The Impact of Wildfire Smoke on Real Estate Market

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This version: March 2024

Abstract

Using detailed housing transaction data in the U.S. covering 2010-2019 period, we find that wildfire-generated smoke negatively predict both housing valuation and real estate market liquidity. Listings in smoke-exposed areas experience longer outstanding days, suffer a widening opening-closing price spectrum, thus leading to overall market activity reduction. The exogeneity of smoke incidence to local economic activities suggests a causal relationship of how wildland-fire by-product determines the U.S. housing market. Besides concentrating in areas experiencing multiple incidences in a year, smoke reveals its strongest effect on property market within the first 6 to 12 months before dissipating one year later. We observe the most pronounced effect in areas whose population is generally concerned about climate change. Our findings attribute smoke influencing on housing market to migration channel.

Keywords: natural disasters, wildfire smoke, real estate market, housing valuation, housing demand, climate change belief, migration

JEL Classification: D83, G50, O15, Q54, R21, R31

INTRODUCTION

Extreme weather events have always been representing one of the greatest sources of uncertainty that destroys household wealth in the form of housing values. In 2021 only, the U.S. witnessed eighteen natural disasters damaging at least 1 billion dollars.[1] According to recent National Centres for Environmental Information (NCEI) report, despite the fact that severe storm and tropical cyclones are the two most frequent disasters occurring in the U.S.; wildfire, among the others, are emerging one of the most destructive events. Starting from just $2.4 billion in 2011, the total damage caused by wildfires jumped drastically to $28.3 billion in 2018 Camp Fire, California. A news release by California Department of Forestry and Fire Protection names Camp Fire "*the deadliest and most destructive fire in California history*" by burning an area of 153,336 acres, destroying 18,804 structures and resulting in 85 civilian fatalities.[2] Carbon Brief attributes both prolonged drought season and longer fire seasons due to warming temperatures to increased wildfire risk in the future.[3]

In response to the likelihood that both frequencies and intensity of adverse weather events are rising due to climate change, a new strand of literature – climate finance – has been burgeoning to not only understand underlying mechanisms, but also provide mitigative measures against catastrophic consequences of changing weather patterns in the future (Hong, Karolyi, & Scheinkman, 2020, Giglio, Kelly, & Stroebel, 2021). While a number of academics focus on the source of uncertainty emerging when the economy is transitioning away from fossil fuel – transition risk;[4] others look into the size of economic damages caused by increasing extreme weather events when climate change materialises – physical risk. That follows, an immense effort on disaster-financial literature has been focusing on

[1] https://www.ncei.noaa.gov/access/billions/time-series
[2] https://www.fire.ca.gov/media/5121/campfire_cause.pdf
[3] https://www.carbonbrief.org/explainer-how-climate-change-is-affecting-wildfires-around-the-world/
[4] See e.g. Bolton, and Kacperczyk (2021), and Apel, Betzer, and Scherer (2023)

disentangling the relation between real estate value and some salient events, such as hurricanes (Bleemer, and van der Klaauw, 2019, Deryugina, Kawano, & Levitt, 2018, Gallagher, & Hartley, 2017), and flood (Kocornik-Mina et al., 2020, Billings, Gallagher, & Ricketts, 2022). Wildfires, on the other hands, have only been unfolding recently in the disaster literature. Constituting the largest personal wealth (Gomes, Haliassos, & Ramadorai, 2021), housing is also the most susceptible commodity to be destroyed during a fire incidence. McConnell *et al.* (2021) and An, Gabriel, and Tzur-Ilan (2023) both find that homeownership reduces significantly after major fires, following by credit distress. Particularly, focusing on the top 5 percent most destructive wildfire events, McConnell *et al.* (2021) document the strongest results of homeownership reduction concentrating within the group of 60 years-old. Sharing the similar finding, An, Gabriel, and Tzur-Ilan pay attention to the 11 most major fire events in the U.S. between 2016-2020. Both studies also document a heightened out-migration probability in areas experiencing the most destructive wildfires, in which 2018 Camp Fire exhibits the strongest effect on migration patterns. On a broader scope, Liao and Kousky (2022) find that wildfire affects municipal revenue and spending patterns in California; while Jia *et al.* (2020) focus on wildfires-related evacuation effort according to population density.

Looking closely on how housing values in wildfire direct-hit areas, Loomis (2004) finds that properties in unburned areas locating 2 miles away from fire incidence witness an approximate 15% drop in price. Using a Southern California sample, Mueller, Loomis, and González-Cabán (2009) document a disproportionate reduction in price varying with multiple fire occurrence. In addition, price discount is different across house price distribution (Mueller and Loomis, 2014). Winkler and Rouleau (2021) find amenities shift caused by experiencing environmental nuisances (extreme heat) and hazards (wildfires) in areas with natural amenities and outdoor recreation opportunities. Thus, such shift from *ex-ante* amenities to *ex-post* dis-amenities reduces the living condition desirability, subsequently is priced into housing prices.

While the most commonly mentioned impact of wildfire is heat generated, its by-products – smoke – is usually overlooked. Researches in health and related fields have long documented how smoke from fires are harmful to human, especially the ones come into contact it directly and frequently. Recent evidences also reveal how wildfire smoke adversely affects labour market. Borgschulte, Molitor, and Zou (2022), leveraging exogeneous wildfire plume that causes air pollution, document a 13 percent earning loss. Zivin, and Neidell (2012) also attribute pollution to reduction in labour supply. An, Gabriel, and Tzur-Ilan (2023) also find evidence suggesting that smoke relating to wildland fires causes higher levels of credit card and mortgage defaults.

Nevertheless, there has been no effort in disentangling the effect of smoke from wildfire smoke to housing values. What further triggers a need to look into the mentioned relationship is due to the non-predetermined effect of wildfire smoke on real estate market. On the one hand, by-product smoke might reduce housing values due to the dis-amenities that the environment offers. Smoke days can either increase the hospitalisation rate (Ye *et al.*, 2021) or reduce outdoor recreation (Gellman, Walls, & Wibbenmeyer, 2022), which in turn reduces the local amenities. On the other hand, unlike wildland-urban interface that offers amenities in terms of better view but comes with high risk of fire damage (Radeloff *et al.*, 2018), the exogeneity of smoke coverage offers an source of uncertainty that cannot be forecasted, which cannot be priced into the property values. Another reason to believe in no-relation between smoke and housing price is that households living in frequently-exposed areas have been developing mitigating measures in the events of smoke, such as installing smoke-sensor device and providing masks and respirators (Holm, Miller, and Balmes, 2021). Yet, in another extreme, households might outweigh the risk of smoke in replacement of other amenities offered by megacities, such as New

York.[5] As a result, there is no *a priory* direction how smoke might predict housing prices and real estate market activity.

The key challenge in measuring the effect of wildland-related smoke on housing market is to identify a setting in which house prices are not endogenously determined by economic factors and vice versa. For example, the proximity to industrialisation zones – one of constant smoke-generating sources – is priced into nearby properties. We leverage the widespread of smoke from wildfires since such by-product does not relate to any economic condition in an area (tract census), which offers a quasi-experiment setting in which treated observations (smoke-covered tracts) are randomly chosen from control ones (non-smoke tracts). Merging smoke data provided by NOAA Hazard Mapping System with real estate transaction data from Zillow in the US from 2010 to 2019, we find that wildland-fires smoke has significant and meaningful impact on real estate market.

Aggregated from daily observations, our monthly smoke data is granular to census tract, thus minimising coarse estimation that might result in Type II error. To ensure that market participants have enough time to react towards smoke experience, we construct our variable of interest by aggregating number of days with smoke incidences occurring in the latest fourth months. We then geographically match our *Number of smoke days* variable to different proxies of real estate market to arrive our tract-month sample. We alleviate the concern of potential noise in smoke measure as nearby factory might contribute as a smoke source by including tract fixed-effects. This also absorbs any time-invariant characteristics that might systematically interfere with the housing price and market. We also control for time-varying events that potentially affect real estate market as a whole by including month-year fixed effects, similar to An, Gabriel, and Tzur-Ilan (2023) and McConnel *et al.* (2021). To account for market

[5] https://www.theguardian.com/us-news/2021/jul/21/new-york-air-quality-plunges-smoke-west-coast-wildfires

conditions in different areas, we weight each observation by the total number of open and closed positions.

Our results reveal that on average, listings in areas exposed to wildfires smoke require longer time period to close. In addition, we provide evidence showing that market participants price random natural dis-amenities into property value by documenting a lower closed relative to initial offering price. Not only housing price, smoke occurrence also reduces property market liquidity by reducing net number of listings in treated regions. The stagnating effect of wildfire smoke on variables of interest are robust after controlling for lagged value of the explained variables.

Despite our arguably rational assumption that smoke generated by wildfire does not endogenously relate to local economic activities in our setting, our results might still be driven by some other fundamental differences between exposed- and non-exposed smoke areas. We thus address this issue by conducting a quasi-experience difference-in-difference (*DiD*) analysis, in which we compare property value in treated vs. control areas during before vs. after smoke incidence, and placebo tests. Our DiD results are consistent with the baseline, in which a listing experiences longer outstanding days on the market, and suffers a larger price discount when closing deal. In addition, market participants observe an increased number of properties floating on the market after smoke incidence and the opposite trend for closed positions, a sign of market illiquidity.

We then investigate the heterogeneity of smoke effect on real estate market. While smoke has widespread effect on real estate market, homebuyers in urban regions tend require more compensation in terms of price depreciation and time-period to make purchase decision relative to their peers in rural areas. In addition, as a listing becomes “stale” when the number of outstanding day on market is high, our results might merely capture the price behaviours of these properties whose homeowners are willing to slash a large proportion of price in order to close the listing when smoke incidence occurs.

