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Wildfire risk, salience & housing demand

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ABSTRACT

In this paper we develop a parsimonious model that links underlying changes in location-specific risk perceptions to housing market dynamics. Given estimates of both the price and quantity effects induced by shocks to agents' beliefs, the model allows us to draw inferences about the underlying changes in risk perceptions that gave rise to observed housing market dynamics. We apply the model's predictions to an empirical analysis of the influence of severe wildfires on housing prices and sales rates in the Front Range of Colorado. Interpreted in the context of the model, our empirical results suggest that natural disasters lead to significant, but short-lived increases in risk perceptions.

1. Introduction

Building on the early work of Tversky and Kahnemann (Tversky and Kahneman, 1974; Kahneman and Tversky, 1979), social scientists increasingly focus on the role that salience plays in explaining individual behavior in the face of risk. Formally defined, salience is "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). In recent work, Bordalo et al. (2012) rationalize salience with a theory of choice over lotteries where agents replace true or objective probabilities over states with subjective, decision weights. Their model can effectively rationalize many ostensible inconsistencies in decision making including preference reversals and frequent risk-seeking behavior.

While well understood at a theoretical level, direct empirical evidence of saliency dynamics, and how they translate into behavioral outcomes, is limited. From a policy perspective, saliency dynamics are particularly relevant for understanding market and individual behaviors in the face of natural hazards risks since households' perceptions of risk are inextricably linked to their willingness to mitigate against risk as well as their preference for living in disaster prone areas. These observations motivate us to ask, "To what extent do natural disasters impact risk salience and how do saliency dynamics subsequently evolve over time?"

Natural disasters are an apt context to investigate salience dynamics for a number of reasons. First, they are plausibly exogenous shocks to agents' beliefs over disaster risk. After witnessing a natural disaster, agents may re-weight their perceived probability of a catastrophic event occurring in the future. Second, saliency dynamics in the face of natural disaster risk have important real world consequences. In particular, when households hold inaccurate beliefs, we may observe sub-optimal private risk mitigation strategies and an inefficient level of public support for disaster management policies. Finally, both the frequency and severity of natural disasters is increasing. Based on data assembled by the National Oceanic and Atmospheric Administration,[1]

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[1] These statistics are based on the National Centers for Environmental Information Billion-Dollar Weather and Climate Disasters database available here: https://www.ncdc.noaa.gov/billions/events/US/1980-2017.

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out of the 10 ten most costly disasters to impact the United States since 1980, 6 occurred in the last decade.[2] This trend is particularly strong in the case of wildfires. For instance, annual wildland fire statistics provided by the National Interagency Coordination Center (NICC) show that between the 1980s and 2010s, the annual average number of acres burned each year in the United States increased 197%.[3] Between 2010 and 2017, NICC wildfire statistics indicate that an average of 66, 519 wildfires impacted the United States each year.

In this paper, we develop a new approach to investigating the saliency dynamics of a natural disaster by formulating a simple theoretical model of preference-based sorting which links housing price and housing transaction dynamics to underlying changes in risk perceptions. We then empirically model the link between wildfire occurrences and housing market dynamics using the theoretical framework as a lens through which we can gain inference on the underlying shifts in risk perceptions that arise as a result of these wildfires.

In our model, residents choose between two communities which may experience potentially differential shocks to risk saliency following the occurrence of a natural disaster. The model allows us to interpret relative price and quantity dynamics in terms of the relative strength of salience shocks between extant residents located in “high-risk” communities (which we refer to as treated locations) and potential buyers initially located in “zero-risk” communities (which we refer to as control regions). If risk-saliency following a disaster does not vary across extant residents and potential buyers, our model predicts a decrease in prices, but no change in the proportion of homes that sell; all agents update their subjective beliefs about the probability of a fire, 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. We explore these observations more formally below and then link the models predictions to an empirical analysis of wildfire.

In addition to climate-driven increases in wildfire, social dynamics are also playing a role in increasing the societal costs associated with fire. As a result of population de-concentration, 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 et al., 2003; Radeloff et al., 2005). It has been argued that 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). On a second margin, private mitigation behaviors, such as investment in fire-resistant building materials and fuel reduction treatments around one’s property (which may reduce property-specific risks as well as the overall risk of fire in forested lands) appear to occur at much lower levels than would be socially optimal. (Shafran, 2008; Steelman, 2008). Both the decision to develop in disaster-prone areas as well as the decision to privately mitigate against risk are influenced by households’ perceptions of disaster risk.

We center our empirical analysis on wildfires which occurred in WUI areas of the Colorado Front Range (COFR) and utilize data detailing the universe of housing transactions for 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 drivers of risk saliency. These include *proximity* to wildfire and *view* of wildfire burn scars – factors which also capture the dis-amenity effects of fire – in addition to property-specific indexes of the actual *latent risk of wildfire* which may be associated with susceptibility to saliency shocks. 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.

To preview our key findings, we show that housing values in high-risk zones, relative to housing values in low-risk zones, incur an immediate price shock in the year following a wildfire. However, this effect is only temporary; prices of homes in high-risk areas quickly return to baseline levels two to three years after a fire. This empirical finding suggests that natural disasters lead to immediate, but short-lived increases in risk-perceptions. We also find a relative, but short-lived increase in the proportion of homes that sell in high-risk areas. Interpreted in light of the key findings of our theoretical model, these empirical results seem to demonstrate that disasters induce stronger changes in risk saliency among residents located in risk-prone regions at the time of an event.

We proceed as follows. We begin by providing a background on the existing work on housing markets and natural hazards risk in Section 2. We summarize our theoretical model of price-capitalization and preference-based sorting in response to changing risk perceptions in Section 3. We then characterize our study area and the details behind the construction of our geo-spatial data in Section 4. We present our empirical methodology in Section 5 and our findings in Section 6. We summarize and conclude in Section 7.

[2] This statistic was generated by identifying the top ten most costly disasters based on their CPI-adjusted estimated cost (in billions) and flagging those which impacted the United States between 2008 and 2018.

[3] These statistics were computed from data available from the National Interagency Fire Center available at https://www.nifc.gov/fireInfo/fireInfo_stats_totalFires.html. These data provide information detailing the total number of fires and total acres burned each year in the United States between 1926 and 2017; however, data prior to 1983 were assembled using a different reporting process than is currently in use. As such, we compute the the average number of acres burned for the 1980s by averaging the total number of acres burned each year between 1983 and 1989; over this time period, 2, 481, 611 acres of land burned each year. Likewise, we compute the average number of acres burned for the 2010s by averaging the total number of acres burned each year between 2011 and 2017; over this time period, 7, 373, 428 acres of land burn each year in the United States.

2. Background

At its core, this work utilizes a basic theoretical model as a lens through which the impact of wildfires on risk salience can be inferred from housing market dynamics. Our conception of risk salience arises from the early work of Tversky and Kahnemann (see for instance: Tversky and Kahneman, 1974; Kahneman and Tversky, 1979). These authors provided new insight into how agents make decisions in the face of risk. They suggested that in the presence of uncertainty, decision-makers will often resort to simple heuristic principles in order to reduce the computational burden of predicting or assessing the likelihood of events. Specifically, Tversky and Kahnemann's *Availability Heuristic* posits that agents may "assess the frequency of a class or the probability of an event by the ease with which instances or occurrences can be brought to mind." (Tversky and Kahneman, 1974). As a result, while simplifying the computational burden, agents may find themselves acting on a set of beliefs that are systematically inaccurate and biased towards information provided by more recent or poignant events. This early work continues to resonate as social scientists focus increased attention on the role that salience plays in explaining individual behavior in the face of risk.

We link conceptions of risk saliency to an empirical analysis of housing markets and wildfire – considering both prices and transaction rates. While transaction rates remain largely unexplored in this context, there is a large extant literature on the effects of wildfire on housing prices. Examples include Loomis (2004); Troy and Romm (2004); Donovan et al. (2007); Mueller and Loomis (2008); Huggett et al. (2008); Mueller et al. (2009); Champ et al. (2009); Stetler et al. (2010), and Mueller and Loomis (2014).

Loomis (2004) 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. Likewise, using a sample of wildfires in Southern California, Mueller and Loomis (2008) and Mueller et al. (2009) find that home prices located within 1.75 miles of a wildfire drop on the order of approximately 9.7% in the year immediately following a fire. Finally, Stetler et al. (2010) consider the impacts of fire in northwest Montana. Similar to our work, the authors consider the impacts of fire through a spatial (i.e. distance to fire) and a visual (i.e. view of a burn scar) dimension, but differs from our work in that they do not consider the effects a fire has on the discount homeowners subsequently place on homes in designated risk areas.

Donovan et al. (2007) evaluate 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-ratings. 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.

In terms of price effects, our empirical work is in some ways closest to that of Kousky (2010), Bin and Landry (2013) and Atreya et al. (2013) who analyze the effects of major floods on housing prices.[4] Bin and Landry (2013) 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%–8.8% hurricane-induced flood-risk discount which lasts for 5–6 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 7–9 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. From a risk saliency perspective, the potential for inference from the extant hedonic work on floods and fires is limited. To demonstrate that changes in risk perceptions underlie the observed price changes, we would want to be certain that other, more direct channels are not responsible. Three specific areas of potential concern are: 1) proximate neighborhood infrastructure was harmed by the event; 2) having damaged properties nearby generates a spillover effect a la Campbell et al. (2011); and 3) the presence of composition effects – driven by differences in the structural characteristics of houses that sell before and after fire.

To circumvent these difficulties, Hallstrom and Smith (2005) compare 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 act on the information conveyed by a severe storm. Similar to Bin and Landry (2013) and Atreya et al. (2013), Atreya and Ferreira (2015) investigate the impact of a flood on flood-risk saliency by comparing changes in homes prices in the floodplain before and after a significant flood in Albany, George. A unique feature of this study is that the authors attempt to disentangle saliency and damages by distinguishing properties in inundated and non-inundated portions of the floodplain. Within the hedonic literature, other notable works include Tobin and Montz (1988), Bernknopf et al. (1990), McCluskey and Rausser (2001), Gayer et al. (2002), Carbone et al. (2006), Hansen et al. (2006), Rajapaksa et al. (2016) and Herrnstadt and Sweeney (2017).

Going beyond the hedonic literature, Anderson et al. (2018) suggests that salient events, through their influence on political support for expenditures on public mitigation programs, may lead to inefficiently high levels of public spending on programs such as fuels treatments. Using national data on regional floods and flood insurance policies, Gallagher (2014) finds that flood insurance take-up increases the year after a flood, but steadily decreases to baseline levels thereafter. Finally,

[4] In other works, the impact of additional environmental hazards and risks have been considered 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).

McCoy and Zhao (2018) investigate the impact of Hurricane Sandy on flood risk saliency by estimating the impact the Hurricane had on changes in the rate at which homeowners in the floodplain invest in capital improvements in their homes.

3. A model of natural disasters, risk-salience and preference-based sorting

We consider an economy comprised of a measure 1 continuum of individuals who choose to live in one of two locations $j \in \{t, c\}$. We conceptualize t as a region that is prone to treatment by a natural disaster and c as a control area which has zero risk of a natural disaster. In the context of wildfire, for example, t is an area providing amenity values to some, but with heightened wildfire risk. Formally, for individual i, we denote the relative amenity value of t as a_i which is distributed according to the cumulative distribution function $F_a(\cdot)$. Should a fire occur, individuals in location t experience damages d. We assume that agents hold heterogeneous beliefs over the probability of a natural disaster, π_i, whose distribution in the population is described by the cumulative distribution function $F_\pi(\cdot)$ which is assumed to be independent of $F_a(\cdot)$.

Conditional on choosing location j, each individual consumes a fixed quantity of housing at price p_j. We fix the price level in c at $\overline{p}_c$ and allow the price level in the treated area (p_t) to adjust endogenously in order to clear both housing markets. All individuals are endowed with the identical income level y.

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

$$u_{c,i} = y - \overline{p}_c.$$

Utility from choosing to live in t depends on whether or not a fire occurs. In the non-disaster state, utility is given by:

$$u_{t,i}^{nd} = y - p_t + a_i,$$

while utility conditional on a disaster occurring is given by:

$$u_{t,i}^{d} = y - p_t + a_i - d.$$

Thus, agent ω's subjective expected utility from choosing t is given by:

$$u_{t,i} = y - p_t + a_i - \pi_i \cdot d.$$

We denote the individual specific component of utility by $\omega_i = a_i - \pi_i \cdot d$ whose distribution is given by:

$$F_w(w) = \int F_a(w + \pi d) dF_\pi.$$

Finally, we assume that a unit measure of housing supply q is split across the two communities so that $q_t + q_c = 1$ with $q_t, q_c > 0$.

In equilibrium, individuals choose the location which maximizes their subjective utility giving rise to stratification around a critical value of ω, $\omega_0^\star$, with individuals choosing location t when:

$$\omega \geq p_t - \overline{p}_c = \omega_0^\star. \tag{1}$$

The equilibrium price level in t, p_t, is then identified by the requirement that land markets clear which is expressed in equation (2):

$$F_\omega\left(\omega_0^\star\right) = q_c. \tag{2}$$

That is, p_t adjusts such that the proportion of individuals satisfying $\omega < \omega_0^\star$ exactly equals the proportion of the housing supplied in c. We denote by p_t^0 the market clearing price in the baseline equilibrium. Finally, we conceptualize the salience-effects of a natural disaster by assuming that when a disaster occurs in the treatment region, agents experience a non-decreasing update to their subjective beliefs about the probability of a disaster. This approach is motivated by the model of Bordalo et al. (2012) under which decision makers overemphasize states that draw attention, in effect, weighting states of the world with more salient payoffs more heavily. Assuming that this salience-effect may be stronger for those living in t at the time of the fire, we allow for heterogeneity in the size of the probability shift, $\Delta\pi$, across individuals based on their location in the baseline equilibrium:

$$\Delta\pi_t \geq \Delta\pi_c \geq 0, \;\; \Delta\pi_t > 0.$$

We also assume that a disaster leads to a non-increasing shift in the relative amenity value of region t, Δa, that is homogeneous across individuals. Thus, following a disaster, the utility achieved in location t may now also depend on an individual's location in the initial equilibrium:

$$u_{t|c} = y - p_t + \omega - \Delta\pi_c d + \Delta a \tag{3}$$

$$u_{t|t} = y - p_t + \omega - \Delta\pi_t d + \Delta a. \tag{4}$$

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

OBSERVATION 1: Conditional Stratification and Dis-Amenity Confounds.

