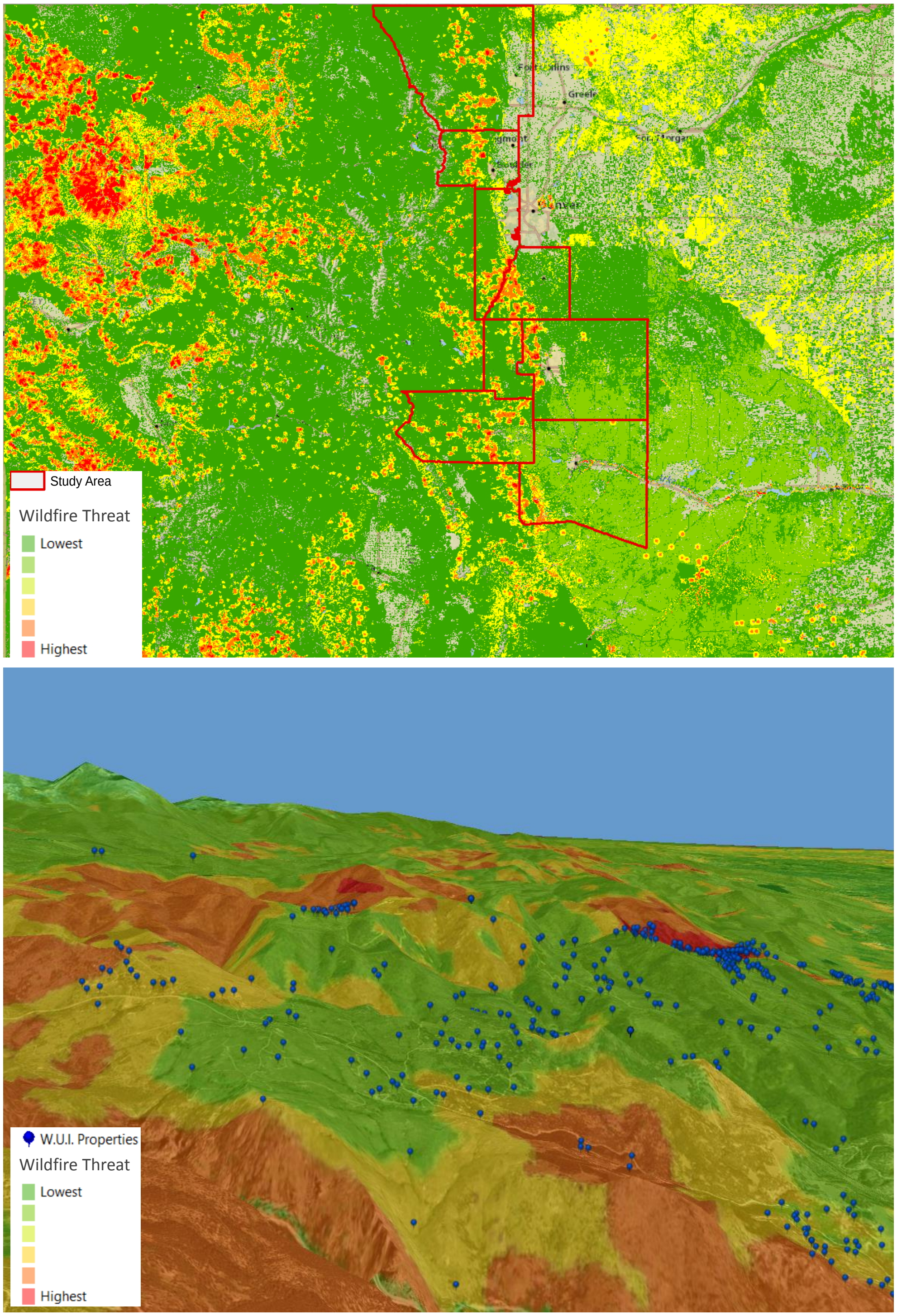

Figure 3. Latent Risk: Wildfire Threat Index

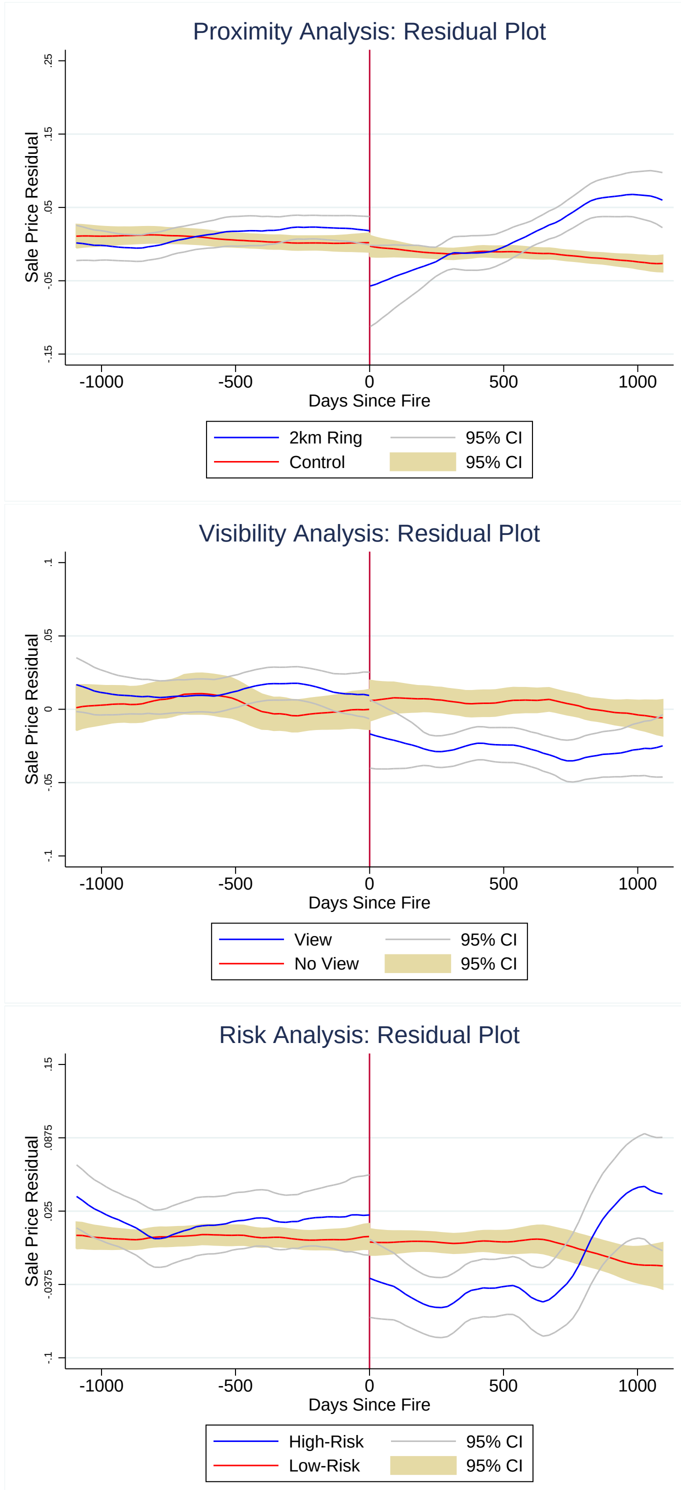

FIGURE 4. Residual Plots

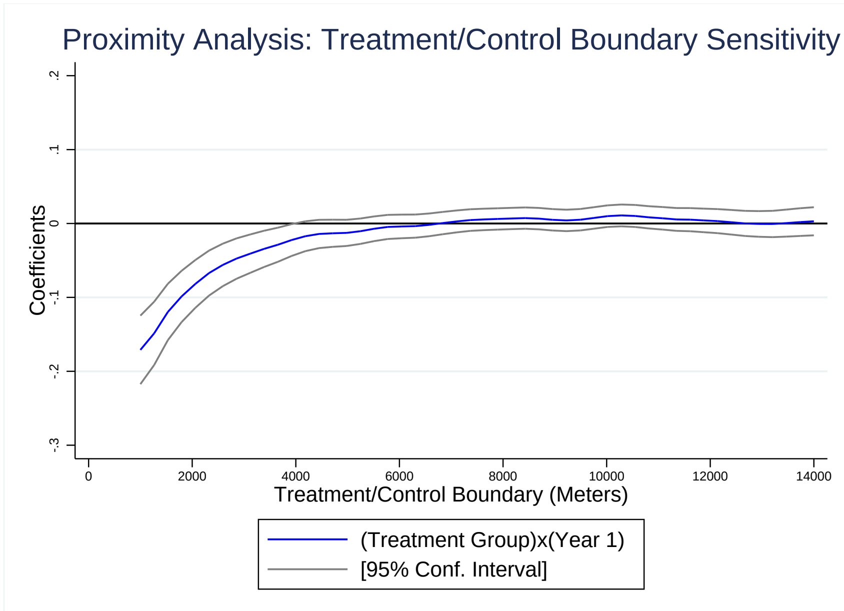

FIGURE 5. Proximity: Sensitivity to Treatment / Control Boundary

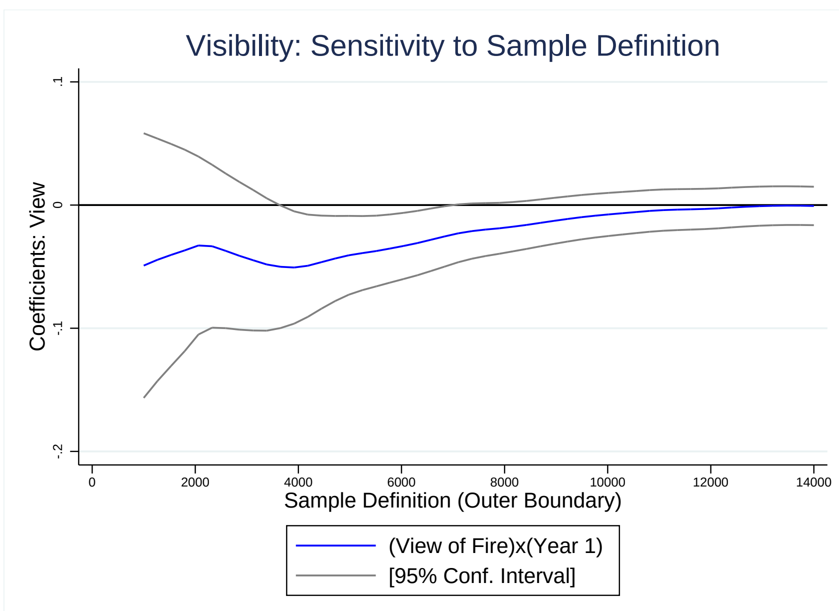

FIGURE 6. Visibility: Sensitivity to Sample Definition

Table 1. Colorado Wildfires

Fire Name	*Start Date*	*End Date*	*Received FEMA Declaration*	*Total Public Assistance Grants*	*Acres*	*Injuries*	*Fatalities*	*Personnel Involved*	*Fire Crews*	*Structures Lost*	*Suppression Costs*