Nevertheless, we actually document opposite: the effect of smoke on housing price tends to concentrate among newly listed properties in the market. Particularly, given the two properties with analogously similar characteristics, we observe a price drop of additional 1.1% in more recently listed properties.

Following Mueller, Loomis, and González-Cabán (2009), we look into the potentially heterogeneous reaction of both price and market liquidity react towards different smoke incidences. By investigating two subsamples varying in smoke frequencies, we find that our findings concentrate within frequently-smoke-exposed areas, which suggests that households living these frequent-exposed areas have already priced smoke risk into housing value. Despite the acclimatisation of citizen to smoke frequency, new fume-covered events still negatively affect property price and market liquidity within 6 to 12 months, but vanishes after 18 months. We also find coefficient indifferent from zero in a change specification, proving the short-term effect of smoke.

As belief plays an important role in housing prices (Bernstein, Gustafson, & Lewis, 2019, Baldauf, Garlappi, & Yannelis, 2020), we integrate the concern about climate change into our analysis with the expectation that areas with a high proportion of households worrying about changing weather patterns witness a more significant drop in housing price. We find support for our hypothesis as the coefficient of interest not only is significant, but also carries larger magnitude in multiple-smoke-exposed subsample than in full sample.

Last, we find that the smoke effect on real estate market is transmitted via migration channel. Aggregating the sample into county-year observation, the number of people living in a county exposing to smoke reduced by 20 in every 1,000 people. The denser the smoke, the higher likelihood of experiencing population outmovement. Again, the effect of smoke has a long-lasting effect by affecting the rate of movement rather than just the annual fluctuation. The more pronounced effect of smoke on migration is on a change specification, in which an additional one day of medium to heavy smoke on average predicts 768 people moving away on a year-to-year change. This is consistent with the current wildfire literature (McConnell *et al.*, 2023, Winkler and Rouleau, 2020).

Leveraging the quasi-experiment of smoke plume, we are among one of the first attempts to causally determine the effect of wildland fires by-product on real estate markets. In addition to direct heat impact, our findings contribute to the far-reaching detrimental consequences of wildfires besides corporate performance (Kong, 2022), household's credit card usage and mortgage defaults (Stuart, Gabreal, & Tzur-Ilan, 2023). We show the economic consequence in addition to heath impact of wildfire smoke. In a systematic review, Liu *et al*. (2015) document that wildland smoke increase the risk of respiratory and cardiovascular diseases, especially in children, the elderly, and those with underlying chronic diseases. Landscape smoke is also linked to increased preterm birth (Heft-Neal *et al.*, 2022), reduced birth weight (Amjad *et al.*, 2021), and mortality (Johnston *et al.*, 2012). Borgschulte, Molitor, and Zou (2022) attribute quarterly earnings loss to both employment reduction and labour force exit due to drifting wildfire smoke. We contribute to this line of literature by showing that smoke generated from wildland fire also affect real estate market in regions faraway from fire centres. In a bigger picture, we contribute to the literature of natural disasters on economic consequences.[6] Despite not the main focus on this study, we also identify another cause for households taking pre-emptive measure – migration – against consequences of changing weather patterns, i.e. sea-rise level (Hauer, 2017, Keenan, Hill, & Gumber, 2018).

Next, our findings fit to how weather is priced into real estate literature. The literature of how climate shapes the behaviours of various financial assets has been burgeoning since the rising awareness of how changing weather patterns.[7] Another closely related brand of literature looks directly at how

[6] See e.g. Kellenberg, and Mobarak (2011) for literature review, homeownership rate decrease (Sheldon, & Zhan, 2019), housing price drop (Boustan et al., 2017), economic activities (Dell, Jones, and Olken, 2014)

[7] See e.g., literature review (Hong, Karolyi, & Scheinkman, 2020, Giglio, Kelly, & Stroebel, 2021), investors' attention (Krueger, Sautner, & Starks, 2020, Bolton, & Kacperczyk, 2021), corporate bonds (Javadi, & Masum, 2021, Huynh, & Xia,

weather affects various aspect of finance.[8] In addition to sea-rise level (Bernstein, Gustafson, & Lewis, 2019, Murfin, & Spiegel, 2020), belief (Baldauf, Garlappi, & Yannelis, 2020, Bakkensen, & Barrage, 2022) and political partisan (Bernstein, Billings, Gustafson, & Lewis, 2022), we show that homeowners take into account the dis-amenities caused by wildland smoke.

We provide evidence proving that in addition to wildfires (McCoy, and Walsh, 2018), the incidence of smoke also alters significant but short-lived increase in agent's risk perception. The perception of risk saliency is ultimately important in understanding individual's investment behaviour. As housing wealth consists the largest proportion of personal wealth, we show that homeowners update their risk saliency by pricing smoke exposure into property's values but diminishing within the second year, proving the short-lived effect of smoke. We thus contribute to the literature by showing that short-term effect of weather condition on housing market, in addition to long-term consequence of climate change (Giglio, S., Maggiori, M., & Stroebel, 2015, Giglio, Maggiori, Rao, Stroebel, & Weber, 2021).

We proceed as follows. In section 2, we discuss our data and how we construct our sample and identification strategy. Section 3 presents our baseline results, cross-sectional analysis, and result robustness. We provide mechanisms through which smoke affects real estate in Section 4, and Section 5 concludes.

DATA AND IDENTIFICATION STRATEGY

Data and Variable Definition

Similar to Bernstein, Gustafson, and Lewis (2019), we use real estate data from the Zillow Transaction and Assessment Dataset (ZTRAX). ZTRAX contains detail offering and closing prices of listings

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2021), firm performance (Ardia, Bluteau, Boudt, & Inghelbrecht, 2022), assets returns (Pástor, Stambaugh, & Taylor, 2022), municipal bonds (Painter, 2020, Goldsmith-Pinkham, Gustafson, Lewis, & Schwert, 2022), *etc.*

[8] Sales (Addoum, Ng, & Ortiz-Bobea, 2020), economic growth (Dell, Jones, & Olke, 2012), market efficiency (Hong, Li, & Xu, 2019), bond and stock price (Huynh, & Xia, 2021), cost of equity (Huynh, Nguyen, & Truong, 2020), *etc.*

together with exact geo-coded location, allowing us to match with granular census tract. To illustrate that Zillow data covers the majority of U.S. real estate transactions, we plot the number of listings available for sales in each county for 2010-2019 period in **Figure 1**. While there are some "hot spots" where there are more transactions taken place than others, the figure still signifies that ZTRAX provides a good proxy for real estate market activities. We use three variables to proxy for housing valuation and real estate market liquidity. Our first variable Ln(*Total Days Outstanding)* is the natural logarithm of day counts covering the period required for a listing status to change from opening to closing position. *Price Difference* represents the difference of closing relative to opening price of the property. Last, *Net Listing* is the difference of the number listed and closed properties in the same month-tract census.

We then map real estate measures to smoke coverage from wildfires from Hazard Mapping System (HMS) Fire and Smoke Product by NOAA. The HMS Smoke and Fire analysis provides observation of both active fires and smoke coverage using satellite images. Analysts, every day at 1PM and 11PM Eastern time, create and update needed information to data generated by algorithms from different satellite products before publishing for public use. Notably, data are undergone quality control to exclude fires with persistent sources (e.g., gas flaring) or those in urban environments (e.g., structural fires), limiting the possible noises from other economic activities. Based on apparent thickness of the smoke in satellite imagery at the different values, smoke coverage is labelled as *light*, *medium*, and *heavy* according to NOAA convention.[9]

We then create our measures of interest based on smoke density, *Medium-Heavy Smoke Days*, by summing total number of days a census tract covered in either medium or heavy plume density.[10] Although smoke data is available back to 2003, not until June 2010 that smoke density is consistently reported. Hence, we choose start our sample from midyear 2010 to December 2019. We plot the annual

[9] https://www.ospo.noaa.gov/Products/land/hms.html#about
[10] We also use *Total number of smoke days* that include all three different smoke density for robustness in our appendix.

coverage of medium-heavy smoke density in **Figure 2**. Smoke, initially concentrated in South and Southeast regions in 2011, gradually moved up to Northwest in 2012-2015 before expanding to Midwest and Southwest in recent years. The sporadic pattern of smoke incidence illustrated by Figure 2 graphically supports our assumption that wildfire by-product shares no relation with real estate market *ex ante*.

As house wealth composes one half of total household net worth (Iacoviello, 2011), the decision of purchasing usually takes more than one month to complete.[11] Furthermore, the average time period require to close a listing is 102 days, according to Zillow data. Thus, in order to accommodate appropriate time length for smoke affecting real estate value, we aggregate daily to monthly observation. Smoke measure is the total number of days in the latest four months in which smoke incidence occurs. The smoke sample is then merged to listing measures by census tract. The process ends up with more than 1,400,000 census tract-month observations starting from June 2010 to December 2019 in the U.S.