In equilibrium, conditional on their realized relative amenity value for t, individuals completely stratify based on subjective probability beliefs, with all of those with subjective beliefs below some threshold level $\overline{\pi}$ locating in region t. Similarly, conditional on realized subjective risk probabilities, individuals completely stratify based on amenity values, with all of those with amenity values above some threshold level $\overline{a}$ locating in the region t as well. Additionally, non-zero amenity effects from a disaster will potentially confound empirical identification of saliency effects.

Conditional stratification arises directly from the equilibrium sorting condition in equation (1) while the potential for dis-amenity confounds are apparent from equations (3) and (4).

OBSERVATION 2: Positive Saliency Shocks Reduce p_t.

The post-disaster equilibrium price in t is strictly less than the pre-disaster equilibrium price: $p_t^1 < p_t^0$.

Observation (2) follows directly from the following. First, because $\Delta\pi > 0$ and $\Delta a \leqslant 0$, for any $p_t \geq p_t^0$, there exists $\delta > 0$ such that for any $\omega \in [\omega_0^\star,\ \omega_0^\star + \delta)$, $y - p_t + \omega - \Delta\pi_t + \Delta a < y - \overline{p}_c$. Because $F_\omega(\cdot)$ 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 $\Delta\pi_c \geq 0$, 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 $p_t^1 < p_t^0$.

In the remaining observations, we focus exclusively on the impact of shocks to risk salience and thus for parsimony, and without loss of generality, suppress the dis-amenity effects.

OBSERVATION 3: No Resorting Under Equal Shocks to Risk Salience.

If the disaster saliency doesn't vary with baseline equilibrium location choice ($\Delta\pi_t = \Delta\pi_c = \Delta\pi$) 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 (2) is increasing in $\Delta\pi$. Specifically: $\partial p_t^1/\partial\Delta\pi = -d$.

The first half of Observation (3) stems from the fact that when $\Delta\pi_t = \Delta\pi_c$ 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 $\widehat{F}_\omega(\omega) = F_\omega(\omega + \Delta\pi d)$ where each individual's value of ω has essentially been shifted down by $\Delta\pi$. Thus, in equilibrium, the sorting of individuals across the two locations must be preserved. The second half of Observation (3) follows from totally differentiating the post-disaster equivalent of equation (2):

$$\widehat{F}_\omega\left(p_t^1 - \overline{p}_c\right) = F_\omega(p_t^1 - \overline{p}_c + \Delta\pi d) = q_c.$$

OBSERVATION 4: Unequal Shocks to Risk Salience Lead to Resorting.

If disaster saliency is higher for individuals initially located in t $\left(\Delta\pi_t > \Delta\pi_c\right)$ then there will exist $\delta_t, \delta_c > 0$ such that following the disaster 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 (4) is as follows. First, note that because $\Delta\pi_t > \Delta\pi_c$ if it is optimal for all individuals with $\omega \geq \omega_0^\star$ to choose t post-disaster then there exists $\delta > 0$ such that for any $\omega \in [\omega_0^\star - \delta,\ \omega_0^\star)$,

$$y - p_t^1 - \Delta\pi_c d + \omega > y - p_t^1 - \Delta\pi_t d + \omega_0^\star \geq y - \overline{p}_c.$$

In other words, if p_t^1 is such that all individuals who were initially located in t choose to remain in t post-disaster, then for some values of $\omega < \omega_0^\star$ it will now be optimal to locate in t post-disaster as well. However, by construction, the measure of $\left\{\omega \mid \omega \geq \omega_0^\star - \delta\right\}$is greater than q_t and this cannot 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 $y - p_t^1 - \Delta\pi_t d + \omega < y - \overline{p}_c$. 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 $\left(\delta_t,\ \delta_c\right)$ are identified by the optimality conditions. The range of $\omega \geq \omega_0^\star$ values for which region c is optimal in the post-disaster equilibrium must satisfy:

$$y - p_t^1 - \Delta\pi_t d + \omega < y - \overline{p}_c.$$

Thus, the relevant range for ω is:

$$\omega_0^\star \leq \omega < p_t^1 - \overline{p}_c + \Delta\pi_t d = \delta_t.$$

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

$$y - p_t^1 - \Delta\pi_c d + \omega > y - \overline{p}_c.$$

And the relevant range for ω is:

$$\delta_c = p_t^1 - \overline{p}_c + \Delta\pi_c d \leq \omega < \omega_0^\star.$$

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:

$$F_{\omega}\left(p_t^1 - \overline{p}_c + \Delta\pi_t d\right) - F_{\omega}\left(\omega_0^{\star}\right) = F_{\omega}\left(\omega_0^{\star}\right) - F_{\omega}\left(p_t^1 - \overline{p}_c + \Delta\pi_c d\right). \tag{5}$$

Recalling that $F_{\omega}\left(\omega_0^{\star}\right) = q_c$, the new market clearing price is implicitly defined by[5]:

$$\frac{F_{\omega}\left(p_t^1 - \overline{p}_c + \Delta\pi_t d\right) + F_{\omega}\left(p_t^1 - \overline{p}_c + \Delta\pi_c d\right)}{2} = q_c. \tag{6}$$

To summarize our theoretical results, the treated and control regions in our model delineate locations based on residents' experience with or their perceived likelihood of a natural disaster. 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 do not 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.

The intuition underlying these results is as follows. The baseline equilibrium is characterized by a subset of the agents in the model sorting into t (those with a value of $\omega > \omega_0^{\star}$) and a subset of agents in the model sorting into c (those with a value of $\omega < \omega_0^{\star}$). Recalling that $\omega_i = a_i - \pi_i d_i$, this baseline equilibrium is therefore characterized by agents with systematically smaller baseline priors on the likelihood of a disaster (π_i) – and thus systematically higher values of ω_i – sorting into the fire-prone region t. When a fire happens, agents update their priors (π_i) by the amount $\Delta\pi_i$, in effect, weighting the likelihood of a disaster more heavily.

In the event that a fire induces an equal shock to salience ($\Delta\pi_i = \Delta\pi$ for all i) willingness to pay for homes in the fire prone region falls, but therefore falls symmetrically for agents in t at the time of a fire and agents in c at the time of fire. The overall decrease in the willingness to pay for homes in t manifests with a decrease in prices in t. However, to the extent that the magnitude of the decrease in willingness to pay for homes in t by agents initially located in t at the time of a fire is proportional to the magnitude of the decrease in the willingness to pay for homes in t by agents initially located in c, the model does not predict any resorting of individuals from c to t.

In contrast, if a fire has a stronger shock to salience among residents initially located in t at the time of fire (i.e.$\Delta\pi_i = \Delta\pi_t$ for all i in t, $\Delta\pi_i = \Delta\pi_c$ for all i initially in c, and $\Delta\pi_t > \Delta\pi_c$), while the willingness to pay for homes in t falls for all agents, the willingness to pay for homes in t falls relatively more among agents initially located in t. Thus, unequal shocks to salience effectively place a wedge between the lowest price agents in t would be willing to accept and the highest price agents initially in c would be willing to pay for a home in a fire-prone region: To the extent that homeowners in t have a stronger shock to their priors, the decrease in the lowest price these agents would be willing to sell their home for is relatively smaller in absolute value than the corresponding decrease in the highest price an agent outside of t would be willing to pay for said home. Through this channel, the model effectively predicts that unequal shocks to salience manifest with a portion of agents initially located in t selling their homes to agents initially located in c.

In constructing the model, we make three simplifying assumptions. First, we assume that individuals choose to live in one of two locations. Second, we assume that location c has zero risk of a natural disaster. Finally, we assume homogeneous income levels. These assumptions simplify the presentation of the model, improve transparency regarding the mechanism driving each observation, and facilitate derivation of our general results. While tractability of a general analytical solution would become an issue, the model's key insights would still hold if it were extended to consider multiple communities. Similarly, extending the model to consider communities differentiated by a continuous measure of risk would not undermine our main findings.

The main driver of our results is the fact that symmetric saliency shocks reduce demand for higher risk regions, but preserve relative preference orderings across agents in each community whereas asymmetric saliency shocks have the added effect of inducing changes in relative preference orderings resulting in geographic sorting on the basis of agents' ex-post beliefs regarding the likelihood of a disaster. This fundamental driver is robust to a wide range of alternative model specifications. However, this discussion is predicated on the assumption that d_i (which captures the dis-amenity effects from experiencing a fire which can also be interpreted as tolerance for risk) is independent of other individual attributes. If d_i is correlated with other attributes, the model becomes more complicated. For example, if income is correlated with risk tolerance, we might expect transaction rate dynamics under assymetric saliency shocks to potentially behave more similar to the transaction rate dynamics under symmetric saliency shocks.

Finally, while we focus on saliency shocks, our theoretical results carry through for amenity shocks as well. Amenity shocks contrast to saliency changes in that they are observable and may be relatively more persistent. In such cases, it may be difficult to disentangle amenity changes from saliency dynamics. As we discuss below, this potential confound motivates our empirical analysis of latent risk which involves identifying portions of the landscape where the dis-amenity effects of wildfire are plausibly absent.

[5] Total differentiation of the market clearing condition in equations (6) and (5) 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 (5) and (6) in Appendix A.

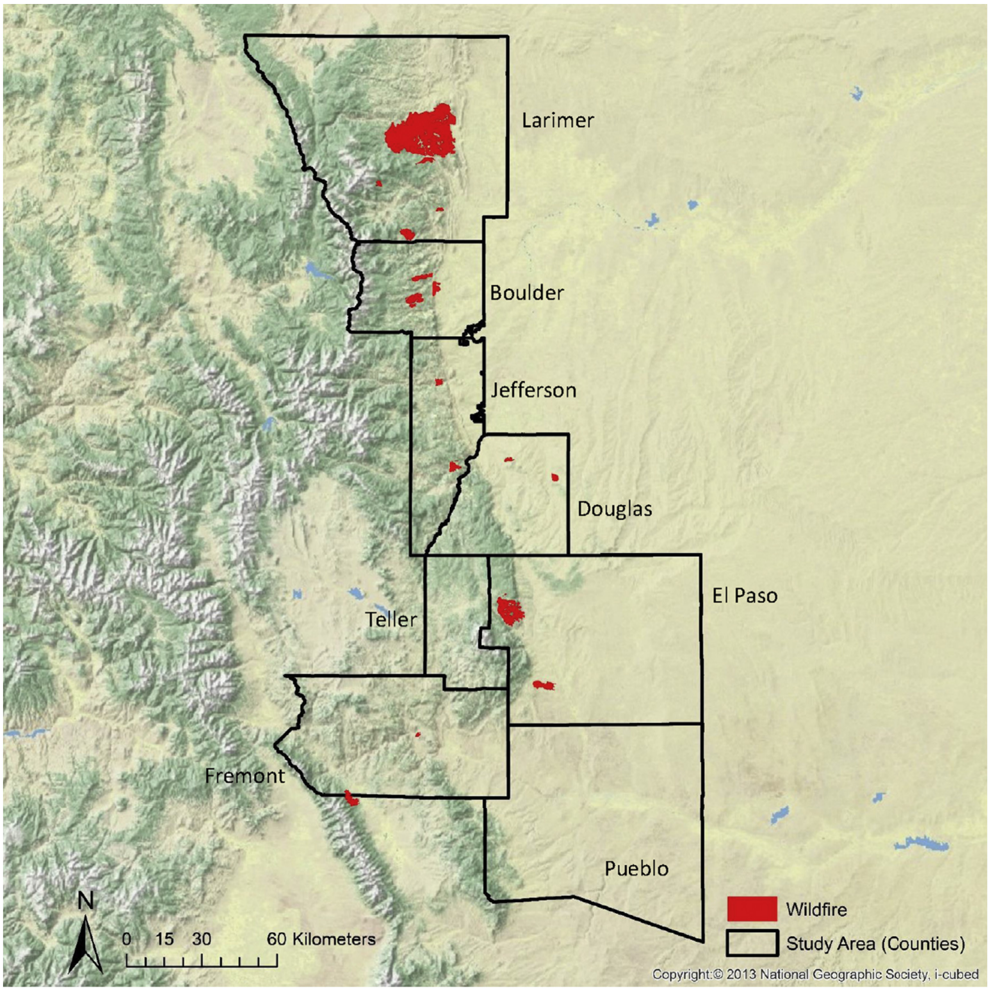


Fig. 1. Study area and wildfire burn scars.