Big Elk	7/17/2002	7/26/2002	y	373,067	4,344	12	3	290	6	1	3,700,000
Overland	10/29/2003	10/30/2003	y	-	3,230	0	0	276	9	62	400,000
Cherokee Ranch	10/29/2003	10/31/2003	y	59,933	1,042	3	0	45	1	3	300,000
Picnic Rock	3/30/2004	4/7/2004	y	519,746	9,006	7	0	61	2	2	2,200,000
Olde Stage	1/7/2009	1/8/2009	y	-	3,167	2	0	5	0	3	-
Quarry	3/6/2009	3/9/2009	n	-	5,137	0	0	9	0	4	250,000
Parkdale Canyon	6/21/2010	6/25/2010	n	-	606	0	0	117	1	4	1,400,000
Cow Creek	6/24/2010	7/3/2010	n	-	969	0	0	189	3	0	2,100,000
Reservoir	9/12/2010	9/16/2010	y	1,890,446	778	1	0	375	8	6	2,000,000
Four Mile Canyon	9/13/2010	9/17/2010	y	4,009,529	5,861	4	0	907	20	172	9,500,000
Indian Gulch	3/20/2011	3/25/2011	y	1,274,397	1,570	0	0	275	4	0	2,100,000
Burning Tree	3/24/2011	3/25/2011	n	-	1,662	0	0	200	1	0	-
Crystal	4/1/2011	4/11/2011	y	1,216,363	2,937	3	0	126	2	13	2,800,000
Duckett	6/12/2011	6/24/2011	y	987,749	4,610	1	0	26	1	0	6,600,000
Lower North Fork	3/26/2012	4/2/2012	y	-	3,218	1	3	0	0	27	4,400,000
Hewlett	5/14/2012	5/22/2012	n	-	7,685	2	0	202	3	0	3,400,000
High Park	6/9/2012	6/30/2012	y	3,122,300	87,505	3	1	686	5	371	38,400,000
Waldo Canyon	6/23/2012	7/10/2012	y	-	18,248	5	2	67	1	347	15,700,000