Identification Strategy

In order to investigate how smoke affects real estate values, we regress different smoke measures against our listing variables of interest. Particularly:

$$Y_{it} = \beta_0 + \beta_1 \mathit{Smoke\ Days}_{it} + \text{FEs} + \varepsilon_{it} \tag{1}$$

In which Y_{it} is the listing measures (i.e. *Net listings*, *Price difference*, and *Ln(Total days outstanding)*) of tract *i* in month *t*. Smoke days in the number of days that a census tract *i* is covered in medium-heavy smoke thickness. We include tract fixed-effects to absorb any time-invariant characteristics that might endogenously determine housing price (i.e. houses located near factory might expose to constant air pollution). Our identification strategy lies on the assumption of smoke intermittence. Given the fact that HMS smoke data have undergone quality-control to eliminate smoke-

[11] According to Zoopla: https://www.zoopla.co.uk/discover/buying/the-timeline-of-buying-a-home-how-long-is-too-long/

generated sources by human, census tract fixed-effects further alleviates the concern that our smoke measures merely captures air pollution by absorbing any other constant smoke-releasing origins. Furthermore, we account for any nation-wide events or policies that effect both real estate market liquidity and house values by including month-year fixed-effects. Our results are weighted on aggregate number of listings (i.e. sum of listing opening and closing positions) on the market at each point of time to account for market heterogeneity in different locations. Standard errors are double clustered at tract and month level.

Despite the arguably rational assumption that the nature of smoke is exogenous to local economic activities, we attempt a cleaner identification strategy by employing a difference-in-difference analysis in our quasi-experience setting. Treating every single event of smoke separately, we assign an indicator variable *Post* taking value of 1 from month m at which smoke incidence occurs to the year end. Another dummy variable, *Treat*, is assigned to 1 if the tract, at any time of the year, is covered in smoke. We then estimate the following model:

$$Y_{it} = \beta_0 + \beta_1 Post * Treat + FEs + \varepsilon_{it} \tag{2}$$

In which, the coefficient of interest, β_1, captures the difference of property market reaction to occurrence between non- and smoke-covered tract census. Similar to (1), we include the same set of fixed-effects, tract and month-year, to absorb both time invariant and time-varying characteristics within a region, thus leaving the sole variation to smoke occurrence. Similar to Equation (1), the observation is also weighted based on the total number of both open and closed listings floating on the market in that month when entering the equation so as to control for difference real estate market condition between areas.

Last, as suggested by the literature that the effect of natural disasters on real estate or capital market depends on whether the event is fast- (e.g. hurricanes, storms, wildfires) or slow-onsets (e.g.

prolonged drought season, rising temperature, flood risk), we also seek to identify how smoke affects property market by estimating the past 6-, 12-, 18-, and 24-month smoke occurrence on explained variables with same fixed-effects in (1) and (2). Thus, the regression is as follows:

$$Y_{it} = \beta_0 + \beta_1 \textit{Smoke Exposure}_{i,t-6} + \beta_2 \textit{Smoke Exposure}_{i,t-12} + \beta_3 \textit{Smoke Exposure}_{i,t-18} + \beta_4 \textit{Smoke Exposure}_{i,t-24} + \text{FEs} + \varepsilon_{it} \quad (3)$$

In which $\textit{Smoke Exposure}_{i,t-k}$ is measured similarly to our baseline regression (1) but in previous *k* months. Thus, the (in)significance of β_k provide prolonging evidence how smoke affects real estate market. Equation (3) includes the same fixed-effects as in Equation (1) and (2).

RESULTS

Descriptive Statistics

Table 1 presents variable descriptive statistics. On average, an area experiences one day covered in *medium-heavy* smoke in every four months, with a standard deviation of 1.092. Nevertheless, an upper 95th percentile value can reach to 4 days, which means a census tract can be exposed to smoke incidence up to twelve days in a year. When accounting for *light* plume density, citizens in a region experience, on average, a total of 17 smoke days. In terms of our explained variables, a listing requires an approximate 150 days to close, with a 5th and 95th percentile values ranging from 31 to 344 days, respectively. The mean natural logarithm value of net listing is 3.37, meaning that the net-off outstanding positions are 136 in every month. A listing witnesses a mean of -2.36% price drop in closing relatively to opening price with its 95th percentile reaching 0.79% price appreciation. Last, there are 53 out of 100 people worry about climate change with a standard deviation of 6.52. Variable definition is in Appendix A.

Baseline Results

We first identify how smoke affect both real estate value and market condition by running Equation (1) and present the results in **Table 2**. In either smoke measures, we observe a negative effect of smoke across different measures of real estates. Particularly, Column (1) show that listings located in smoke-covered areas experience a prolonged outstanding days on the market relatively to the ones in non-smoke regions. A coefficient value of 0.382 means that on average, one day exposed to smoke lengthens the outstanding period by one day. This might sound economic insignificance. Nevertheless, given the average housing value in the U.S. in 2022 is nearly $330,000, one extra day on the market yields a loss of $13,000 at the risk-free rate to the owner. [12,13] On the extreme case in which a region is covered in smoke for 37 days, the economic loss of housing market is substantial. Column (3) show that properties exposed to smoke from fires are sold at more discount than their cohort with an mean of 3%. Again, relative to the average 2022 house price in the U.S., one day of smoke subjects the house owner to a loss of $9,900. Last, a negatively significant coefficient in Column (5) suggests that wildfire-generated smoke stagnates real estate activities. By aggregating daily to quarterly frequency, we still observe the similar effect on Panel B of Table 2 with a similar or even larger magnitude.[14] We furnish our analysis by including lagged value of dependent variable to control any autoregressive effect of the real estate market. The results are shown in Columns (2), (4), and (6) in both panels for our three variables of interest, respectively. Again, we still find significant impact of smoke negatively impact both real estate market liquidity and housing values.

Our analysis is based on the assumption that smoke occurrence is sporadic and unrelated to geographical characteristics. Nevertheless, listings in wildland-urban interface cities might subject to a

[12] According to Zillow, the 2022 average housing value in the U.S. is $328,745. Available at https://www.zillow.com/home-values/102001/united-states/

[13] $330,000* 3.95% = $13,035. Risk-free rate is available at: https://home.treasury.gov/policy-issues/financing-the-government/interest-rate statistics

[14] The results of total smoke day also confirms the similar findings, albeit a drop in magnitude in **Appendix B Table 2**. We attribute the size different due to noise from light smoke days as it is difficult to clearly distinguish a light smoke day from normal air condition.

higher likelihood of experiencing smoke than their cohort in rural areas, casting doubt to our causal interpretation (i.e. reverse causality). We thus validate our exogeneity assumption in **Appendix B Table 1**. In particular, we regress future smoke incidence against three variables of interest for real estate market. Due to the nature of our explanatory variable construction covering smoke incidences within the latest four months, we use 3- to 4-forward period to fully accommodate for any smoke events that occur in the future and do not account for any smoke incidences happening within current month. Results in Appendix B Table 1 show that coefficient is indifferent from zero, which provide support for our assumption that smoke events are sporadic and exogenous to geographical characteristics.

Despite our result robustness, there is possibility that our observed smoke effect might just be coincidental with sharp reduction of housing prices when a listing has been floating for a long time in the market. We rule out the possibility of "stale" properties by segregating the sample based on the median value of total day outstanding. In **Table 3**, we find that smoke effect is more pronounced in properties that are newly put on market (Column 1) relative to longer-listed group (Column 2), both in terms of significance and coefficient size. In particular, a further 2.1% drop in value when comparing two analogously similar properties in "old" to "newly" spectrum.[15] Put differently, a newly-listed property experiences a sharper price reduction relatively to older listings, even the latter might witness more smoke events. We thus provide evidence refuting the likelihood that our findings are driven by coincidental movement of housing price and smoke events.

Cross-sectional Analysis

We then further our analysis by looking the heterogeneous effect of smoke on real estate market. Upon evaluating a property, location captures to the foremost homebuyers' attention as listings in urban areas tend to have higher price relative to the similar in rural regions. To proxy for different locational

[15] -0.033 – 0.012 = -0.021

characteristics, we obtain Rural-Urban Commuting Area (RUCA) Code from the U.S. Department of Agriculture that classifies a census tract into a continuum of 1 to 10, in which 1 represents for Metropolitan area core, and 10 is Rural areas. **Table 4** presents our cross-sectional analysis on urbanity status by interacting smoke measure with RUCA code. In particular, we still document a widespread effect of smoke on real estate market: smoke significantly prolongs time to make purchase decision (0.706), widen closing and opening price (-0.045), and reduce net listing (-1.196). On the other hand, smoke tends to have less pronounced effect in rural areas in terms of *Total days outstanding* and *Price difference* since the interaction term has opposite sign to that of individual smoke coefficient. In particular, a listing experiences (i) an average of one-day shorter to close,[16] and (ii) 1% less price depreciation when moving from Metropolitan area low commuting (RUCA = 3) to Micropolitan area core (RUCA = 4). [17] The effect is also observed in *Net listing*, albeit the coefficient is insignificant at conventional levels.

Using a sample in Southern California, Mueller, Loomis, and González-Cabán (2009) find that while first fire drops 10% price, repeated fire causes up to 23% reduction in property value. We thus hypothesise that not only real estate market but also housing prices located in areas exposed to multiple smoke incidences exhibit different trend relatively to first-time exposed regions.

We validate our hypothesis in **Table 5** with different measures of real estate. Using an indicator variable that takes value of 1 if a census tract encounters with more than once smoke incidence in a year (i.e. “Multiple”), and zero otherwise (i.e. “First”), we investigate the heterogeneity of homebuyers' behaviour in two subsamples. To ensure consistency across our analysis, all specifications across columns include tract and month-year fixed-effects as in Equation (1). Results in Table 5 reveal that smoke frequency predicts both market liquidity and housing price. Particularly, while we find muted

[16] $e^{0.212} = 1.24$
[17] We find similar results using Total smoke days in **Appendix B Table 3**.

effect of smoke across three variables of interest in areas exposed to smoke less than once a year; regions exposed with multiple smoke incidences not only witness a prolonged period to close a listing with significant price depreciation, but also experience market illiquidity. Particularly in columns (2), (4), and (6), we find that one day increase of medium-heavy smoke day increases 2 days of property outstanding, a 3% drop relative to opening price, and decrease at lease 5 houses floating on market..[18] We thus provide accumulated effect of repeated adverse weather condition on both housing valuation and market activity.