4. Study area and data

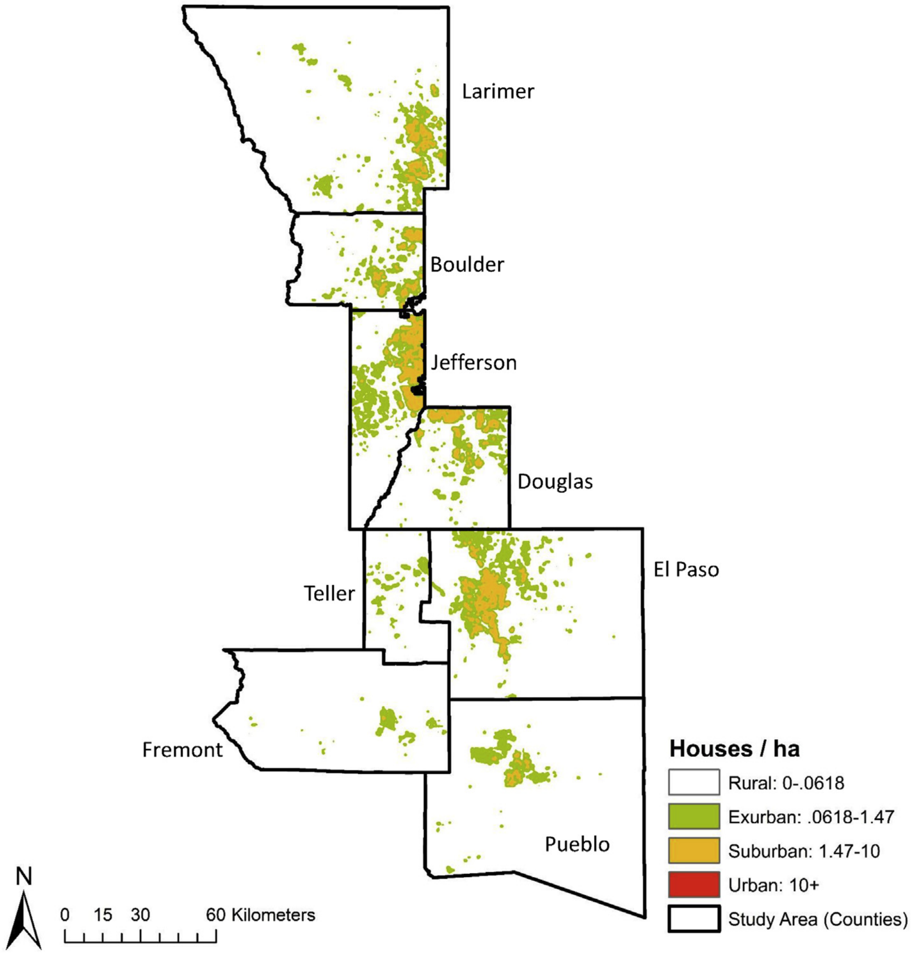
The Colorado Front Range forms a barrier between the easternmost range of the Rocky Mountains and the Great Plains regions of eastern Colorado. The region's population increased by 30% from 1990 to 2000 with the growth predominantly concentrated in the interface and intermix communities of the WUI. (Travis et al., 2002). As depicted in Fig. 1, we conduct our analysis across 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.[6] (Radeloff et al., 2005). The WUI is composed of interface and intermix regions. In both types of WUI regions identified by the data provided by the SILVIS Lab, 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 1325 acres large that is at least 75% vegetated.

We obtained a list of wildfire incidents from FEMA's disaster declaration web-page.[7] We use FEMA as a reference point for identifying severe wildfires which records each fire's start-date. 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[8] maintained by the National Inter-agency Fire Center. Spatial data-sets for each fire's burn scar were acquired from

[6] http://silvis.forest.wisc.edu/.

[7] http://www.fema.gov/disasters.

[8] Link: https://fam.nwcg.gov/fam-web/. The ICS-209 incident numbers for each fire in our sample are: CO-ARF-238; CO-BLX-116; CO-DGX-1208; CO-LRX-000022; CO-BLX-9008; CO-FCQ-175; CO-FRX-000590; CO-RMP-000197; CO-LRX-000545; CO-BLX-000321; CO-JEX-000217; CO-DGX-000264; CO-LRX-1096; CO-PSF-000801; CO-JEX-000176; CO-ARF-000228; CO-LRX-329; CO-PSF-000636.



Notes: This graph, which illustrates the density of housing units in our study area, was produced in *ArcMap 10.4* using the *Kernel Density Tool* with a 50m x 50m output cell size and an 1000m search radius. Map units are expressed in houses per hectare (houses / ha).

Fig. 2. Study area and housing density.

the Geospatial Multi-Agency Coordination Group (GeoMAC)[9] and Monitoring Trends in Burn Severity (MTBS)[10]. We include in our analysis any fire with a burn area exceeding 500 acres which appears in either the GeoMAC or MTBS data-sets. The spatial distribution of the wildfires in our study area are depicted in Fig. 1.

As illustrated in Fig. 1, the majority of the wildfires in our study area are concentrated along the lower forested montane areas of the Colorado Front Range. Here, elevation ranges from approximately 1700 m–2600 m. Statewide, annual average temperatures have increased by 1.1 °C in the past 30 years with similar increases in the lower montane region of the Colorado Front Range. (McGuire et al., 2012; Lukas et al., 2014; Rother and Veblen, 2016). The southern portion of the lower forested montane region of the COFR is typically composed of ponderosa pine while the northern portion is composed of both pondersoa pine and douglas-fir. (Veblen et al., 2000). The front range has experienced notable changes in disturbance regimes as a result of fire suppression (Veblen et al., 2000) as well as changes in land-use activity (Riebsame et al., 1996; Theobald et al., 2000; Travis et al., 2002). In our study area, between 2000 and 2012 the front range experienced on average 1.5 fires each year burning a total of 161,575 ha.[11] According to Rother and Veblen (2017), forests in the lower montane zone have been slow to recover from fire. For instance, Rother and Veblen (2016) indicate that for a sample of fires in the low-elevation areas of our study area which burned roughly 162,000 acres between 1996 and 2003, only 2%–38% of sampled sites indicated signs of recovery which is attributed to both higher severity fires and warmer climates. Further, even after 8–15 years have passed, 59% of surveyed plots

[9] http://www.geomac.gov/index.shtml.
[10] http://www.mtbs.gov/.
[11] Please refer to Veblen et al. (2000) for detailed description of the forest ecology of our study area as well as historic and modern fire regimes.

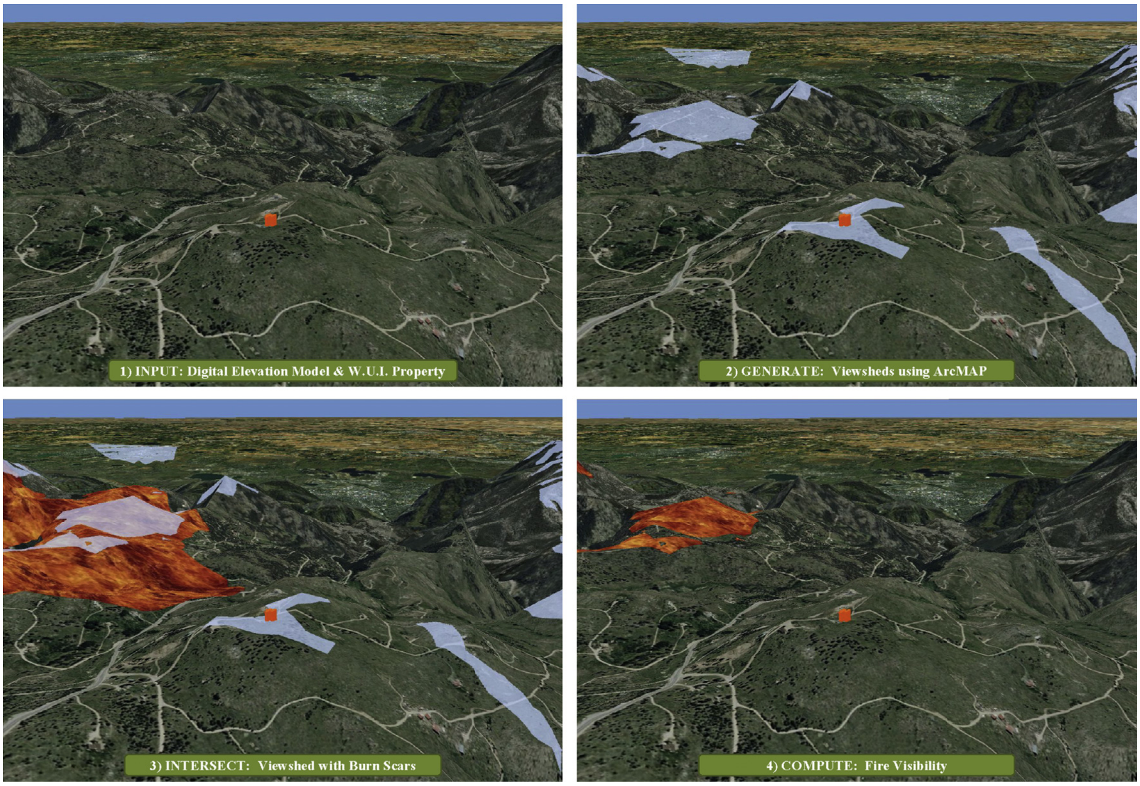


Fig. 3. Illustration of viewshed analysis.

failed to contain any conifer seedlings; 83% of the sampled sites were characterized by a very low density of seedlings. (Rother and Veblen, 2016).

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 counties of interest to our study, we observe the universe of transaction histories for 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); 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 geo-referenced locations for each property, we ran a batch geo-coding routine in ArcMap10 which returns the latitude and longitude coordinates for each properties roof-top or parcel-centroid. The density of housing units in our sample is illustrated in Fig. 2.

We limit transactions to arm's length sales of owner occupied, residential single family residences. Properties lying in the 1st or 99th percentile with respect to square footage or sale price, or the 99th percentile with respect to the number stories, baths, beds, units or rooms were dropped. Houses with a negative age[12] were removed as well. Finally, the transaction dates in our data correspond to closing dates for each home sale which may lead us to mis-classify the timing of the home sale, relative to the timing of a fire. To mitigate concerns stemming from the discrepancy from the actual sale date of each home and the closing date, we drop observations from the sample with a transaction date recorded 0–45 days after a fire.

To determine the portion of the landscape visible from each property in our sample, we perform a Viewshed Analysis[13] in ArcMap10. This method has been used in hedonic models to address the visual impacts of shale gas wells (Muehlenbachs et al., 2015), wind turbines (Sunak and Madlener, 2012), natural landscapes (Walls et al., 2015), and wildfire (Stetler et al., 2010). Given a Digital Elevation Model (DEM) of the terrain which we obtained from the National Map,[14] 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 Fig. 3 for a sample fire and WUI property.

[12] We calculate age using the year each property was sold and the year each property was built.

[13] To increase the computational speed of this algorithm, we limit the search over the DEM to a radius of 20 km of each property.

[14] http://nationalmap.gov/.

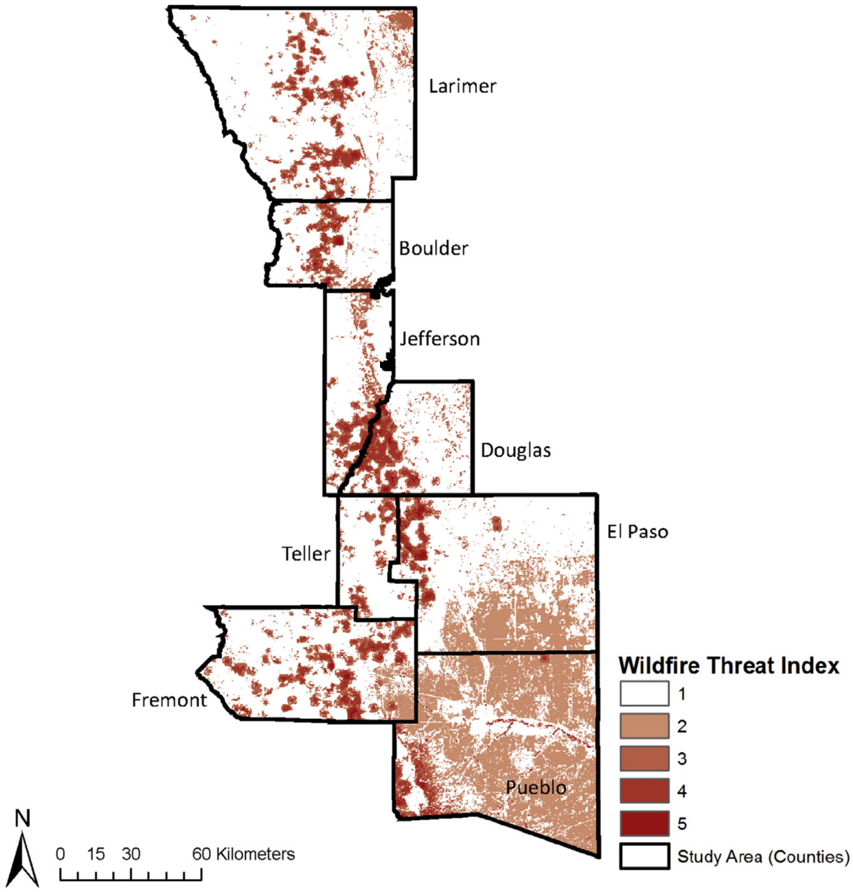


Fig. 4. Study area and wildfire risk.

We measure latent wildfire risk with the Wildfire Threat Index (WTI) developed by the Colorado Wildfire Risk Assessment Project (CO-WRAP[15]) 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 30 m and allows for consistent comparison of wildfire risk between different parts of the State. The WTI ranges from "Lowest Threat" (WTI = 1) to "Highest Threat" (WTI = 5) and is depicted in Fig. 4.

5. Empirical methodology

Our basic empirical approach entails hedonic models of residential housing prices, as well as an analysis of the proportion of homes that sell, across various dimensions of treatment. Contemporaneous shifts in local and macroeconomic housing markets complicate the task of identifying the causal effects of a natural disaster using 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 exposure to fire and compares market dynamics in each treatment group to the outcomes of properties in a control group that do not receive said treatment, but that are otherwise influenced by the same contemporaneous factors. The treatment groups we consider in this paper include *proximity* to wildfire, *view* of wildfire, and *latent wildfire risk*.