Table 2. Difference-in-Differences: Proximity

	(1) ln(price)	(2) ln(price)	(3) ln(price)
Sample Restrictions:	<30km	<30km	<10km
(2km Ring) x (Year 1)	-0.0870***	-0.0849***	-0.0829***
	(0.0241)	(0.0238)	(0.0219)
(2km Ring) x (Year 2)	-0.0756***	-0.0759***	-0.0779***
	(0.0266)	(0.0263)	(0.0249)
(2km Ring) x (Year 3)	-0.0674**	-0.0667**	-0.0677**
	(0.0340)	(0.0338)	(0.0319)
Observations	90,955	90,955	53,904
R-squared	0.729	0.730	0.767
Fire x Treatment Group Trends:	Yes	Yes	Yes
Year x Quarter x Fire FE:	No	Yes	Yes

Note: Robust standard errors in parentheses. ***p<.01, **p<0.05, *p<0.1. Geographic controls include: Second order polynomials in viewshed size, slope and elevation in addition to county fixed effects. Structural controls include second order polynomials in square footage and building age as well as basement square footage and indicators for number of bedrooms, number of bathrooms. Models are limited to W.U.I. properties located within 30km of wildfire burn scars which transact within (+/-) 3 years of the fire in their region unless otherwise noted.

Table 3. Difference-in-Differences: Visibility

	(1) *ln(price)*	(2) *ln(price)*	(3) *ln(price)*
(View of Fire) x (Year 1)	-0.0415***	-0.0396**	-0.0313**
	(0.0156)	(0.0156)	(0.0148)
(View of Fire) x (Year 2)	-0.0475**	-0.0445**	-0.0350*
	(0.0203)	(0.0200)	(0.0193)
(View of Fire) x (Year 3)	-0.0509*	-0.0473*	-0.0396
	(0.0265)	(0.0262)	(0.0251)
(Distance) x (Year 1)	-	-	0.000243***
	-	-	(4.83e-05)
(Distance SQ.) x (Year 1)	-	-	-4.04e-08***
			(8.12e-09)
(Distance) x (Year 2)	-	-	0.000280***
	-	-	(5.64e-05)
(Distance SQ.) x (Year 2)	-	-	-4.65e-08***
			(9.45e-09)
(Distance) x (Year 3)	-	-	0.000363***
	-	-	(6.98e-05)
(Distance SQ.) x (Year 3)	-	-	-6.30e-08***
			(1.17e-08)
Observations	15,911	15,911	15,911
R-squared	0.818	0.824	0.834
Fire x Treatment Group Trends:	Yes	Yes	Yes
Year x Quarter x Fire Fixed Effects:	No	Yes	Yes

Note: Robust standard errors in parentheses. ***p<.01, **p<0.05, *p<0.1. Geographic controls include: Second order polynomials in viewshed size, slope and elevation in addition to county fixed effects. Structural controls include second order polynomials in square footage and building age as well as basement square footage and indicators for number of bedrooms, number of bathrooms. Models are limited to W.U.I. properties located within 5km of wildfire burn scars which transact within (+/-) 3 years of the fire in their region unless otherwise noted.