Difference-in-Difference (DiD) analysis

Aforementioned, our analysis lies on the assumption of smoke intermittence. Nevertheless, there might exist omitted variables hindering our interpretation of causal smoke effect on housing valuation. We thus design a quasi-experience to capture the reaction of property buyers between smoke- (*Treat* = 1) and non-smoke (*Treat* = 0) regions in pre- (*Post* = 0) vs. post- (*Post* = 1) smoke incidence. **Table 6** presents the coefficient of *Post***Treat* denoted in Equation (2).[19] In the first two columns, the coefficient of interest shows that relative to non-smoke areas, properties listed in smoke-exposed tracts take longer time to complete the deal (Column 1), and are sold at a more discounted price (Column 2). As we control for census tract and month-year fixed-effects, the design allows us to look into the effect of smoke within the same area while controlling for any events that might affect the whole market over time. Speaking differently, a coefficient of -0.617 means that: a smoke-exposed listing experiences an approximate 2-days delay to close the deal comparing to other listings in the same area when smoke does not occur. Furthermore, smoke-exposed listing's offering price is, on average, 0.151% lower relative to opening price.

[18] **Appendix B Table 4** provides the same findings when using Total Smoke Days.
[19] Our tract FEs and Month-Year FEs subsume individual coefficients of *Post* and *Treat*.

To better look into the effect of smoke on property market, we replace explained variables with natural logarithm of *List* and *Closed*, which is the number of newly listed and closed positions in a month at a census tract, respectively. The results in Column (3) and (4) show that smoke significantly increases the number of listed while simultaneously reduces the number of closed deals, resulting to an increase of accumulated floating stock available in the market and reduction of overall market liquidity. Hence, our *DiD* analysis is consistent with our baseline results.[20]

Short-term vs. Long-term effect of smoke on Real estate market

The current literature suggests that weather extreme hazards tend to exert their impacts on different time horizon. On the one hand, Cohen, Barr, and Kim (2021) find that after the occurrence of fast onset event, such as, hurricanes, housing price reduces immediately, but bounces to normal level after one to two years. On the other hand, Ortega and Taṣpınar (2018), Gibson and Mullins (2020), and Addoum, Eichholtz, Steiner, and Yönder (2021) find the consistent penalties for flood risk after the event of Hurricane Sandy on New York real estate market, and attribute this persistent price drop to a shift in long-term risk perception. Other chronic risks, such as sea-level rise (Bernstein, Gustafson, & Lewis, 2019, Baldauf, Garlappi, & Yannelis, 2020, Murfin, & Spiegel, 2020) are also linked to long-term discount of housing prices.

We contribute to the heterogeneous lasting effect of extreme weather events by showing the result of smoke effect on real estate market in **Table 7**. Regressing past bi-annual smoke incidences on explained variables up to two years, we find that the smoke reveals a decaying impact on housing market within the first year. Particularly, smoke event happening 6- to 12-month ago prolongs the number of days outstanding by 0.233 to 0.678, respectively, in Column 1. Also, Column 2 shows that closing price

[20] We provide the same analysis using Total number of smoke days in **Appendix B Table 5**. The results are similar to our Medium-Heavy smoke days, albeit a small drop in magnitude.

is lower than opening price from 2.6% to 3.2% in the same time period. Last, property market becomes stagnant within the year of smoke incidence, but not the following year in Column 3. One note worth-taking point is that the coefficient of previous 1-year is larger than that of latest 6-month smoke events. This suggests that market participants consider multiple smoke incidences occurring within 12-month period when pricing house values.

Similar to Table 2, we expect that under very rare circumstances property market condition might change unexpectedly; otherwise, market liquidity and price stableness are sticky over months within a year. We thus control for price and liquidity stickiness by including lagged value of explained variables in Columns (2), (4), and (6). The results the latter specifications offer the same finding that smoke effect gradually vanishes within a year.[21]

Result Robustness and Geographical Characteristics

In this section, we show that our results are robust in different techniques to refine sample as well as taking into account locational characteristics that might endogenously determine housing values. Given high frequency and pervasiveness of fire incidences in California, our findings might be driven by listings' idiosyncratic traits in this region.[22] We thus exclude all observations in California to make sure that our results document a widespread effect of sporadic smoke on real estate market rather than sample bias. Using the same fixed-effects system in Equation (1), Columns (1) to (3) in **Table 8** confirm the persistent stagnating effect of smoke on real estate market, and not concentrating in any particular areas. We also include lagged one-period value of explained variable to account for any autocorrelation as in

[21] Similar findings are observed using Total smoke days in **Appendix B Table 6**.
[22] https://www.bloomberg.com/news/articles/2022-10-10/california-announces-development-guidelines-based-on-fire-threat

Columns (2), (4), and (6) in baseline results in Table 2, proving the manifestation of incremental smoke effect on current housing valuation.[23]

On the other hand, one might concern that such market behaviour only exhibits when the risk of wildfire is salient, i.e. fire seasons. Due to high temperature in accompanying with dry and hot weather conditions, wildland fires peak during summer months in the U.S.[24,25] We thus drop observations taking place in June, July, and August in our sample to make sure that our findings are not driven by wildfire risk. Results in Column (4) – (6) in Table 8 still document a significant effect of smoke on reducing housing valuation, and real estate market activities as a whole. Looking closely, the coefficient magnitude is even larger than the baseline results, from 14% (-0.032/-0.028) in price difference up to 36% (-1.512/-1.112) in net listings. We thus rule out the possibility of smoke effect on real market is attributable to wildfire risk saliency.

Last, we shift our focus on listings located in coastal areas since real estate proximate to coastline offers numerous amenities, i.e. beach access (Atreya, & Czajkowski, 2014). Nevertheless, such areas are susceptible to inundation and flood risk due to sea-rise level when temperatures rise (Bernstein, Gustafson, & Lewis, 2019). Lending the same line of logic, we investigate whether there is any mediating effect offered by amenities in coastal areas when smoke occurs. Using an indicator variable proxying for coastal status, we interact with our smoke measure and present the results in Column (7) – (9) in Table 8.[26] We observe the persistent effect of smoke in non-coastal areas in terms of number of days outstanding and price difference, but not net listing, as each coefficient is significant at 1% level. On the other hand,

[23] In an untabular test, we stringently exclude all observations in California and its neighbouring states, i.e. Nevada, Arizona, and Oregon. We still document that not only coefficients are significant at the same level, but the magnitude is also qualitatively equal to that in Table 8. Hence, we provide robust results showing that smoke-exposed regions witness increased time period to close a deal with more price depreciation and less market activities, despite different sample refinement techniques.

[24] https://rainbowrestores.com/frequently-asked-questions/when-is-wildfire-season#:~:text=The%20peak%20month%20of%20wildfire,%2C%20Florida%2C%20Arizona%20and%20Oklahoma.

[25] https://www.epa.gov/climate-indicators/climate-change-indicators-wildfires

[26] As coastal status does not vary, its coefficient is absorbed by our tract fixed-effects.

the interaction terms across all three variables of interest are significant different from zero, not to mention that the coefficient size is larger than that of non-coastal areas. We thus document evidence suggesting that homeowners still take into account smoke incidence when making purchase decisions, despite amenities offered by coastline areas.[27]

To further showing that our results are not driven by any particular specification choices, we perform a sensitivity check and present the results in **Table 9**. In particular, Columns (1) - (3) include County-Month FEs to control for any events happening within a month at a county that might affects housing price. As real estate market activity is susceptible to annual changes in state regulatory environment (i.e. tax rate), if any; we thus include state-year fixed-effects in Columns (4) - (6) to account for such changes. Last, Columns (7) - (9) take into consideration of any autocorrelation from the explained variables, in addition to the dens fixed-effects systems in the previous columns. Despite our controls for time-varying factors in either county or state level, we still document a significant effect of smoke on stagnating housing market by both driving up listing outstanding days and widening the gap between opening and offering price.

How climate change belief aggravates the effect of smoke on real estate

Baldauf, Garlappi, and Yannelis (2020) and Bernstein, Billings, Gustafson, and Lewis (2022) document that climate change belief is priced into property's value in the case of sea-rise level. Following the same approach, we define an indicator variable *Worry* that takes value of 1 if the proportion of population worrying about climate change is happening is greater than the country's median value, and zero

[27] In an attempt to identify whether smoke has any non-linear effect on housing valuation and real estate market, we regress higher degrees of smoke measures against our variables of interest. Results in **Appendix C Table 1** provide evidence showing that except for housing price, smoke does not reveal any non-linear impact on other measures of real estate market. In addition, the linear effect of smoke is only visible using medium-heavy but not total smoke days. Non-linear effect of smoke on housing price depreciation indicates that when listings exposed to smoke see an initial reduction in closing relatively to opening price. Nevertheless, price starts appreciating at a certain the number of smoke days. This price behaviour indicates that citizens living in intensive smoke-exposed areas acclimatise the event, and thus take pre-emptive measures, in which case the geographical amenities might outweigh the downside of wildfire plume.

otherwise using the Yale Climate Opinion Maps. We then interact *Worry* with smoke measure and present our results in **Table 10**. To account for heterogeneity, we perform regression analysis for different sub-samples based on frequency of smoke occurrence, in which Columns (1), (4), and (7) use the full sample, while Columns (2), (5), and (8) only focus on first-time smoke experience, and Columns (3), (6), and (9) are for multiple times smoke exposure.