These three treatment definitions differ along several dimensions. In our *proximity* analysis, we compare housing price and housing transaction rate dynamics between properties in proximate and less proximate regions of wildfires. This treatment definition is, in part, motivated by its prevalence in the hedonics literature. Proximity may translate into increased saliency, however, we are primarily interested in studying the impacts of fire on price through this dimension in order to identify portions of the landscape for which dis-amenity confounds (as captured by proximity to fire) are present. We subsequently use this information to more cleanly identify a pure, saliency effect in our latent risk analysis by restricting attention to portions of the study area for which spatial dis-amenities are absent. For similar reasons, we also conduct a *visibility* analysis by comparing

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

housing market dynamics between properties with and without a view of a fire.

Finally, and of primary interest to this study, the *latent risk* treatment seeks to identify a salience shock that would arise due to an awareness by buyers and sellers of the relative latent risk associated with the topography and land cover of a given location. In this analysis, we compare housing market outcomes between homes in and out of areas with a high latent risk of fire. To the extent that owners who are living in the WUI are more aware of these topography and landcover related risk factors than are potential buyers, who do not typically live in the area, they may be expected to experience a greater saliency shock relative to potential, non-resident buyers. Further, by choosing treatment and control parcels that are relatively distant from and that have no view of a burn scar, this analysis greatly diminishes concerns about the potential for differences between treatment and control parcels in terms of the direct effects, dis-amenity and otherwise, associated with the proximity and view treatments.

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 drop from our sample observations that lie within 7 km of multiple fires. For each treatment group, our hedonic models take the form:

$$\ln p_{itm} = \alpha \cdot Post_{itm} + \beta \cdot Treat_{im} \times Post_{itm} + \gamma^m \cdot Treat_{im} + T'_{tm}\omega_1 + Z'_i\omega_2 + G'_{it}\omega_3 + \epsilon_{itm}, \tag{7}$$

where $Post_{itm}$ is a post-fire dummy and $Treat_{im}$ is a treatment group indicator variable. 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[16] indicator variables $\left\{ Year^k_{itm} \right\}^3_{k=1}$. This transforms the baseline specification in (7) into:

$$\ln p_{itm} = \sum_{k=1}^{3} \left(\alpha^k \cdot Year^k_{itm} + \beta^k \cdot Treat_{im} \times Year^k_{itm} \right) + \gamma^m \cdot Treat_{im} + T'_{itm}\omega_1 + Z'_i\omega_2 + G'_{it}\omega_3 + \epsilon_{itm}. \tag{8}$$

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, in our more robust specifications we include linear, fire-specific time trends which can vary by treatment group, T'_{itm}. 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'_{it}, include: second-order polynomials in viewshed size, slope and elevation; county fixed effects; year by quarter fixed effects; and, in our most robust specifications, year by quarter by county fixed effects.

The treatment dimensions ($Treat_{im}$) include: Proximity to fire (2 km$Ring_{im}$); view of fire ($View\ of\ Fire_{im}$); and latent wildfire risk ($High\ Latent\ Risk_{im}$). (2 km$Ring_{im}$) is a treatment group indicator variable equal to one for any property located within a 2 km ring of a wildfire, and zero otherwise. Likewise, ($View\ of\ Fire_{im}$) is a treatment group indicator variable equal to one for any property with a view of a wildfire burn scar, and zero otherwise. Finally, ($High\ Latent\ Risk_{im}$) equals one for any property located in a high latent risk zone (areas with wildfire threat indices greater than or equal to two) and zero otherwise. The descriptive statistics of our sample are provided in Table 1.

In order to estimate the impact of fire on the proportion of homes that sell across each dimension of treatment, we first compute the log of the proportion of treated homes, $\ln\left(Sales\ Rate_{Treatment,\tau}\right)$, and the log of the proportion of control homes, $\ln\left(Sales\ Rate_{Control,\tau}\right)$, that sell in each of the 12 quarters immediately preceding, $\tau = \{-12, -11, \dots, -1\}$, and each of the 12 quarters immediately following, $\tau = \{0, 1, \dots, 11\}$, a fire:

$$\ln\left(Sales\ Rate_{Treatment,\tau}\right) = \ln\left[\frac{\text{No. of sales in the treatment group in time } \tau}{\text{No. of homes built in the treatment as of time } \tau}\right],$$

and,

$$\ln\left(Sales\ Rate_{Control,\tau}\right) = \ln\left[\frac{\text{No. of sales in the control group in time } \tau}{\text{No. of homes built in the control group as of time } \tau}\right],$$

for each time period, τ.

Next, letting the subscript $j \in \{Treatment, Control\}$ denote each group of interest, the difference-in-differences analog of equation (8) for estimating the impact of fire on the proportion of homes that sell is:

$$\ln\left(Sales\ Rate_{j\tau}\right) = \sum_{l=1}^{3} \left(\alpha^l \cdot Year^l_{j\tau} + \beta^l \cdot Treat_j \times Year^l_{j\tau} \right) + \gamma \cdot Treat_j + T'_{j\tau}\pi_1 + G'_{\tau}\pi_2 + \epsilon_{j\tau}, \tag{9}$$

where $Treat_j$ is a binary variable equal to one for observations in the data corresponding to the treatment group, and zero otherwise. Likewise, $T'_{j\tau}$ is a linear, group specific time trend and G'_{τ} is a set of quarter fixed effects.

[16] Because our data only covers the years 2000 thru 2012, we are somewhat limited in the length of time leads and lags we can include in our analysis and still maintain a balanced panel with a large number of fires. The 6 year window that we use in our analysis already effectively limits us to analyzing fires that occurred between 2003 and 2009.

Table 1
Descriptive statistics.

Variable	Proximity Samples			Visibility Sample	Latent Risk Samples		
	<30 km	<20 km	<10 km	<4 km	<30 km	<20 km	<10 km
Sale Price	300,308.60	302,952.90	320,005.20	378,955.00	334,697.80	356,331.40	373,697.70
	(170,620.50)	(171,421.80)	(179,657.50)	(200,296.30)	(204,930.70)	(211,495.90)	(220,917.60)
2 km Ring	0.04	0.04	0.07	0.38	–	–	–
	(0.20)	(0.20)	(0.26)	(0.48)	–	–	–
High Latent Risk	0.11	0.11	0.10	0.11	0.11	0.10	0.11
	(0.31)	(0.31)	(0.30)	(0.32)	(0.31)	(0.30)	(0.32)
View of Fire	0.46	0.48	0.49	0.58	–	–	–
	(0.50)	(0.50)	(0.50)	(0.49)	–	–	–
Year 1	0.14	0.15	0.16	0.16	0.15	0.16	0.16
	(0.35)	(0.35)	(0.36)	(0.37)	(0.36)	(0.37)	(0.37)
Year 2	0.13	0.13	0.15	0.15	0.13	0.14	0.16
	(0.34)	(0.34)	(0.36)	(0.36)	(0.33)	(0.35)	(0.37)
Year 3	0.09	0.09	0.11	0.12	0.08	0.08	0.12
	(0.28)	(0.29)	(0.32)	(0.33)	(0.26)	(0.27)	(0.33)
Square Feet	2486.10	2466.31	2449.73	2768.24	2654.35	2585.52	2678.35
	(1019.18)	(1001.38)	(949.59)	(981.50)	(1080.00)	(1008.52)	(944.01)
Age (Years)	15.43	15.57	13.90	11.91	13.97	14.41	11.25
	(14.40)	(14.50)	(14.69)	(13.94)	(14.24)	(14.84)	(13.15)
Number of Beds	3.37	3.38	3.37	3.38	3.31	3.32	3.34
	(0.84)	(0.84)	(0.83)	(0.91)	(0.89)	(0.88)	(0.87)
Number of Baths	2.72	2.73	2.79	2.92	2.75	2.81	2.91
	(0.82)	(0.82)	(0.82)	(0.90)	(0.91)	(0.93)	(0.91)
Pool	0.08	0.08	0.07	0.10	0.08	0.06	0.03
	(0.64)	(0.62)	(0.58)	(0.69)	(0.64)	(0.52)	(0.41)
Basement Square Feet	419.76	416.29	413.72	499.79	485.17	480.10	465.07
	(563.60)	(558.11)	(562.90)	(639.14)	(665.06)	(661.13)	(660.76)
Elevation (m)	1861.81	1854.28	1841.39	1899.37	2027.24	2022.20	1979.64
	(215.12)	(204.35)	(175.12)	(141.32)	(326.93)	(317.11)	(275.36)
Slope (degrees)	3.43	3.45	3.65	4.70	5.03	5.46	5.09
	(2.86)	(2.85)	(2.79)	(3.24)	(4.19)	(4.28)	(3.80)
Viewshed Size (m^2)	6.71E+07	6.71E+07	6.69E+07	4.89E+07	3.97E+07	3.39E+07	3.43E+07
	(5.61E+07)	(5.59E+07)	(5.63E+07)	(4.87E+07)	(4.28E+07)	(3.48E+07)	(3.25E+07)
Distance to Fire (m)	9563.90	8912.10	6312.59	2415.32	12,991.45	10,212.58	7737.99
	(5133.41)	(4108.96)	(2437.92)	(1179.26)	(6624.58)	(3378.77)	(1394.24)
Observations	88,518	84,863	52,603	9742	15,271	12,386	6820

Notes: This table reports sample means with sample standard deviations in parenthesis. Latent risk samples exclude properties with a view of a fire and that are less than 5 km of a fire.

6. Results

We begin our formal analysis by estimating equation (8) along two dimensions: *Proximity* to wildfire and *view* of wildfire burn scars; dimensions of treatment which largely capture the dis-amenity effects of fire. Using the difference-in-differences estimates of the impacts of fire on home prices across these dimensions, we determine the spatial extent of our study area for which fire-driven dis-amenity confounds are diminished. We then proceed in section (6.2) by investigating the saliency effects of fire by estimating our models of latent risk limiting attention to portions of our study area where dis-amenity effects of wildfire are less of a concern.

6.1. Identifying the spatial extent of dis-amenity confounds

The difference-in-differences estimates of equation (8) will identify the causal effects of wildfire across each treatment dimension 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.[17] Since we do not observe counter-factual outcomes, we cannot explicitly test the first assumption. 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 by county fixed effects, structural controls, and geographic controls. For the proximity and view treatments, Figs. 5 and 6 fit group-specific, kernel-weighted local polynomials on the residuals of these regressions.[18] In the visibility plot presented in Fig. 6, the pre-fire trends of each treatment group are generally similar to each control

[17] In addition, wildfires must not coincide with any other shock differentially affecting each group.

[18] The graphs displayed in Figs. 5 and 6 were generated in *STATA 14.1* using the *lpolyci* command with the default degree of zero, a ninety day bandwidth, and an epanechikov kernel. The set of structural controls include second-order polynomials in square footage and age, basement square footage, indicator variables for number of bedrooms, bathrooms, and the presence of a pool. The set of geographic controls include second order polynomials in viewshed size and slope.

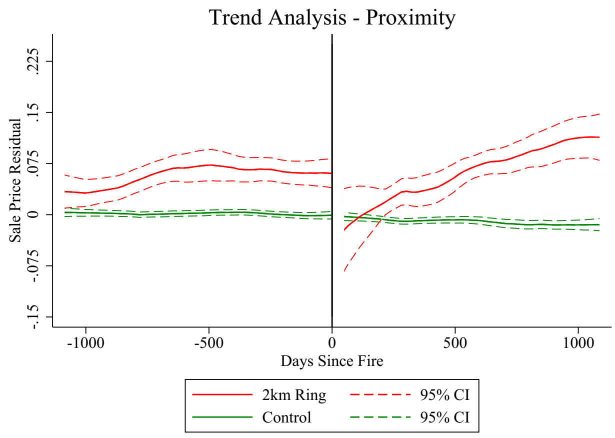


Fig. 5. Sale price trend analysis - proximity.

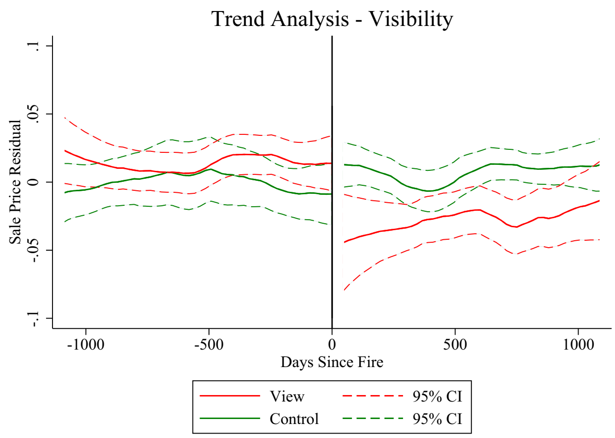


Fig. 6. Sale price trend analysis - visibility.

group,[19] but as shown in Fig. 5, we detect a slight upward, relative price trend[20] for properties located in 2 km wildfire rings which we control for in our proximity analysis by fitting fire-specific time trends fit separately for the treatment and the control group.

Table 2 presents coefficient estimates of equation (8) comparing the outcomes of treated properties located within 2 km of a wildfire to control properties in the adjacent area.[21] Column (1) includes year by quarter and county fixed effects, while columns (2)–(6) include year by quarter by county fixed effects. Columns (3)–(6) further include group specific (treatment/control), linear time trends.