Table 4. Difference-in-Differences: Latent Risk

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(price)	*ln(price)*	*ln(price)*	*ln(price)*	*ln(price)*	*ln(price)*
Sample Restrictions:	<30km	<30km (>5km)	<30km (>5km)	<30km (>5km, No View)	<20km (>5km, No View)	<10km (>5km, No View)
(High Latent Risk) x (Year 1)	-0.0594***	-0.0735***	-0.0660***	-0.0716**	-0.0917**	-0.0878**
	(0.0225)	(0.0244)	(0.0247)	(0.0320)	(0.0357)	(0.0430)
(High Latent Risk) x (Year 2)	-0.0368	-0.0543	-0.0287	-0.0604	-0.0422	-0.0359
	(0.0321)	(0.0374)	(0.0377)	(0.0439)	(0.0493)	(0.0585)
(High Latent Risk) x (Year 3)	0.0540	-0.0318	-0.00910	0.0155	0.0384	-0.0123
	(0.0494)	(0.0645)	(0.0637)	(0.0757)	(0.0854)	(0.0886)
Observations	30,493	23,565	23,565	15,712	12,733	6,987
R-squared	0.684	0.656	0.656	0.693	0.692	0.655
Fire x Treatment Group Trend	Yes	Yes	Yes	Yes	Yes	Yes
Year x Quarter x Fire FE	No	No	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses. ***p<.01, **p<0.05, *p<0.1. Geographic controls include: Second order polynomials in viewshed size, slope and elevation in addition to county fixed effects. Structural controls include second order polynomials in square footage and building age as well as basement square footage and indicators for number of bedrooms, number of bathrooms. Models are limited to W.U.I. properties located within 30km of wildfire burn scars which transact within (+/-) 3 years of the fire in their region unless otherwise noted.

Table 5. Duration Analysis: Proximity

	Cox Model: Hazard Ratios
Sample Restrictions	*<30km*
(2km Ring) x (Year 1)	1.053
	[0.442]
(2km Ring) x (Year 2)	1.107
	[0.225]
(2km Ring) x (Year 3)	1.215**
	[0.046]
Observations	598,956

Note: P-values are reported in brackets, ***p<.01, **p<0.05, *p<0.1. Standard errors clustered at property level. Geographic controls include: Second order polynomials in viewshed size, slope and elevation in addition to year-quarter-fire, county, and fire by treatment group fixed effects. Structural controls include second order polynomials in square footage and building age as well as basement square footage and indicators for number of bedrooms, number of bathrooms. Models are limited to W.U.I. properties located within 30km of wildfire burn scars unless otherwise noted.

Table 6. Duration Analysis: Visibility

	Cox Model: Hazard Ratios
Sample Restrictions	*<5km*
(View of Fire) x (Year 1)	0.896
	[0.159]
(View of Fire) x (Year 2)	0.882
	[0.147]
(View of Fire) x (Year 3)	0.924
	[0.421]
Observations	97,916

Note: P-values are reported in brackets, ***p<.01, **p<0.05, *p<0.1. Standard errors clustered at property level. Geographic controls include: Second order polynomials in viewshed size, slope and elevation in addition to year-quarter-fire, county, and fire by treatment group fixed effects. Structural controls include second order polynomials in square footage and building age as well as basement square footage and indicators for number of bedrooms, number of bathrooms. Models are limited to W.U.I. properties located within 30km of wildfire burn scars unless otherwise noted.

Table 7. Duration Analysis: Latent Risk

	Cox Model: Hazard Ratios
Sample Restrictions	<30km (>5km, No View)
(High Latent Risk) x (Year 1)	1.19*
	[0.071]
(High Latent Risk) x (Year 2)	1.088
	[0.521]
(High Latent Risk) x (Year 3)	0.884
	[0.517]
Observations	280,739

Note: P-values are reported in brackets, ***p<.01, **p<0.05, *p<0.1. Standard errors clustered at property level. Geographic controls include: Second order polynomials in viewshed size, slope and elevation in addition to year-quarter-fire, county, and fire by treatment group fixed effects. Structural controls include second order polynomials in square footage and building age as well as basement square footage and indicators for number of bedrooms, number of bathrooms. Models are limited to W.U.I. properties located within 30km of wildfire burn scars unless otherwise noted.