The aggravating effect of climate change worry is the most pronounced in areas exposing to multiple smoke incidence within a year. In particular, we observe that listings in areas where the majority of population are worried about climate change require on average an additional 2 days to close, relative to their neighbours.[28] Given the current 2023 residential real estate market stands at a value of 88.91 trillion dollars, two days outstanding represent a loss of 14.62 billion dollars in a back-of-the-envelope calculation.[29] In addition, a sold property in the former group witnesses a drop of an approximate 3.9% in price, while the coefficient in the latter is indifferent from zero. On the other hand, we document that climate smoke incidence does not affect market liquidity as the interaction terms of neither measures are not significantly different from zero, supporting the short-term effect of smoke on real estate market. The analysis using full sample yields the same results, albeit a small drop in magnitude.[30]

Migration Channel

We then move on pointing out the mechanism of how smoke affects both real estate value and market liquidity. Running the Equation (1), but replacing the explained variables with different county population measures, results in **Table 11** speak in favour of smoke driving the population away in areas of exposure. In particular, Column (1) in Panel A suggests a negative impact of smoke on total county

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[28] $e^{0.575} = 1.77$
[29] 2*((88.91*10^12)/365)*3% = $14.62b, T-bill rate = 3%, https://www.treasurydirect.gov/government/interest-rates-and-prices/certified-interest-rates/annual/fiscal-year-2023/
[30] Interacting climate change worry with Total smoke days, we provide the similar findings in **Appendix B Table 7**.

population using log-transformed value. By including both county and state-year fixed-effects, we effectively look at the variation of population in each county against smoke incidence while controlling for any events happening throughout the year within each state. Column (2) controlling for lagged 1-year county population offers the same finding.

We further pinpoint this effect using the annual change in population, net migration, and net migration rate in Column (3) to (5), respectively. As specifications in these three columns look into the annual change of population within a county, we derive our explanatory variable by taking the annual difference of smoke days to match with the nature of the explained variables. Thus, the county fixed-effects is cancelled in Column (3) to Column (5), leaving only State-Year fixed-effect. *Population Change*, proxying for the difference of population within a year, in Column (3) shows that one day exposing to medium-heavy smoke, on average, reduce 768 people within a county. This could be attributable to migration or deaths, among other reasons. Net migration in Column (4), which is a cleaner proxy for the annual net of in- and out-migration, shows that one extra day exposing to medium-heavy smoke occurring in the previous year leads to an approximate 5 people migrating away from smoke-covered regions. Replacing annual population change by net migration rate, which is the difference between in-and out-migration in a county, we still observe a 19 out of 1,000 people in areas experiencing smoke in previous year in Column (3).[31]

Focusing on the direct impact of wildfire, McConell *et al*. (2021) find that areas with the most destructive caused by fires see a heightened out-migration, but no effect on in-migration, with a significant drop in homeownership. Boustan, Kahn, and Rhode (2012) and Cattaneo *et al.* (2019) also document an increase in migration patterns away from disaster areas. In recent effort, An, Gabriel, and Tzur-Ilan (2023) show that wildland fires heighten credit distress and out-migration and decline house

[31] Using Total Smoke Days, we find the same results in **Appendix B Table 8**.

prices, while related smoke increases credit card and mortgage defaults. Our results supplement this line of literature by showing that in addition to only direct heat impact, wildfire by-product, i.e. smoke, affect the real estate market and housing price via migration mechanism by causing dis-amenities to the surroundings.

CONCLUSION REMARKS

Existing as a widespread damaging event, wildfire has been becoming one of the most concerned issues in recent years due to its massive destruction. In addition to direct heat impact, we empirically show that wildland fires by-product, i.e. smoke, exerts its extensive consequences to both property price and market condition in areas located faraway from fire centres. Not only being priced into housing value, smoke incidence also stiffens the property market liquidity by both lengthening number of days floating and adversely affecting net number of listed properties. Our results on quasi-experience by conducting difference-in-difference analysis confirms the same findings.

Consistent with literature of direct impact from wildfire, we find evidence of heterogeneous reaction of homeowners in regions that experience first and multiple smoke incidence, in which the latter witnesses a larger drop in price relative to the former. We also provide evidence to disregard the alternative explanation that long-standing, i.e. "stale", listings in the market are selling at more discount price by showing that the newer listed properties with more frequent smoke-exposed condition suffer more price drop. In addition, smoke effect is more pronounced in listings located within populated areas relative to those in rural regions. Nevertheless, the effect of smoke is short-term, which lasts to 6 and peaks at 12 months after smoke events before returning to normal after two years, suggesting short-lived but significant change in risk perception of populations. Our results are robust using different criteria to refine the sample, or to account for wildfire seasons. Furthermore, we find that the effect of smoke is most pronounced in areas with the majority of population is concerned that climate change is happening, pointing to the role of belief in real estate valuation. Last, the evidence suggests that smoke reveals its impact on property market by dispelling people away from smoke-exposed areas due to dis-amenities caused to surrounding environment.

Accompanying with higher temperature, prolonged and drier drought seasons provide fuel for wildfire in the face of climate change. Despite the causes, wildfires do and will persist as a threat to population living near high-risk areas, i.e. urban-wildland interface. Among earliest attempts, we prove causal evidence that wildfire extends its far-reaching detrimental effect to regions located miles away from fire incidence by fire-generated smoke, which affects household's weather by not only reducing value but also stagnating real estate market in these areas. Our findings shed a light on how contingent weather condition can affect property valuation, which in turn reduces household wealth.

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Table 1: Descriptive Statistics

This table presents descriptive statistics of variables used in the study. Period covers from 2010 to 2019 in the U.S. *Medium-Heavy Smoke Days* is the number of days covered with medium to heavy smoke density in the latest four months. *Total Smoke Days* include all days with light, medium, to heavy smoke density in the latest four months. *Ln(Total days outstanding)* is natural logarithm of the total number of days for a listing from opening to closing . *Total price difference* is the percentage of closing price relative to opening price. *Ln(Total net listing)* is the natural logarithm of listing difference between opening and closed properties. *Climate Change Worry* takes value of 1 if the proportion of county population worried about climate change is higher than the country's median value in 2020 Yale Climate Change Opinion Survey.

Variable	N	5th	Mean	95th	S.D.
Medium-Heavy Smoke Days	1,415,774	0	0.712	4	1.902
Total Smoke Days	1,415,774	0	3.538	17	6.377
Ln(Total days outstanding)	1,476,169	346.574	477.241	587.493	97.180
Price difference	1,476,316	-7.829	-2.358	0.793	3.136
Ln(Net listings)	1,476,160	109.861	337.024	637.161	184.502
Climate Change Worry	1,476,316	44	53.471	65	6.517

Table 2: Baseline Results

This table presents the baseline results of how smoke affect real estate values and market. Panel A presents the effect of medium to heavy smoke coverage at month frequency, while Panel B uses quarterly observations. Columns (1) – (3) use Average number of days required for a listing to close. Columns (4) – (6) use price difference between closed and opening prices of a listing. Columns (7) – (9) use the net number of listings. All regressions are weighted based on the total number of opening and closed within month. All regressions include Tract fixed-effects and Month-Year fixed-effects. The test statistics are included in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable					
Panel A: Monthly Observations	**Ln(Total days outstanding)**		**Price Difference**		**Net listing**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Medium-Heavy Smoke Days	0.382***	0.280***	-0.030***	-0.028***	-1.173**	-1.112***
	(0.064)	(0.040)	(0.004)	(0.003)	(0.502)	(0.250)
Constant	465.098***	307.515***	-2.054***	-1.852***	561.281***	134.532***
	(0.073)	(15.528)	(0.004)	(0.021)	(0.602)	(7.961)
Adj-R2	0.809	0.840	0.421	0.432	0.727	0.891
N	1,415,157	1,300,520	1,415,303	1,300,733	1,415,158	1,300,517
Lagged Dependent variable		Y		Y		Y
Tract FEs	Y	Y	Y	Y	Y	Y
Month-Year FEs	Y	Y	Y	Y	Y	Y
Tract & Month Clustering	Y	Y	Y	Y	Y	Y

	Dependent Variable					
Panel B: Quarterly Observations	**Ln(Total days outstanding)**		**Price Difference**		**Net listing**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Medium-Heavy Smoke Days	0.571**	0.479**	-0.029**	-0.027**	-2.700***	-3.330***
	(0.120)	(0.136)	(0.007)	(0.007)	(0.337)	(0.450)
Constant	466.168***	233.002***	-1.981***	-1.764***	666.256***	125.959***
	(0.083)	(9.301)	(0.004)	(0.043)	(0.222)	(8.456)
Adj-R2	0.876	0.901	0.518	0.524	0.741	0.917
N	510,135	510,109	510,183	510,183	510,150	510,116
Lagged Dependent variable		Y		Y		Y
Tract FEs	Y	Y	Y	Y	Y	Y
Quarter-Year FEs	Y	Y	Y	Y	Y	Y
Tract & Quarter Clustering	Y	Y	Y	Y	Y	Y