As indicated above, the graphical illustration of the data shows that properties in close proximity to fire experienced a trend which diverged from the pre-existing trend associated with less proximate homes. Thus, while Fig. 5 illustrates an immediate decrease in prices, to the extent that there exists an overall increasing trend in the treatment group, nominal prices in years two and three appear higher in the treatment group. This is reflected formally in columns (1) and (2) of Table 2. For this reason, our preferred specifications are those shown in columns (3) to (6) which include separate linear time trends for the treatment and control group. Once controlling for underlying trends in the data, model estimates shown in column (3) indicate an immediate and highly significant 12.6% post-fire discount in the first year following a fire. Moreover, while this effect slightly decreases in magnitude after two years, we identify significant price reductions among properties within 2 km of a fire in years two and three. As reflected in columns (4)–(6), these results are robust to a smaller set of control properties[22] and to controlling for the

[19] The p-value corresponding to a test for the difference in the pre-trends between the treatment group and control group is .915.

[20] The p-value corresponding to a test for the difference in the pre-trends between the treatment group and control group is .076.

[21] Model results presented in Table 2 with standard errors clustered at the year by quarter by county level are shown in Table 8 of Appendix B.

[22] The magnitude of these results are also qualitatively similar to Mueller and Loomis (2008), Mueller et al. (2009) and Mueller and Loomis (2014) who find that house prices located within 1.75 miles of a wildfire drop approximately −9.7% in the year immediately following a fire as well as Loomis (2004) who estimates a 15% reduction in home prices in an unburned community that was located approximately two miles from a Colorado wildfire.

Table 2
Difference-in-differences (price analysis): Proximity.

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Restrictions:	<30 km	<30 km	<30 km	<20 km	<10 km	<10 km
Dependent Variable:	ln(price)	ln(price)	ln(price)	ln(price)	ln(price)	ln(price)
(2 km Ring) x (Year 1)	−0.0574***	−0.0557***	−0.126***	−0.127***	−0.117***	−0.116***
	(0.0188)	(0.0183)	(0.0291)	(0.0289)	(0.0260)	(0.0260)
(2 km Ring) x (Year 2)	0.0129	0.0133	−0.103***	−0.103***	−0.0998***	−0.100***
	(0.0121)	(0.0120)	(0.0296)	(0.0295)	(0.0272)	(0.0273)
(2 km Ring) x (Year 3)	0.0671***	0.0661***	−0.103***	−0.104***	−0.0966***	−0.0989***
	(0.0151)	(0.0150)	(0.0381)	(0.0379)	(0.0350)	(0.0351)
Year x Quarter FE	*y*	*n*	*n*	*n*	*n*	*n*
County FE	*y*	*n*	*n*	*n*	*n*	*n*
Year x Quarter x County FE	*n*	*y*	*y*	*y*	*y*	*y*
Linear Time Trends	*n*	*n*	*y*	*y*	*y*	*y*
View Controls	*n*	*n*	*n*	*n*	*n*	*y*
Observations	88,518	88,518	88,518	84,863	52,603	52,603
R-squared	0.727	0.729	0.729	0.735	0.765	0.767
P[(2 km Ring x Year 3)>(2 km Ring x Year 1)]	0.0000	0.0000	0.1200	0.1100	0.1425	0.1855

Notes: ***p < 0.01, **p < 0.05, *p < 0.1. Robust (Huber-White) standard errors in parentheses. Columns (1)–(6) report coefficient estimates of the treatment group by post-fire interaction terms specified in equation (8). The treatment group indicator 2 km *Ring* equals one for any property located within 2 km of a fire and zero otherwise. P[(2 km Ring x Year 3) > (2 km Ring x Year 1)] indicates the p-value associated with the test: (2 km Ring) x (Year 3) > (2 km Ring) x (Year 1). Each model includes: Geographic controls (second order polynomials in viewshed size, slope and elevation); structural controls (second order polynomials in square footage and building age, basement square footage, and indicator variables for number of bedrooms and number of bathrooms); and treatment group by fire fixed effects. Models are limited to W.U.I. properties which transact within (+/-) 3 years of a fire.

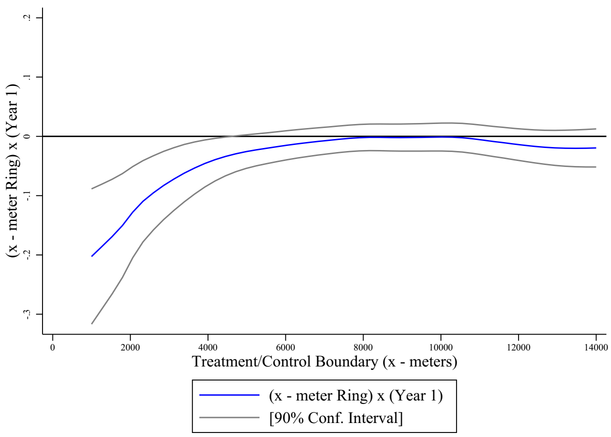


Fig. 7. Proximity: Sensitivity to treatment/control boundary.

impacts of fire through the View treatment.[23] In each specification in Table 2, we report the p-value associated with the test: (2 km Ring) × (Year 3) > (2 km Ring) × (Year 1). In our robust specifications, columns (3)–(6), we fail to reject the null hypothesis at conventional levels of significance; however, the p-values associated with this test in the two largest samples, columns (3) and (4), provide some evidence that the small decrease in magnitude of the first year estimates is not due to statistical error alone.

To test the sensitivity of our model to the cutoff delineating treated and non-treated areas, we limit our sample to properties within 30 km of a wildfire and, starting with an 1 km ring, estimate equation (8) as we increase the size of the treatment ring in 250 m increments. Fig. 7 plots coefficient estimates together with their 90% confidence intervals. We take note that the magnitudes of these effects are pronounced and increase into the range of −20% within 1 km. Beyond 2 km, our coefficient estimates and our confidence in them rapidly diminish to zero and beyond 5 km they are zero.

Turning attention to the impacts of fire through the View treatment, Table 3 presents coefficient estimates of equation (8) comparing prices between properties with and without a view of a wildfire burn scar.[24] By default, each property's viewshed calculation will extend to the limits of our DEM. As shown in the first panel of Fig. 3, 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

[23] Specifically, in column (6) we control for View of fire by including the treatment indicator for view interacted with a fire fixed effect and three, three-year post-fire indicator variables.

[24] Model results presented in Table 3 with standard errors clustered at the year by quarter by county level are shown in Table 9 of Appendix (B).

Table 3
Difference-in-differences (price analysis): Visibility.

Dependent Variable:	(1) ln(price)	(2) ln(price)	(3) ln(price)	(4) ln(price)
(View of Fire) x (Year 1)	−0.0356**	−0.0269*	−0.0644***	−0.0664***
	(0.0152)	(0.0144)	(0.0223)	(0.0232)
(View of Fire) x (Year 2)	−0.0300*	−0.0271*	−0.0837***	−0.0807***
	(0.0153)	(0.0146)	(0.0286)	(0.0297)
(View of Fire) x (Year 3)	−0.0399**	−0.0309*	−0.113***	−0.109***
	(0.0166)	(0.0170)	(0.0377)	(0.0394)
Year x Quarter FE	*y*	*n*	*n*	*n*
County FE	*y*	*n*	*n*	*n*
Year x Quarter x County FE	*n*	*y*	*y*	*y*
Linear Time Trends	*n*	*n*	*y*	*y*
Distance Controls	*n*	*n*	*n*	*y*
Observations	9742	9742	9742	9742
R-squared	0.815	0.823	0.824	0.834

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust (Huber-White) standard errors in parentheses. Columns (1)–(4) report coefficient estimates of the treatment group by post-fire interaction terms specified in equation (8). The treatment group indicator *View of Fire* equals one for any property with a view of a fire and zero otherwise. Each model includes: Geographic controls (second order polynomials in viewshed size, slope and elevation); structural controls (second order polynomials in square footage and building age, basement square footage, and indicator variables for number of bedrooms and number of bathrooms); and treatment group by fire fixed effects. Models are limited to W.U.I. properties located within 4 km of a wildfire which transact within (+/-) 3 years of a fire.

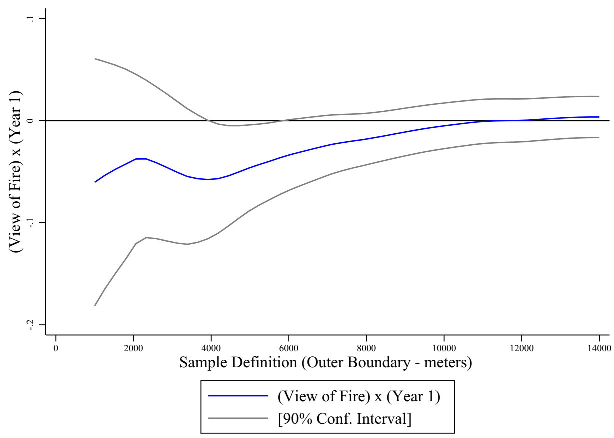


Fig. 8. Visibility: Sensitivity to sample definition.

to be able to discern temporal variations in the landscape. To account for this potential issue, we limit our analysis to properties located within 4 km of a fire.[25] Referring to the coefficient estimates for the view of fire, post-fire interaction terms in column (3) of Table 3, (View of Fire) × (Year k), we find that having a view of a burned area results in a significant 6.4% drop in price immediately following a wildfire.[26] The impacts of fire on price through View are persistent even after three years have passed and, as shown in column (4), robust to second order polynomials with respect to distance to fire fit separately before and after each event.

In our latent risk analysis, we omit any property with a view of a burn scar from our sample, however, for completeness, we also test the sensitivity of our model to the 4 km cutoff we impose by presenting sequential estimates of (View of Fire) × (Year 1) starting with a 1 km cutoff and ending with a 14 km cutoff. The coefficient estimates for each of these regressions together with their 90% confidence intervals are plotted in Fig. 8. The figure shows that the effect of view diminishes gradually with distance in terms of magnitude and statistical significance, although point estimates are less than zero even at distances between 8 km and 10 km.

[25] Here, we are limiting our sample to residential homes that have a physical location less than 4 km from a wildfire and identifying as treated those homes with a view of said fire.

[26] Stetler et al. (2010) estimates that having a view of a fire leads to a 2.6% reduction in price.

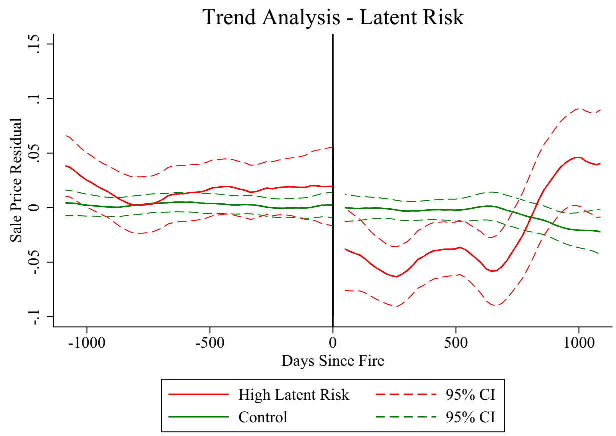


Fig. 9. Sale price trend analysis - latent risk.

6.2. *Saliency analysis*

We turn our attention to investigating the saliency effects of wildfire. Motivated by our analyses in the previous sections, we control for potentially correlated dis-amenity confounds by omitting properties located less than 5 km of a wildfire, or that have a view of a wildfire burn scar.[27] We estimate the impact of fire on the relative price of homes located in high latent risk zones in Section (6.2.1) and the impact of fire on the sales rate of homes in Section (6.2.3).

6.2.1. *Hedonic price analysis*

We start with a graphical illustration of the data. In Fig. 9, we plot sale price residuals for properties located in high-risk and low-risk areas, before and after fire.[28] Fig. 9 shows that before a fire occurs, homeowners tend to place a premium on properties located in fire-prone regions. This finding is suggestive of 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, a similar conclusion also met by Donovan et al. (2007).

Fig. 9 also shows that in the period of time leading up to a fire, the trend in the price of homes in high-risk zones is similar to the trend in the price of homes in low-risk zones.[29] This finding provides evidence to suggest that, in the absence of fire, the average change in housing prices for homes in high-risk zones would have been proportional to the average change in the prices of homes in low-risk zones. Finally, Fig. 9 provides visual evidence of the short and long term effects of wildfire on the price of housing in high-risk areas. In the years following a wildfire, we observe that the price of housing in low-risk areas continues on its pre-existing trend; however, properties located in high-risk areas experience a sharp drop. Following the initial decline, prices of properties in high latent risk zones decay quickly toward their pre-fire level.

We report the estimation results of the latent risk interactions, which are also based on equation (8), in Table 4. Descriptive statistics for each sample by treatment status are reported in Table 5. The coefficients of interest are the estimates of the latent risk, post-fire interaction terms, (High Latent Risk)×(Year *k*). Columns (1)–(3) in Table 4 present model estimates based on properties located between 5 km and 30 km of a fire and that do not have a view of a wildfire burn scar[30]. Columns (4) and (5) utilize more restrictive samples – limiting the outer boundary of the sample to 20 km and 10 km, respectively.[31] We include year by quarter by county fixed effects in columns (2)–(5) and group-specific linear time trends in columns (3)–(5).

Referring to the estimates reported in column (3), we observe a 9.4% latent risk discount in the year immediately following a wildfire; this effect is statistically significant at the 5% level. This first-year effect slightly increases in magnitude to −10.9% and −12.3% when we limit our sample cutoff to 20 km and 10 km, respectively. However, in each model we estimate, coefficients decrease in magnitude and become insignificant in the second year. Coefficient estimates further attenuate towards zero

[27] The wildfire risk data utilized in this paper to delineate high and low risk residences is time-invariant. Thus, one might express concerns regarding the extent to which latent risk is endogenous to wildfire occurence and, in effect, possibly lead to attenuated coefficient estimates. However, in our emprical approach, in addition to removing properties that have a view of a fire, we also remove properties that are within 5 km of fire. To the extent that these properties are not in the near vicinicty of a wildfire burn, it is much less likely that that their landscapes are altered after an event.

[28] The graph displayed in Fig. 9 was generated in *STATA 14.1* using the *lpolyci* command with the default degree of zero, a ninety day bandwidth, and an epanechikov kernel. Sale price residuals were obtained from a regression of log-prices year by quarter by county fixed effects, structural controls (second-order polynomials in square footage and age, basement square footage, indicator variables for number of bedrooms, bathrooms, and the presence of a pool) and geographic controls (second order polynomials in viewshed size and slope).

[29] The p-value corresponding to a test for the difference in the pre-trends between the treatment group and control group is .937.

[30] Model results presented in Table 4 with standard errors clustered at the year by quarter by county level are shown in Table 10 of Appendix (B).

[31] Estimation results do not qualitatively change with the inclusion of non-WUI properties.

Table 4
Difference-in-differences (price analysis): Latent risk.

	(1)	(2)	(3)	(4)	(5)
Sample Restrictions:	<30 km	<30 km	<30 km	<20 km	<10 km
Dependent Variable:	ln(price)	ln(price)	ln(price)	ln(price)	ln(price)
(High Latent Risk) x (Year 1)	−0.0500**	−0.0502*	−0.0939***	−0.109***	−0.123***
	(0.0249)	(0.0257)	(0.0356)	(0.0397)	(0.0456)
(High Latent Risk) x (Year 2)	−0.0393	−0.0381	−0.0766	−0.0518	−0.0527
	(0.0262)	(0.0267)	(0.0466)	(0.0526)	(0.0615)
(High Latent Risk) x (Year 3)	0.0480	0.0386	−0.0202	−0.00450	−0.0396
	(0.0562)	(0.0558)	(0.0788)	(0.0892)	(0.0933)
Year x Quarter FE	*y*	*n*	*n*	*n*	*n*
County FE	*y*	*n*	*n*	*n*	*n*
Year x Quarter x County FE	*n*	*y*	*y*	*y*	*y*
Linear Time Trends	*n*	*n*	*y*	*y*	*y*
Observations	15,271	15,271	15,271	12,386	6820
R-squared	0.685	0.690	0.691	0.688	0.648
P[(H.L.R. Year 3) > (H.L.R. Year 1)]	0.0420	0.0585	0.1325	0.0800	0.1385

Notes: ***p < 0.01, **p < 0.05, *p < 0.1. Robust (Huber-White) standard errors in parentheses. Columns (1)–(5) report coefficient estimates of the treatment group by post-fire interaction terms specified in equation (8). P[(H.L.R. x Year 3) > (H.L.R. x Year 1)] indicates the p-value associated with the test: (High Latent Risk) x (Year 3) > (High Latent Risk) x (Year 1). The treatment group indicator *High Latent Risk* equals one for any property with a wildfire threat index greater than or equal to two and zero otherwise. Each model includes: Geographic controls (second order polynomials in viewshed size, slope and elevation); structural controls (second order polynomials in square footage and building age, basement square footage, and indicator variables for number of bedrooms and number of bathrooms); and treatment group by fire fixed effects. Models are limited to W.U.I. properties which transact within (+/-) 3 years of a fire, and exclude properties less than 5 km of a fire or that have a view of a fire.

after three years have elapsed. In each specification we report the p-value associated with the test: (High Latent Risk) × (Year 3) > (High Latent Risk) × (Year 1). In three of the five specifications we reject the null hypothesis at either the 10% or 5% level. In columns (3) and (4), we fail to reject the null at conventional levels of significance, but only marginally with p-values equal to .1325 and .1385, respectively.[32]

These empirical findings contrast with the related literature in several ways. Most notably, we show that the price effects of fire across the latent risk dimension attenuate over the course of one to two years. Bin and Landry (2013) and Atreya et al. (2013)estimate that homeowners significantly discount homes in designed flood risk zones following a disaster, however, their estimates show that these discounts persist for five to nine years. One of the differences between our study is that we explicitly incorporate spatial data delineating the path of a wildfire. As such, their estimates may be partially reflecting the spatial dis-amenities of hurricane or flood damage and possibly the direct effects of hurricane or flood damage on homes in their sample.[33] One of the advantages of the methodology we advance in our paper is that prior to conducting our saliency analysis, we directly control for the direct effects of disaster damage (i.e. the price effects due to a homeowners property being damaged) by omitting properties in the burn area in addition to controlling for the dis-amenity confounds due to a disaster by explicitly estimating the spatial extent where these effects are present and omitting homes in our sample which fall within this range.

Atreya and Ferreira (2015) control for the direct effects of flood damage using flood inundation maps. Using a difference-in-differences estimation strategy, the authors compare the price effects in inundated and non-inundated portions of the flood risk zone (as well as inundated properties out of the flood risk zone) to price effects among non-inundated homes out of the flood risk zone. The authors show that inundated homes in the floodplain incur an immediate 48% price reduction, inundated homes out of the floodplain incur an immediate 36% price reduction, and no significant price effect among non-inundated homes in the flood risk zones. Building off of Atreya and Ferreira (2015), McCoy and Zhao (2018) study the saliency effects of Hurricane Sandy using a similar difference-in-differences estimation strategy by leveraging spatial data on storm damages. In contrast to Atreya and Ferreira (2015), McCoy and Zhao's (2018) empirical results suggest that homeowners acted on the information conveyed by Hurricane Sandy; however, these authors also show that these effects attenuate quickly with respect to distance to storm damage. As such, McCoy and Zhao's (2018) findings help to rationalize why Atreya and Ferreira (2015) do not estimate an average price response among all homeowners in non-inundated portions of the floodplain: Atreya and Ferreira's (2015) finding that inundated homes in the floodplain incur a *larger* price reduction than similar inundated homes out of the floodplain lends credence to this argument.

[32] We further test the sensitivity of our results to different latent risk definitions in Appendix (C).

[33] In Bin and Landry's (2013) analysis, major damage due to the hurricane they study accrued to only to 1% of the total housing units in their study area. This observation helps to alleviate concerns regarding confounding variation due to the direct effects of storm damage; although, does not completely alleviate concerns regarding confounding variation due to potentially localized dis-amenity confounds. Likewise, while Atreya et al. (2013) acknowledge that hurricane related property damage may be present in their study area, they provide strong evidence to suggest their effects are not due solely to flood damages alone by documenting a notable rise in flood insurance policies in force following the flood they analyze.

Table 5
Descriptive statistics: Latent risk samples.

Variable	<30 km			<20 km			<10 km		
	High Latent Risk	Low Latent Risk	Difference	High Latent Risk	Low Latent Risk	Difference	High Latent Risk	Low Latent Risk	Difference
Sale Price	314,772.50	337,044.40	−22,271.90	356,215.50	356,344.10	−128.60	355,335.90	376,051.80	−20,715.90
	(200,959.10)	(205,273.40)	[0.00]	(209,659.30)	(211,704.40)	[0.984]	(169,492.40)	(226,572.20)	[0.002]
Year 1	0.18	0.15	0.04	0.19	0.16	0.03	0.22	0.16	0.06
	(0.39)	(0.35)	[0.00]	(0.40)	(0.37)	[0.003]	(0.41)	(0.36)	[0.00]
Year 2	0.15	0.12	0.03	0.17	0.14	0.03	0.21	0.16	0.05
	(0.36)	(0.33)	[0.005]	(0.37)	(0.34)	[0.009]	(0.41)	(0.36)	[0.001]
Year 3	0.05	0.08	−0.03	0.05	0.09	−0.03	0.06	0.13	−0.07
	(0.22)	(0.27)	[0.00]	(0.22)	(0.28)	[0.00]	(0.24)	(0.34)	[0.00]
Square Feet	2811.36	2635.85	175.51	2829.07	2558.98	270.09	2899.31	2650.02	249.29
	(1088.63)	(1077.51)	[0.00]	(1047.68)	(1000.63)	[0.00]	(903.86)	(945.38)	[0.00]
Age (Years)	11.71	14.24	−2.53	11.34	14.75	−3.41	8.81	11.56	−2.75
	(13.20)	(14.33)	[0.00]	(13.09)	(14.98)	[0.00]	(12.23)	(13.23)	[0.00]
Number of Beds	3.29	3.31	−0.02	3.33	3.32	0.01	3.27	3.35	−0.08
	(0.88)	(0.89)	[0.348]	(0.91)	(0.87)	[0.794]	(0.91)	(0.87)	[0.021]
Number of Baths	2.68	2.75	−0.07	2.80	2.82	−0.01	2.82	2.92	−0.10
	(0.90)	(0.91)	[0.002]	(0.93)	(0.93)	[0.646]	(0.90)	(0.91)	[0.005]
Pool	0.06	0.09	−0.02	0.05	0.06	0.00	0.03	0.03	−0.01
	(0.55)	(0.65)	[0.119]	(0.51)	(0.53)	[0.865]	(0.36)	(0.42)	[0.514]
Basement Square Feet	448.07	489.54	−41.47	472.52	480.93	−8.41	432.01	469.31	−37.31
	(641.90)	(667.62)	[0.015]	(658.87)	(661.40)	[0.673]	(631.37)	(664.36)	[0.124]
Elevation (m)	1928.80	2038.83	−110.03	1972.76	2027.59	−54.82	1966.59	1981.32	−14.73
	(295.37)	(328.52)	[0.00]	(278.87)	(320.55)	[0.000]	(228.08)	(280.82)	[0.10]
Slope (degrees)	4.89	5.05	−0.16	5.69	5.44	0.25	5.77	5.00	0.77
	(4.19)	(4.18)	[.145]	(4.34)	(4.28)	[0.052]	(4.60)	(3.67)	[0.00]
Viewshed Size (m^2)	4.74E+07	3.87E+07	8,700,000	3.38E+07	3.40E+07	−200,000	3.00E+07	3.48E+07	−4,800,000
	(5.38E+07)	(4.12E+07)	[0.00]	(3.89E+07)	(3.43E+07)	[0.90]	(3.72E+07)	(3.18E+07)	[0.00]
Distance to Fire (m)	13,732.02	12,904.23	827.79	9725.49	10,265.66	−540.17	7413.49	7779.59	−366.10
	(7884.61)	(6454.78)	[0.00]	(3596.33)	(3350.10)	[0.00]	(1160.90)	(1416.10)	[0.00]
Observations	1609	13,662	–	1217	11,169	–	775	6045	–

Notes: For each sample definition, this table reports sample means with sample standard deviations in parenthesis as well as differences of sample means along with p-values corresponding to tests for the equality of means in brackets. Latent risk samples exclude properties with a view of a fire and that are less than 5 km of a fire.

Table 6
Testing for composition effects.

Treatment Definition:	(1) 2 km Ring	(2) View of Fire	(3) High Latent Risk
$\overline{Q}_{Treat,\ Year\ 1} - \overline{Q}_{Treat,\ Pre-Fire}$	0.0139 [0.55]	−0.0506 [0.23]	−0.023 [0.7]
$\overline{Q}_{Treat,\ Year\ 2} - \overline{Q}_{Treat,\ Pre-Fire}$	0.0108 [0.69]	−0.067 [0.21]	−0.0403 [0.57]
$\overline{Q}_{Treat,\ Year\ 3} - \overline{Q}_{Treat,\ Pre-Fire}$	−0.0108 [0.75]	−0.079 [0.21]	−0.027 [0.75]
$\overline{Q}_{Control,\ Year\ 1} - \overline{Q}_{Control,\ Pre-Fire}$	−0.0065 [0.73]	0.0227 [0.57]	−0.0039 [0.94]
$\overline{Q}_{Control,\ Year\ 2} - \overline{Q}_{Control,\ Pre-Fire}$	−0.0283 [0.22]	0.0039 [0.94]	−0.0346 [0.61]
$\overline{Q}_{Control,\ Year\ 3} - \overline{Q}_{Control,\ Pre-Fire}$	−0.0259 [0.34]	−0.0079 [0.9]	−0.007 [0.93]

Notes: P-values reported in brackets. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Columns (1)–(3) report the results of tests for differences in pre and post-treatment Quantity Index means for the treated and control groups corresponding to each treatment definition: 2 km *Ring* (equals one for any property within 2 km of a fire and zero otherwise); *View of Fire* (equals one for any property with a view of a fire and zero otherwise); and *High Latent Risk* (equals one for any properted with a wildfire threat index greater or equal to two and zero otherwise). The results in Columns (1), (2), and (3) are based on the sample of housing transactions included in model estimates reported in Column (1) of Tables 1–3, respectively.

6.2.2. *Testing for composition effects*

One potential concern is that our hedonic pricing results are driven by changes in the composition of houses that go on the market following a fire. To test for this possibility, we compare the mean characteristics of houses sold in each treatment and control region pre and post-fire. For parsimony, we report comparisons along a single dimension quantity-index constructed for each property based on a linear combination of its structural characteristics.[34] We construct weights for the quantity-index (Q_i) using the coefficients from a single *pre-fire* regression of logged prices on the full suite of structural and geographic characteristics.

In Table 6 we report tests for differences in pre and post-treatment Quantity Index means. In rows one, two, and three we compute the difference of the mean quality-adjusted index of properties that sell one, two, and three years after a fire and the mean index of properties that sell before a fire, restricting attention to treated parcels. In column (1), we evaluate this difference for properties located within 2 km of a wildfire burn scar while in columns (2) and (3) we consider properties with a view of a wildfire burn scar and those located in a wildfire risk area, respectively; p-values of differences are reported in brackets. Rows four, five, and six report mean differences across time for each corresponding control group. These results provide no evidence to suggest that the composition of residential units that transact after a fire systematically differs from the composition of properties that transact before a fire.[35]

6.2.3. *Sales rate analysis*

We now turn to the quantity side of the market. We start with a graphical illustration of the data in Fig. 10 which plots the proportion of homes that sell in high and low-risk areas over time.[36] Fig. 10 shows that leading up to a fire, the trend in the sales rate of homes in high-risk zones is similar to the trend in the sales rate of homes in low-risk zones. After a fire, we observe a relative increase in the proportion of high-risk homes that sell, but this effect attenuates over time.