Table 3: Smoke Effects on Real Estate Valuation

This table presents the effect of smoke days on differences of opening and closing listing prices in two subsamples based on the median of Number of listing days. Column (1) and (2) show the below and above median subsample, respectively. All regressions include Tract FEs and Month-Year FEs. The test statistics are included in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Price Difference	**(1) Below Median**	**(2) Above Median**
Medium-Heavy Days	-0.033***	-0.012**
	(0.003)	(0.005)
Constant	-1.510***	-3.179***
	(0.004)	(0.001)
Adj-R2	0.415	0.271
N	719,253	695,059
Tract FEs	Y	Y
Month-Year FEs	Y	Y
Tract & Month Clustering	Y	Y

Table 4: Heterogeneity of Smoke Effect on Different Urbanity areas

This table presents the effect of smoke days on differences of opening and closing listing prices in two subsamples based on the median of Number of listing days. Column (1) and (2) show the below and above median subsample, respectively. All regressions include Tract FEs and Month-Year FEs. The test statistics are included in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Ln(Total days outstanding) **(1)**	**Price Difference** **(2)**	**Net listing** **(3)**
Medium-Heavy Days	0.706***	-0.045***	-1.196**
	(0.128)	(0.004)	(0.489)
Medium-Heavy Days # Urbanity Indicator	-0.212***	0.010***	0.015
	(0.050)	(0.001)	(0.115)
Constant	465.099***	-2.054***	561.281***
	(0.070)	(0.004)	(0.601)
Adj-R2	0.809	0.421	0.727
N	1,415,148	1,415,294	1,415,149
Tract FEs	Y	Y	Y
Month-Year FEs	Y	Y	Y
Tract & Month Clustering	Y	Y	Y

Table 5: Comparison between first and mutiple smoke exposure

This table presents the heterogeneous results of properties with different smoke incidence exposure. Column (1), (3) and (5) include observations with first time coming into contact with smoke. Columns (2), (4) and (6) include properties with more than one time experiencing smoke coverage. All regressions include Tract FEs and Month-Year FEs. The test statistics are included in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively

Medium - Heavy Smoke Days	**Dependent Variable**					
	Ln(Total days outstanding)		**Price Difference**		**Net listing**	
	First	Multiple	First	Multiple	First	Multiple
	(1)	(2)	(3)	(4)	(5)	(6)
Medium-Heavy Smoke Days	1.222	0.443***	0.012	-0.030***	3.499*	-1.552***
	(1.027)	(0.071)	(0.030)	(0.004)	(1.643)	(0.470)
Constant	446.521***	468.474***	-2.066***	-2.073***	493.417***	566.676***
	(0.103)	(0.089)	(0.002)	(0.004)	(0.130)	(0.605)
Adj-R2	0.872	0.798	0.385	0.435	0.872	0.727
N	179,578	1,065,271	179,535	1,065,342	179,540	1,065,276
Tract FEs	Y	Y	Y	Y	Y	Y
Month-Year FEs	Y	Y	Y	Y	Y	Y
Tract & Month Clustering	Y	Y	Y	Y	Y	Y

Table 6: Difference-in-Difference Analysis

This table presents the results of difference-in-difference analysis of how smoke exposure affects real estate values and market. *Post* is an indicator variable that takes value of 1 when the tract is covered in medium-heavy smoke in month m of year t, and 0 otherwise. *Treat* is an indicator variable taking value of 1 if the tract is exposed to smoke at any time within a year, and 0 otherwise. Standard errors are clustered at tract level. The test statistics are included in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable			
Medium-Heavy Smoke Days	**Ln(Total days outstanding)**	**Price Difference**	**Listed**	**Closed**
	(1)	**(2)**	**(3)**	**(4)**
Post * Treat	0.617***	-0.151***	0.061***	-0.016***
	(0.165)	(0.015)	(0.008)	(0.005)
Constant	466.116***	-2.046***	6.192***	4.725***
	(0.062)	(0.006)	(0.003)	(0.002)
Adj-R2	0.807	0.420	0.794	0.833
N	1,474,624	1,474,771	1,474,771	1,474,771
Tract FEs	Y	Y	Y	Y
Month-Year FEs	Y	Y	Y	Y
Tract-Month Clustering	Y	Y	Y	Y

Table 7: Long-term effect of Smoke exposure on Real estate markets

This table presents the longer-term effect of medium-heavy smoke on real estate market. Medium-Heavy Smoke T_{t-6}, T_{t-12}, T_{t-18}, and T_{t-24} are the lagged 6-, 12-, 18-, and 24-month of smoke occurrence. Days Closed in Columns (1) and (2) is the number of days a listing outstands in the market. Price Difference in Columns (3) and (4) is the percentage of difference between opening and closing prices.. Net listing in Columns (5) and (6) is the difference between the number of opening and closed listings within a month. Standard errors are clustered at tract level. The test statistics are included in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Medium-Heavy Smoke Days	**Dependent Variable**					
	Ln(Total days outstanding)		**Price Difference**		**Net listing**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Medium-Heavy Smoke T_{t-6}	0.233***	0.176***	-0.026***	-0.025***	-1.404**	-0.363
	(0.061)	(0.037)	(0.007)	(0.006)	(0.634)	(0.204)
Medium-Heavy Smoke T_{t-12}	0.678***	0.485***	-0.032***	-0.029***	-4.524***	-1.305***
	(0.156)	(0.095)	(0.006)	(0.006)	(0.615)	(0.311)
Medium-Heavy Smoke T_{t-18}	-0.120	-0.059	-0.001	-0.001	-0.636	0.088
	(0.085)	(0.059)	(0.006)	(0.006)	(0.555)	(0.201)
Medium-Heavy Smoke T_{t-24}	0.062	-0.026	0.002	0.002	-0.953	0.032
	(0.167)	(0.118)	(0.007)	(0.006)	(0.664)	(0.247)
Constant	456.621***	288.822***	-1.875***	-1.727***	587.128***	140.298***
	(0.222)	(19.219)	(0.019)	(0.025)	(1.416)	(8.831)
Adj-R2	0.824	0.849	0.439	0.443	0.715	0.887
N	882,306	868,745	882,407	868,900	882353.0	868,805
Lagged Y_{t-1}		Y		Y		Y
Tract FEs	Y	Y	Y	Y	Y	Y
Month-Year FEs	Y	Y	Y	Y	Y	Y
Tract & Month Clustering	Y	Y	Y	Y	Y	Y

Table 8: Result Robustness and Locational Characteristics

This table presents the effect of wildfire smoke on real estate in different sample construction techniques. Columns (1) to (3) present regression results excluding all observations in California. Column (4) – (6) exclude all observations during fire seasons, i.e. June – August each year. Column (7) – (9) include coastal indicator. All regressions include Tract FEs and Month-Year FEs. The test statistics are included in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively

	Dependent Variable								
	Drop California			Exclude fire seasons			Coastal areas		
Medium – Heavy Smoke Days	**Ln(Total days outstanding)**	**Price Difference**	**Net listing**	**Ln(Total days outstanding)**	**Price Difference**	**Net listing**	**Ln(Total days outstanding)**	**Price Difference**	**Net listing**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Medium-Heavy Days	0.168***	-0.024***	-1.065***	0.340***	-0.032***	-1.512***	0.339***	-0.027***	-0.734
	(0.042)	(0.004)	(0.273)	(0.056)	(0.003)	(0.189)	(0.067)	(0.004)	(0.486)
Medium-Heavy Days # Coastline							0.328***	-0.025***	-3.326***
							(0.075)	(0.006)	(0.337)
Constant	314.760***	-2.071***	134.579***	296.581***	-1.839***	138.886***	465.066***	-2.051***	561.597***
	(15.943)	(0.023)	(7.862)	(19.022)	(0.025)	(10.596)	(0.071)	(0.004)	(0.580)
Adj-R2	0.113	0.008	0.602	0.848	0.440	0.886	0.809	0.421	0.727
N	1,174,966	1,175,175	1,174,959	971,149	971,338	971,177	1,415,157	1,415,303	1,415,158
Lagged Y_{t-1}	Y	Y	Y	Y	Y	Y			
Tract FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month-Year FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Tract & Month Clustering	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 9: Sensitivity Check

This table presents the effect of wildfire smoke on real estate in different sample construction techniques. Columns (1) to (3) present regression results excluding all observations in California. Column (4) – (6) exclude all observations during fire seasons, i.e. June – August each year. Column (7) – (9) include coastal indicator. All regressions include Tract FEs and Month-Year FEs. The test statistics are included in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively

	Dependent Variable								
Medium – Heavy Smoke Days	**Ln(Total days outstanding) (1)**	**Price Difference (2)**	**Net listing (3)**	**Ln(Total days outstanding) (4)**	**Price Difference (5)**	**Net listing (6)**	**Ln(Total days outstanding) (7)**	**Price Difference (8)**	**Net listing (9)**
Medium-Heavy Days	0.437***	-0.027***	-2.273***	0.519***	-0.022***	-1.232**	0.378***	-0.020***	-0.581**
	(0.070)	(0.003)	(0.492)	(0.076)	(0.003)	(0.423)	(0.057)	(0.003)	(0.248)
Constant	465.033***	-2.058***	562.636***	464.932***	-2.064***	561.369***	336.142***	-1.916***	207.626***
	(0.082)	(0.003)	(0.594)	(0.090)	(0.003)	(0.510)	(12.758)	(0.014)	(7.091)
Adj-R2	0.813	0.429	0.733	0.831	0.444	0.839	0.853	0.453	0.905
N	1,413,050	1,413,196	1,413,051	1,413,045	1,413,191	1,413,046	1,298,701	1,298,915	1,298,699
Lagged Y_{t-1}							Y	Y	Y
State-Year FEs				Y	Y	Y	Y	Y	Y
County-Month FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Tract FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month-Year FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Tract & Month Clustering	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 10: How Climate change belief intervenes the impact of smoke on real estate

This table presents the effect of how worry about climate change meditate the effect of smoke on real estate market in the U.S. since June 2010 to December 2019. Worry is an indicator variable that takes value of 1 if the proportion of population worrying about climate change is happening is higher than the country's median, and zero otherwise. Column (1), (4), and (7) include full sample. Columns (2), (5), and (8) include observations with first-time exposing to smoke. Columns (3), (6), and (9) include properties with more than one time coming into contact with smoke. All regressions include Tract FEs and Month-Year FEs. The test statistics are included in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively

	Dependent Variable								
Medium – Heavy Smoke Days	**Days closed**			**Price Difference**			**Net listing**		
	Full	**First-time**	**Multiple**	**Full**	**First-time**	**Multiple**	**Full**	**First-time**	**Multiple**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Medium-Heavy Days	0.005	0.786	-0.099	0.003	0.037	0.006	-1.165	8.130	-1.658*
	(0.114)	(2.024)	(0.115)	(0.005)	(0.101)	(0.005)	(0.818)	(4.806)	(0.787)
Medium-Heavy Days # Worry	0.400***	0.455	0.575***	-0.036***	-0.026	-0.039***	-0.009	-4.837	0.112
	(0.117)	(2.759)	(0.133)	(0.005)	(0.106)	(0.005)	(0.552)	(4.685)	(0.558)
Constant	465.105***	446.522***	468.486***	-2.054***	-2.066***	-2.074***	561.280***	493.402***	566.679***
	(0.069)	(0.090)	(0.085)	(0.003)	(0.001)	(0.003)	(0.602)	(0.105)	(0.605)
Adj-R2	0.809	0.872	0.798	0.421	0.385	0.435	0.727	0.872	0.727
N	1,415,157	179,535	1,065,271	1,415,303	179,578	1,065,342	1,415,158	179,540	1,065,276
Tract FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month-Year FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Tract & Month Clustering	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 11: Migration Channel

This table presents the effect of smoke on population migration patterns within the U.S. covering 2010-2019 period. Smoke measure is the number of smoke days occurring in previous year. Ln(Population) is the natural logarithm of total county population in year t. Population Change is the annual change between year t and year (t-1) of population in a county. Net migration is the difference between in-migration and out-migration in a county in year t. Net migration rate is the difference between the number of migrants entering and those leaving a country in a year over 1,000 people. Standard errors are clustered at county level. The test statistics are included in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively

	Dependent Variable				
Medium-Heavy Smoke Days	**Ln(Population)**	**Ln(Population)**	**Population Change**	**Net Migration**	**Net Migration Rate**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Medium-Heavy Days	-0.020***	-0.006***			
	(0.004)	(0.002)			
ΔMedium-Heavy Days			-767.479***	-4.969***	-0.019*
			(216.401)	(1.654)	(0.011)
Lagged Y_{t-1}		0.942***			
		(0.005)			
Constant	1,027.084***	60.085***	63480.924***	266.410***	-0.142
	(0.042)	(4.980)	(5427.901)	(41.309)	(0.132)
Adj-R2	0.999	0.999	0.084	0.092	0.123
N	31,420	31,420	28.278	28.278	28,278
County FEs	Y	Y			
State -Year FEs	Y	Y	Y	Y	Y
County Clustering	Y	Y	Y	Y	Y

Figure 1: Listing Distribution across U.S. counties in 2010-2019

This figure presents the total number of listings across U.S. counties in 2010-2019 period. The number of listing are aggregated from monthly observations throughout the period by county. The darker the colour, the more listings are on the market.

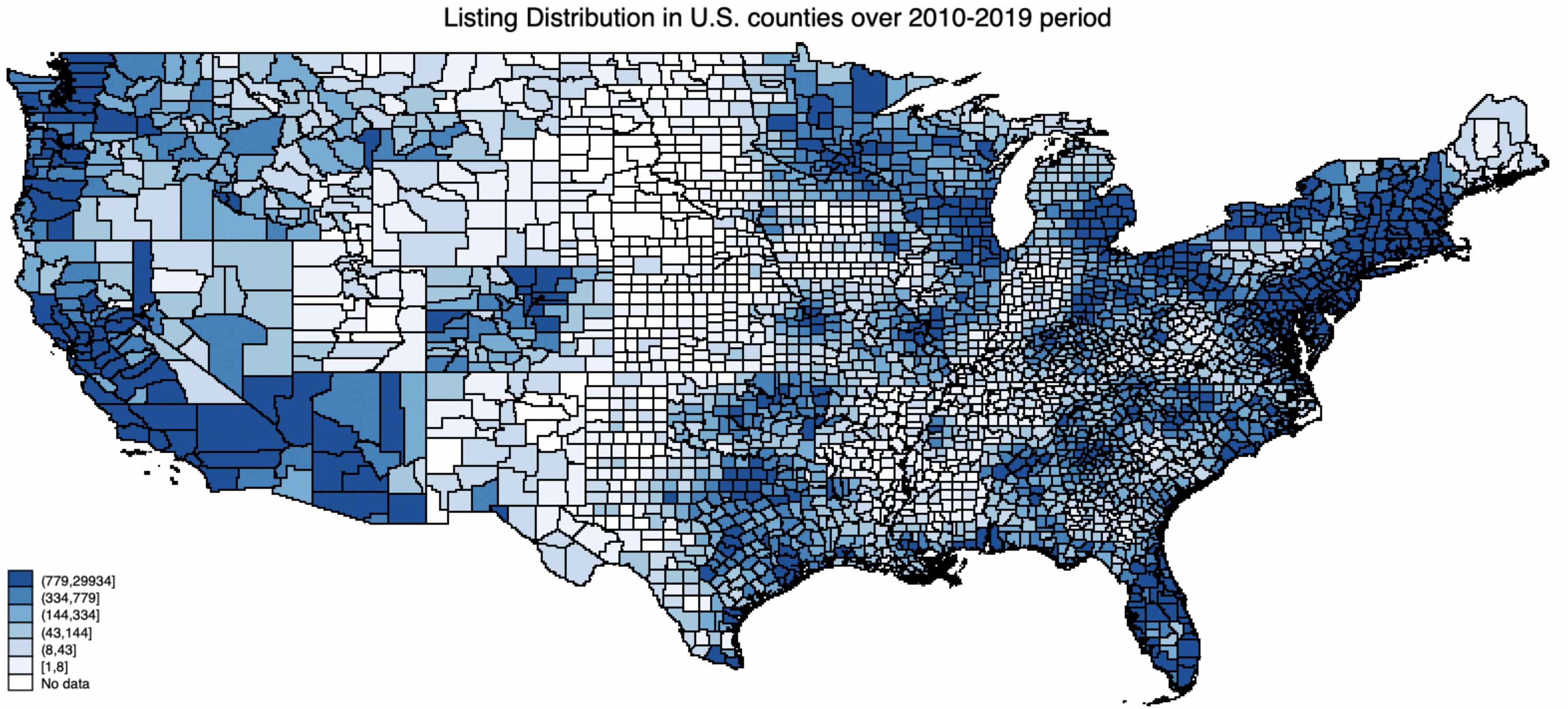
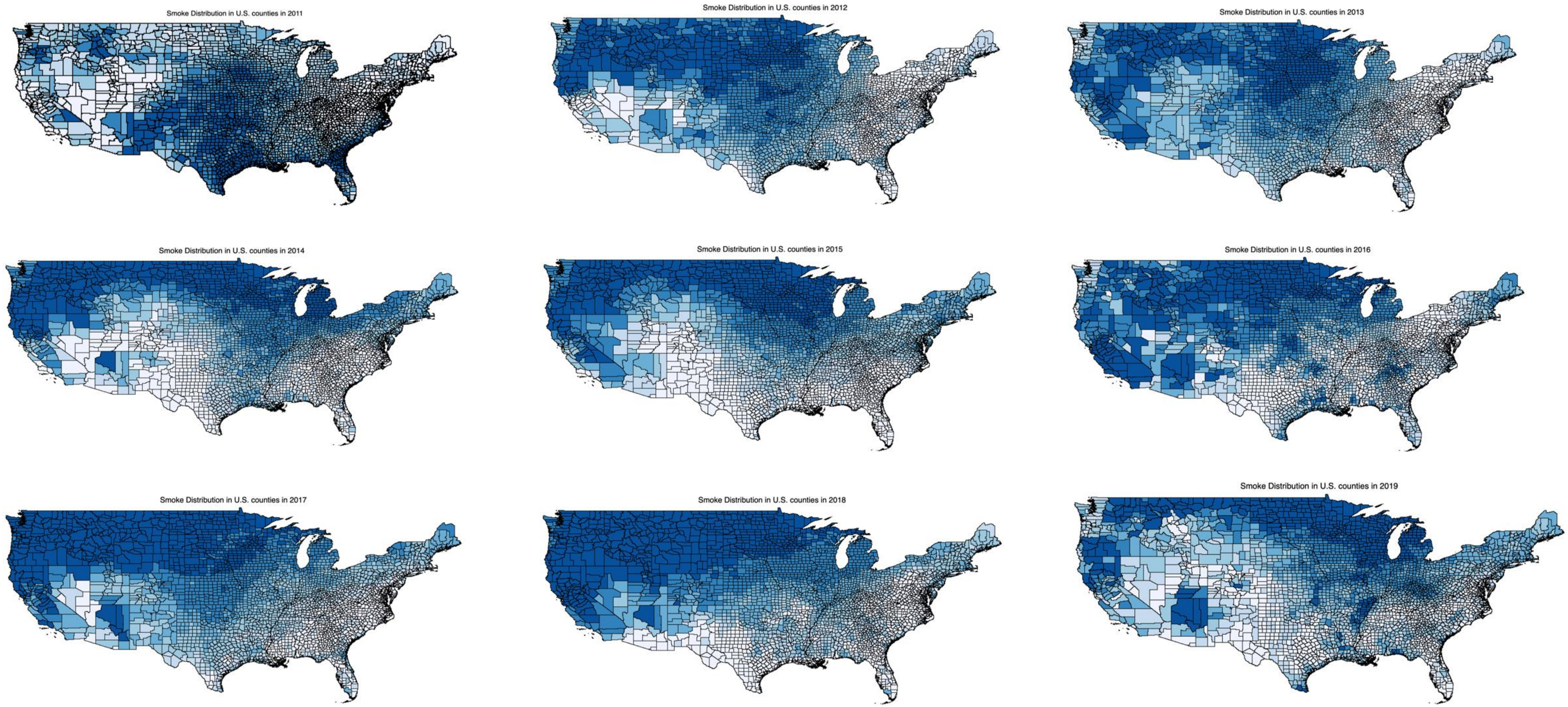