Turning attention to our formal, empirical model, Table 7 presents difference-in-differences estimates of equation (9). Consistent with the graphical illustration of the data, the estimated coefficients for (High Latent Risk) × (Year 1) in columns (1) and (2) show a statistically significant increase in the sales rate of high latent risk properties in the first year following a wildfire. Columns (3) and (4) show that these effects are robust to limiting attention to properties within 20 km and 10 km, respectively. In our robust specifications – those reported in columns (2)–(4) – model estimates of (High Latent Risk) × (Year 2) show that the initial increase in the rate at which homes in high-risk areas sell attenuates and becomes statistically insignificant.

After three years these effects are more than reversed. To rationalize these findings, we highlight a general consensus in the literature that negative and externally generated price shocks typically have the direct effect of placing downward pressure on

[34] There are no qualitative differences in the results of the composition analysis when implemented across individual structural characteristics.

[35] An additional concern is that wildfire risk may also be correlated with recreational amenities. More specifically, the key concern for our saliency analysis is the possibility that our high risk areas are closer to the burn scar than our low risk areas – and thus, they experience a bigger drop in recreational related amenities. We tested our sales results shown in Table 4 to the inclusion of controls for distance to the burn scar. These controls have essentially no impact on our results suggesting that this potential source of bias is not a concern for our analysis.

[36] Fig. 10 was generated in *STATA 14.1* using the *lpoly* command with the default degree of zero, a one-quarter bandwidth, and an epanechikov kernel. 95% confidence intervals are computed using the standard error of the sales rate. The p-value corresponding to a test for the difference in the pre-trends between the treatment group and control group is .769.

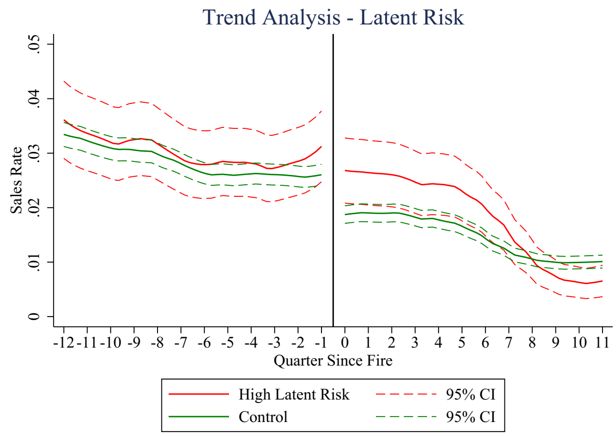


Fig. 10. Sales rate trend analysis - latent risk.

Table 7
Differences-in-differences (sales rate analysis): Latent risk.

	(1)	(2)	(3)	(4)
Sample Restrictions:	<30 km	<30 km	<20 km	<10 km
Dependent Variable:	ln(Sales Rate)	ln(Sales Rate)	ln(Sales Rate)	ln(Sales Rate)
(High Latent Risk) x (Year 1)	0.280***	0.254***	0.204*	0.381**
	(0.0331)	(0.0860)	(0.104)	(0.171)
(High Latent Risk) x (Year 2)	0.238***	0.200	0.143	0.223
	(0.0356)	(0.122)	(0.155)	(0.264)
(High Latent Risk) x (Year 3)	−0.453***	−0.504**	−0.729***	−1.085***
	(0.0933)	(0.201)	(0.249)	(0.375)
Quarter FE	*y*	*y*	*y*	*y*
Linear Time Trends	*n*	*y*	*y*	*y*
Observations	48	48	48	48
P[(H.L.R. Year 3) < (H.L.R. Year 1)]	0.00	0.00	0.00	0.00

Notes: ***p < 0.01, **p < 0.05, *p < 0.1. Newey-West standard errors based on a lag of three are reported in parentheses. Columns (1)–(4) report coefficient estimates of the treatment group by post-fire interaction terms specified in equation (9). P[(H.L.R. x Year 3) < (H.L.R. x Year 1)] indicates the p-value associated with the test: (High Latent Risk) x (Year 3) < (High Latent Risk) x (Year 1). The treatment group indicator *High Latent Risk* equals one for any property with a wildfire threat index greater than or equal to two and zero otherwise. Models exclude properties less than 5 km of a fire or that have a view of a fire.

sales rates. Here, the two often-cited channels include housing equity[37] constraints and aversion to nominal[38] losses. In the year immediately following a fire, asymmetric saliency shocks seem to offset the tendency for sales rates to fall in the presence of shock. However, as soon as the upward pressure on sales rates due to asymmetric saliency erodes, we expect sales rates in the wake of a disaster to ultimately fall which is reflected by a negative coefficient estimate three years since a fire have elapsed.[39]

6.3. Summary of findings and policy implications

Collectively, our empirical findings from our latent risk analyses indicate a short-term price *decrease* corresponding to a similarly short-lived *increase* in the sales rates of properties located in high-risk zones. To better understand the implications of these results, we show in Observation (2) of our theoretical model that positive saliency shocks reduce the post-disaster

[37] The role of housing equity or collateral constraints has been considered by: Stein (1995); David Genesove (1997); Henley (1998); Lamont and Stein (1999), and Chan (2001). The argument here is that nominal price declines may result in an increase in the number of equity or "down-payment" constrained households, in effect, leading to a reduction in mobility and thus a reduction in sales rates.

[38] The role of nominal loss aversion has been addressed by Genesove and Mayer (2001) and Engelhardt (2003). The argument, and as summarized by Engelhardt (2003), is that homeowners may exhibit an aversion to realizing nominal losses in the price of their homes from selling their home in a declining market at the expense of an increase in the time their homes are listed in the marketplace.

[39] Nominal loss aversion and housing equity constraints could be embedded into the model we formulate here by changing how we model the dynamics or movement between old and new equilibrium. While more realistic, this approach would only serve to confound the key findings in Observations (2)–(4) which give new insight into how we can effectively rationalize price *decreases* and transaction rate *increases* in terms of the wedge fires may place between the lowest price extant residents require to sell and the highest price potential buyers are willing to pay driven by the heterogeneous effects fire may have on these residents' perceptions of risk.

equilibrium price in high-risk areas. Interpreted through this lens, our empirical finding that fire leads to a short-term price reduction of high-risk properties suggests that while a recent disaster may induce underlying shifts in households' perceptions of fire risk, these shifts appear to be short-lived, returning to baseline levels after two to three years.

What remains less clear from looking exclusively at changes in home prices is the extent to which fire results in an asymmetric saliency shock between residents living in high-risk zones at the time of fire and potential buyers. We show in Observation (3) of our theoretical model that prices of high-risk properties fall with quantities remaining unchanged when sellers and buyers both experience the same shift in risk perceptions following a fire. In contrast, we show in Observation (4) that price decreases accompany quantity *increases* when fire has a relatively stronger impact on the perceptions of risk among extant residents in high-risk zones at the time of a fire. By documenting a systematic increase in the rate at which high-risk properties sell, the data and the theoretical model suggest that wildfire leads to a relatively stronger shift in the baseline perceptions of risk among households living in fire-prone regions at the time fire ignites[40].

With the threat of wildfire on the rise, developing new strategies to mitigate the risks posed by fire will continue to be an increasingly important task for local and federal policy makers. Some of the strategies utilized by policy makers are centered on post-fire emergency management plans; these include, for instance, evacuation orders and aerial suppression tactics. We have also seen increased use of ex-ante wildfire management techniques including hazardous fuels treatments through thinning and prescribed burns. In recent decades, policy makers have considered the use of information-based regulations as a third tactic. These policies include California's 1998 Natural Hazards Disclosure Act[41] as well as the 1996 Lead Residential Lead-Based Paint Disclosure Program.[42] However, these types of regulations have not been widely adopted for the purposes of managing the risks posed by wildfire.

Quantifying and confronting gaps between perceived and latent fire risk is important on a number of fronts. Most notably, the decisions to privately[43] mitigate against wildfire risk have been shown to be closely tied to perceived fire risk and also argued to be an important avenue for reducing suppression costs and wildfire damages (Champ et al., 2013). Along similar lines, the decision to develop a home in a region characterized by a flammable landscape is a decision that is also arguably influenced by households' perceptions of disaster risk. Holding all else constant, it is reasonable to suspect economically inefficient levels of residential development in forested lands if actors influencing these decisions systematically underestimate the full spectrum of risks they face. To the extent that we show that homebuyers act on the information conveyed by a recent fire, our empirical findings suggest that information-based regulation may be a realistic outlet for addressing potential gaps between perceived risk and latent risk levels. However, our results also indicate that while wildfire appears to drive changes in risk-saliency, these effects are ultimately short-lived. Thus, to be effective, we anticipate that the information conveyed through regulation must be re-inforced over time.

One of the more common forms of information-based regulation designed to address property-specific risks and hazards we have seen in recent decades are policies which disclose risks to potential homebuyers. For example, under the Lead Residential Lead-Based Paint Disclosure Program, federal law law requires sellers to disclose potential lead hazards to buyers prior to forming a contract for sale.[44] Given the behavioral biases we identify in our paper, it is unclear if this type of policy would promote symmetry between perceived fire risk latent fire risk in the long run. However, our empirical findings help to clarify what an effective information provision might look like. Namely, one that provides information to homeowners regarding property-specific risks and that also incorporates a recurring mechanism to incentivize homeowners to acknowledge these risks over time.

7. Conclusion

In this paper we develop a parsimonious model that links underlying changes in location-specific risk perceptions to housing market dynamics. Given estimates of both the price and quantity effects associated with a natural disaster, 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.

In our empirical work, by considering several different dimensions along which the *dis-amenity* effects of wildfire vary, we are able to draw more nuanced inferences regarding the pure, *saliency* effects of fire than previously possible in the extant literature. Here, our empirical results suggest that potential sellers in high risk locations experience a temporary increase in perceived risk. This short-lived (one to two 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 risk.

[40] For completeness, we also present estimates of equation (9) across the proximity and view treatments in Appendix (D).

[41] A summary of this policy is also provided by Troy and Romm (2004).

[42] Information regarding the Lead Residential Lead-Based Paint Disclosure Program is available at the US Environmental Protection Agency's web page: https://www.epa.gov/lead/lead-residential-lead-based-paint-disclosure-program-section-1018-title-x.

[43] Through, for example, private investment in fire-resistant building materials and/or fuel reduction treatments around one's property.

[44] Information on the Lead Residential Lead-Based Paint Disclosure program (Section 1018 of Title X) may be found here: https://www.epa.gov/lead/lead-residential-lead-based-paint-disclosure-program-section-1018-title-x.

These results provide insight into the potential for information treatments to impact risk salience and market behavior in the context of natural hazards. Our analysis suggests that households update their risk beliefs and market behavior in response to disaster-driven information shocks. However, we show that the impact of these information treatments may be short lived. For the Colorado wildfires considered in our study, saliency effects appear to attenuate over the course of two to three years.

Our finding that disasters may temporarily heighten risk perceptions lends credence to the insights set forth by Tversky and Kahnemann's *Availability Heuristic.* (Tversky and Kahneman, 1974). Unexplored in this study, and a fruitful avenue for future work, is the feedback loop between the cognitive factors that influence the temporal dynamics of agents' beliefs and the decisions agents ultimately have to make in an uncertain environment.

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Appendix A. Characterizing price effects and quantity effects

As we indicate in the main text, total differentiation of the market clearing condition in equations (6) and (5) 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 location's salience shock. We summarize these formally in Observations (5) and (6).

OBSERVATION 5: Characterizing Price Effects.

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

$$\frac{\partial p_t^1}{\partial \Delta\pi_t} = \frac{-F'_\omega\left(p_t^1 - \overline{p}_c + \Delta\pi_t d\right)}{F'_\omega\left(p_t^1 - \overline{p}_c + \Delta\pi_t d\right) + F'_\omega\left(p_t^1 - \overline{p}_c + \Delta\pi_c d\right)},$$

and

$$\frac{\partial p_t^1}{\partial \Delta\pi_c} = \frac{-F'_0\left(p_t^1 - \overline{p}_c + \Delta\pi_c d\right)}{F'_\omega\left(p_t^1 - \overline{p}_c + \Delta\pi_t d\right) + F'_\omega\left(p_t^1 - \overline{p}_c + \Delta\pi_c d\right)}.$$

OBSERVATION 6: Characterizing Quantity Effects.

The size of the post-disaster relocation – measure of $\{\omega \mid \delta_c \le \omega < \omega_0^\star\}$ *= measure of* $\{\omega \mid \omega_0^\star \le \omega < \delta_t\}$ *– is increasing in* $\Delta\pi_t$ *and decreasing in* $\Delta\pi_c$*. Specifically, this change is given by*:

$$F_\omega(\omega_0^\star) - F_\omega(\delta_c) = F_\omega(\delta_t) - F_\omega(\omega_0^\star) = \frac{F'_\omega\left(p_t^1 - \overline{p}_c + \Delta\pi_t d\right)\cdot F'_\omega\left(p_t^1 - \overline{p}_c + \Delta\pi_c d\right)}{F'_\omega\left(p_t^1 - \overline{p}_c + \Delta\pi_t d\right) + F'_\omega\left(p_t^1 - \overline{p}_c + \Delta\pi_c d\right)}.$$

Appendix B. Hedonic pricing models with clustered standard errors

Table 8
Difference-in-Differences (Price Analysis): Proximity - Standard Errors Clustered at the Year by Quarter by County Level.

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Restrictions:	<30 km	<30 km	<30 km	<20 km	<10 km	<10 km
Dependent Variable:	ln(price)	ln(price)	ln(price)	ln(price)	ln(price)	ln(price)
(2 km Ring) x (Year 1)	−0.0574	−0.0557	−0.126**	−0.127**	−0.117**	−0.116**
	(0.0427)	(0.0421)	(0.0560)	(0.0561)	(0.0489)	(0.0493)
(2 km Ring) x (Year 2)	0.0129	0.0133	−0.103*	−0.103*	−0.0998**	−0.100**
	(0.0230)	(0.0228)	(0.0558)	(0.0559)	(0.0496)	(0.0498)
(2 km Ring) x (Year 3)	0.0671***	0.0661***	−0.103	−0.104	−0.0966	−0.0989
	(0.0227)	(0.0229)	(0.0705)	(0.0708)	(0.0622)	(0.0626)
Year x Quarter FE	*y*	*n*	*n*	*n*	*n*	*n*
County FE	*y*	*n*	*n*	*n*	*n*	*n*
Year x Quarter x County FE	*n*	*y*	*y*	*y*	*y*	*y*
Linear Time Trends	*n*	*n*	*y*	*y*	*y*	*y*
View Controls	*n*	*n*	*n*	*n*	*n*	*y*
Observations	88,518	88,518	88,518	84,863	52,603	52,603

(*continued on next page*)

Table 8 *(continued)*

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Restrictions:	<30 km	<30 km	<30 km	<20 km	<10 km	<10 km
Dependent Variable:	ln(price)	ln(price)	ln(price)	ln(price)	ln(price)	ln(price)
R-squared	0.727	0.729	0.729	0.735	0.765	0.767
P[(2 km Ring x Year 3)>(2 km Ring x Year 1)]	0.0005	0.0010	0.2275	0.2205	0.2320	0.2720

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Standard errors in parentheses clustered at the year by quarter by county level. Columns (1)–(6) report coefficient estimates of the treatment group by post-fire interaction terms specified in equation (8). The treatment group indicator 2 km *Ring* equals one for any property located within 2 km of a fire and zero otherwise. P[(2 km Ring x Year 3) > (2 km Ring x Year 1)] indicates the p-value associated with the test: (2 km Ring) x (Year 3) > (2 km Ring) x (Year 1). Each model includes: Geographic controls (second order polynomials in viewshed size, slope and elevation); structural controls (second order polynomials in square footage and building age, basement square footage, and indicator variables for number of bedrooms and number of bathrooms); and treatment group by fire fixed effects. Models are limited to W.U.I. properties which transact within (+/-) 3 years of a fire.

Table 9
Difference-in-Differences (Price Analysis): Visibility - Standard Errors Clustered at the Year by Quarter by County Level.

	(1)	(2)	(3)	(4)
Dependent Variable:	ln(price)	ln(price)	ln(price)	ln(price)
(View of Fire) x (Year 1)	−0.0356	−0.0269	−0.0644	−0.0664*
	(0.0382)	(0.0300)	(0.0379)	(0.0337)
(View of Fire) x (Year 2)	−0.0300	−0.0271	−0.0837*	−0.0807
	(0.0278)	(0.0268)	(0.0423)	(0.0421)
(View of Fire) x (Year 3)	−0.0399	−0.0309	−0.113*	−0.109*
	(0.0314)	(0.0277)	(0.0464)	(0.0513)
Year x Quarter FE	*y*	*n*	*n*	*n*
County FE	*y*	*n*	*n*	*n*
Year x Quarter x County FE	*n*	*y*	*y*	*y*
Linear Time Trends	*n*	*n*	*y*	*y*
Distance Controls	*n*	*n*	*n*	*y*
Observations	9742	9742	9742	9742
R-squared	0.815	0.823	0.824	0.834

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Standard errors in parentheses clustered at the county level. Columns (1)–(4) report coefficient estimates of the treatment group by post-fire interaction terms specified in equation (8). The treatment group indicator *View of Fire* equals one for any property with a view of a fire and zero otherwise. Each model includes: Geographic controls (second order polynomials in viewshed size, slope and elevation); structural controls (second order polynomials in square footage and building age, basement square footage, and indicator variables for number of bedrooms and number of bathrooms); and treatment group by fire fixed effects. Models are limited to W.U.I. properties located within 4 km of a wildfire which transact within (+/-) 3 years of a fire.

Table 10
Difference-in-Differences (Price Analysis): Latent Risk - Standard Errors Clustered at the Year by Quarter by County Level.

	(1)	(2)	(3)	(4)	(5)
Sample Restrictions:	<30 km	<30 km	<30 km	<20 km	<10 km
Dependent Variable:	ln(price)	ln(price)	ln(price)	ln(price)	ln(price)
(High Latent Risk) x (Year 1)	−0.0500**	−0.0502*	−0.0939**	−0.109**	−0.123***
	(0.0159)	(0.0250)	(0.0311)	(0.0387)	(0.0249)
(High Latent Risk) x (Year 2)	−0.0393	−0.0381	−0.0766	−0.0518	−0.0527
	(0.0318)	(0.0332)	(0.0696)	(0.0774)	(0.0300)
(High Latent Risk) x (Year 3)	0.0480	0.0386	−0.0202	−0.00450	−0.0396
	(0.0599)	(0.0677)	(0.112)	(0.109)	(0.0487)
Year x Quarter FE	*y*	*n*	*n*	*n*	*n*
County FE	*y*	*n*	*n*	*n*	*n*
Year x Quarter x County FE	*n*	*y*	*y*	*y*	*y*
Linear Time Trends	*n*	*n*	*y*	*y*	*y*
Observations	15,271	15,271	15,271	12,386	6820
R-squared	0.685	0.690	0.691	0.688	0.648
P[(H.L.R. Year 3) > (H.L.R. Year 1)]	0.0620	0.0955	0.2470	0.1225	0.0865

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Standard errors in parentheses clustered at the county level. Columns (1)–(5) report coefficient estimates of the treatment group by post-fire interaction terms specified in equation (8). P[(H.L.R. x Year 3) > (H.L.R. x Year 1)] indicates the p-value associated with the test: (High Latent Risk) x (Year 3) > (High Latent Risk) x (Year 1). The treatment group indicator *High Latent Risk* equals one for any property with a wildfire threat index greater than or equal to two and zero otherwise. Each model includes: Geographic controls (second order polynomials in viewshed size, slope and elevation); structural controls (second order polynomials in square footage and building age, basement square footage, and indicator variables for number of bedrooms and number of bathrooms); and treatment group by fire fixed effects. Models are limited to W.U.I. properties which transact within (+/-) 3 years of a fire, and exclude properties less than 5 km of a fire or that have a view of a fire.

Appendix C. Sensitivity to latent risk definition

Here we test the sensitivity of our latent risk results to different latent risk definitions. Column (1) of Table 11 replicates our baseline results reported in column (3) of Table 4. Column (1) compares properties in high latent risk areas with wildfire threat indices greater than or equal to two to properties in low risk areas with wildfire threat indices equal to one. Less than one percent of the homes in high risk areas have a threat index equal to four or five; column (2) replicates column (1) excluding these properties. Column (3) further excludes properties with a threat index equal to two. In each case, model results indicate an initial high latent risk price discount that attenuates over the course of two to three years.

Table 11
Difference-in-Differences (Price Analysis): Latent Risk Analysis (Sensitivity to Latent Risk Definition).

Dependent Variable:	(1) ln(price)	(2) ln(price)	(3) ln(price)
(High Latent Risk) x (Year 1)	−0.0939***	−0.113***	−0.0834**
	(0.0356)	(0.0363)	(0.0391)
(High Latent Risk) x (Year 2)	−0.0766	−0.0883*	−0.0694
	(0.0466)	(0.0469)	(0.0592)
(High Latent Risk) x (Year 3)	−0.0202	0.0266	−0.0599
	(0.0788)	(0.0757)	(0.101)
Year x Quarter FE	*n*	*n*	*n*
County FE	*n*	*n*	*n*
Year x Quarter x County FE	*y*	*y*	*y*
Linear Time Trends	*y*	*y*	*y*
Observations	15,271	15,123	14,477
R-squared	0.691	0.692	0.687
P[(H.L.R. Year 3) < (H.L.R. Year 1)]	0.1325	0.0125	0.3995

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust (Huber-White) standard errors in parentheses. Columns (1)–(3) report coefficient estimates of the treatment group by post-fire interaction terms specified in equation (8). In Column (1), the treatment group indicator *High Latent Risk* equals one for any property with a wildfire threat index greater than or equal to two and zero otherwise; these estimates replicate the results reported in Column (3) of Table 3. Column (2) tests the sensitivity of Column (1) to excluding properties with a wildfire threat index equal to four or five. Column (3) tests the sensitivity of Column (2) to further excluding properties with a wildfire threat index equal to two. Please see Table 3 for a description of the geographic controls, structural controls, and fixed effects used in each model.

Appendix D. Sales rate analysis - Proximity and view

For completeness, we also present estimates of equation (9) across the proximity and view treatments; results for proximity are reported in Table 12 while our results for view are reported in Table 13. However, ex-ante, it is not clear what we might expect from these treatment dimensions. First, the proximity and view treatments may potentially capture the saliency components of a wildfire which may, or may not be shared equally between extant residents and potential buyers. On the other hand, we think that these treatment definitions largely reflect the dis-amenity effects of fire. As we explain previously, we can interpret price and quantity changes through the lens of the empirical model to gain insight into underlying shifts in agents preference for location-specific housing attributes, including changes spatially delineated dis-amenities. However, these treatment definitions come with an important caveat: Homeowners in close proximity to a wildfire or that have a view of wildfire – in addition to experiencing shifts in preferences due to potentially correlated saliency and dis-amenity changes – are also more likely to be in areas that experienced direct market impacts of a fire, such as loss to damaged infrastructure, which are likely reflected in both price and sales rate decreases. In contrast, we substantially mitigate bias due to these concerns in our latent risk analysis by considering the impacts of fire on homeowners in a close enough vicinity of a disaster to be subject to the saliency effects of a disaster, but distant enough to not be subject to the direct effects (dis-amenity and otherwise) associated with being close to or having a view of a wildfire burn scar. That being said, these ideas appear to be warranted based on the results shown in Tables 12 and 13 which generally indicate decreases in the transaction rates of homes across the view and proximity treatments.[45]

[45] We highlight that column (1) of Table 13 suggests statistically significant decreases, but column (2), which controls for group specific time trends, does not. Specifically, in column (2) of Table 13, the p-values for estimates of (View of Fire) x (Year 1), (View of Fire) x (Year 2), and (View of Fire) x (Year 3) are .179, .166, and .233, respectively. However, while the point estimates in column (2) are statistically insignificant at conventional levels, they are relatively large in magnitude, and negative.

Table 12
Differences-in-Differences (Sales Rate Analysis): Proximity.

	(1)	(2)	(3)	(4)
Sample Restrictions:	<30 km	<30 km	<20 km	<10 km
Dependent Variable:	ln(Sales Rate)	ln(Sales Rate)	ln(Sales Rate)	ln(Sales Rate)
(2 km Ring) x (Year 1)	0.00819	−0.0924	−0.117	−0.172**
	(0.0664)	(0.0745)	(0.0735)	(0.0658)
(2 km Ring) x (Year 2)	−0.0361	−0.187**	−0.214**	−0.341***
	(0.0445)	(0.0821)	(0.0812)	(0.0565)
(2 km Ring) x (Year 3)	−0.235***	−0.436***	−0.464***	−0.651***
	(0.0469)	(0.102)	(0.100)	(0.0786)
Year x Quarter FE	*y*	*y*	*y*	*y*
Linear Time Trends	*n*	*y*	*y*	*y*
Observations	48	48	48	48
P[(2 km Ring x Year 3)<(2 km Ring x Year 1)]	0.002	0.000	0.000	0.000

Notes: ***p < 0.01, **p < 0.05, *p < 0.1. Newey-West standard errors based on a lag of three are reported in parentheses. Columns (1)–(4) report coefficient estimates of the treatment group by post-fire interaction terms specified in equation (9). P[(2 km Ring x Year 3)<(2 km Ring x Year 1)] indicates the p-value associated with the test: (2 km Ring x Year 3)<(2 km Ring x Year 1). The treatment group indicator 2 km Ring equals one for any property located within 2 km of a fire and zero otherwise.

Table 13
Differences-in-Differences (Sales Rate Analysis): Visibility.

	(1)	(2)
Dependent Variable:	ln(Sales Rate)	ln(Sales Rate)
(View of Fire) x (Year 1)	−0.556***	−0.370
	(0.161)	(0.265)
(View of Fire) x (Year 2)	−0.763***	−0.484
	(0.134)	(0.336)
(View of Fire) x (Year 3)	−0.905***	−0.533
	(0.137)	(0.433)
Year x Quarter FE	*y*	*y*
Linear Time Trends	*n*	*y*
Observations	48	48
P[(View of Fire x Year 3)<(View of Fire x Year 1)]	0.006	0.224

Notes: ***p < 0.01, **p < 0.05, *p < 0.1. Newey-West standard errors based on a lag of three are reported in parentheses. Columns (1)–(2) report coefficient estimates of the treatment group by post-fire interaction terms specified in equation (9). P[(View of Fire x Year 3)<(View of Fire x Year 1)] indicates the p-value associated with the test: (View of Fire x Year 3)<(View of Fire x Year 1). The treatment group indicator *View of Fire* equals one for any property with a view of a fire, and zero otherwise.

Appendix E. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jeem.2018.07.005.

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