Figure 2: Smoke Distribution over 2011 – 2019 period

This figure present annual medium-heavy smoke coverage in all U.S. counties from 2011 to 2019 period.



Appendix A: Variable Definition

Medium-Heavy Smoke Days is the number of days covered with medium to heavy smoke density that a census tract experience in the latest four months. Plume density follows NOAA convention.

Total Smoke Days include all days with light, medium, to heavy smoke density that a census tract in the latest four months. The density information is qualitatively labelled as light, medium, and heavy based on the apparent thickness (opacity) of the smoke in the satellite imagery. Those three distinct groups are meant to approximate smoke concentrations ranging between 0-10, 10-21, and 21-32 micrograms per cubic meter, respectively.

Ln(Total days outstanding) is natural logarithm of the total number of days for a listing status changing from opening to closing.

Price difference is the percentage of closing price relative to opening price.

Ln(Net listing) is the natural logarithm of listing difference between the number of opening and closed properties.

Climate Change Worry takes value of 1 if the proportion of county population worried about climate change is higher than the country's median value in 2020 Yale Climate Change Opinion Survey.

Ln(Population) is the natural logarithm of total county population in year t at a county.

Population Change is the annual change between year t and year (t-1) of population in a county.

Net Migration is the difference between in-migration and out-migration in a county in year t

Net Migration Rate is the difference between the number of migrants entering and those leaving a country in a year over 1,000 people.

Appendix B: Supplemental Tables

Table 1: Placebo tests for Smoke Measures

This table presents the results of placebo test of how smoke affects real estate market and pricing. Panel A and uses number of days with medium-heavy smoke density and total smoke days, respectively. Column (1), (3) and (5) use current and 3 months forward. Columns (2), (4), and (6) use 4 months forward. All regressions include Tract FEs and Month-Year FEs. The test statistics are included in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable					
Medium – Heavy Smoke Days	**Days closed**		**Price Difference**		**Net listing**	
	F3	**F4**	**F3**	**F4**	**F3**	**F4**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Medium-Heavy Smoke Days	-0.002	-0.090	-0.006	0.006	0.145	-0.015
	(0.086)	(0.092)	(0.006)	(0.005)	(0.462)	(0.488)
Constant	470.377***	471.769***	-2.123***	-2.154***	558.425***	558.146***
	(0.133)	(0.144)	(0.009)	(0.007)	(0.725)	(0.781)
Adj-R2	0.774	0.767	0.422	0.423	0.728	0.730
N	1,296,227	1,284,295	1,296,318	1,284,380	1,296,205	1,284,259
Tract FEs	Y	Y	Y	Y	Y	Y
Month-Year FEs	Y	Y	Y	Y	Y	Y
Tract & Month Clustering	Y	Y	Y	Y	Y	Y

Table 2: Baseline Results for Total Smoke Days

This table presents the baseline results of how smoke affect real estate values and market. Panel A presents the effect of total number of days exposed to smoke coverage at month frequency, while Panel B uses quarterly observations. Columns (1) – (3) use Average number of days required for a listing to close. Columns (4) – (6) use price difference between closed and opening prices of a listing. Columns (7) – (9) use the net number of listings. All regressions are weighted based on the total number of opening and closed within month. All regressions include Tract fixed-effects and Month-Year fixed-effects. The test statistics are included in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable					
Panel A: Monthly Observations	**Days closed**		**Price Difference**		**Net listing**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Total Smoke Days	0.084**	0.071***	-0.011***	-0.010***	-0.021	-0.393***
	(0.029)	(0.018)	(0.001)	(0.001)	(0.221)	(0.110)
Constant	465.078***	307.263***	-2.026***	-1.827***	559.972***	135.045***
	(0.165)	(15.555)	(0.007)	(0.022)	(1.276)	(7.909)
Adj-R2	0.809	0.840	0.421	0.432	0.727	0.891
N	1,415,157	1,300,520	1,415,303	1,300,733	1,415,158	1,300,517
Lagged Dependent variable		Y		Y		Y
Tract FEs	Y	Y	Y	Y	Y	Y
Month-Year FEs	Y	Y	Y	Y	Y	Y
Tract & Month Clustering	Y	Y	Y	Y	Y	Y
	Dependent Variable					
Panel B: Quarterly Observations	**Days closed**		**Days closed**		**Days closed**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Total Smoke Days	0.187*	0.192**	-0.011**	-0.010**	-0.855*	-1.389***
	(0.060)	(0.055)	(0.002)	(0.002)	(0.317)	(0.231)
Constant	465.904***	232.210***	-1.961***	-1.747***	667.400***	127.531***
	(0.214)	(9.187)	(0.005)	(0.044)	(1.127)	(7.764)
Adj-R2	0.876	0.901	0.518	0.524	0.740	0.917
N	510,135	510,109	510,183	510,183	510,150	510,116
Lagged Dependent variable		Y		Y		Y
Tract FEs	Y	Y	Y	Y	Y	Y
Quarter-Year FEs	Y	Y	Y	Y	Y	Y
Tract & Quarter Clustering	Y	Y	Y	Y	Y	Y

Table 3: Heterogeneity of Smoke Effect on Different Urbanity areas

This table presents the effect of smoke days on differences of opening and closing listing prices in two subsamples based on the median of Number of listing days. Column (1) and (2) show the below and above median subsample, respectively. All regressions include Tract FEs and Month-Year FEs. The test statistics are included in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Ln(Total days outstanding) **(1)**	**Price Difference** **(2)**	**Net listing** **(3)**
Total Smoke Days	0.131**	-0.015***	-0.021
	(0.052)	(0.002)	(0.224)
Total Smoke Days # Urbanity Indicator	-0.033*	0.003***	0.001
	(0.018)	(0.000)	(0.045)
Constant	465.089***	-2.027***	559.972***
	(0.159)	(0.007)	(1.277)
Adj-R2	0.809	0.421	0.727
N	1,415,148	1,415,294	1,415,149
Tract FEs	Y	Y	Y
Month-Year FEs	Y	Y	Y
Tract & Month Clustering	Y	Y	Y

Table 4: Comparison between first and mutiple smoke exposure for Total Smoke Days

This table presents the heterogeneous results of properties with different smoke incidence exposure. Column (1), (3) and (5) include observations with first time coming into contact with smoke. Columns (2), (4) and (6) include properties with more than one time experiencing smoke coverage. All regressions include Tract FEs and Month-Year FEs. The test statistics are included in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively

Total Smoke Days	**Days closed**		**Price Difference**		**Net listing**	
	First	Multiple	First	Multiple	First	Multiple
	(1)	(2)	(3)	(4)	(5)	(6)
Total Smoke Days	0.707	0.121***	0.005	-0.011***	0.841	-0.162
	(0.431)	(0.034)	(0.014)	(0.001)	(0.515)	(0.211)
Constant	446.230***	468.298***	-2.068***	-2.041***	493.301***	565.655***
	(0.231)	(0.207)	(0.006)	(0.008)	(0.186)	(1.309)
Adj-R2	0.872	0.798	0.385	0.435	0.872	0.726
N	179,578	1,065,271	179,535	1,065,342	179,540	1,065,276
Tract FEs	Y	Y	Y	Y	Y	Y
Month-Year FEs	Y	Y	Y	Y	Y	Y
Tract & Month Clustering	Y	Y	Y	Y	Y	Y

Table 5: Difference-in-Difference Analysis for Total Smoke Days

This table presents the results of difference-in-difference analysis of how smoke exposure affects real estate values and market. *Post* is an indicator variable that takes value of 1 when the tract is covered in smoke in month m of year t, and 0 otherwise. *Treat* is an indicator variable taking value of 1 if the tract is exposed to smoke at any time within a year, and 0 otherwise. Standard errors are clustered at tract level. The test statistics are included in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable			
Total Smoke Days	**Days closed**	**Price Difference**	**Listed**	**Closed**
	(1)	**(2)**	**(3)**	**(4)**
Post * Treat	0.311**	-0.120***	0.026***	-0.014**
	(0.152)	(0.010)	(0.005)	(0.006)
Constant	466.136***	-2.021***	6.197***	4.728***
	(0.104)	(0.007)	(0.004)	(0.004)
Adj-R2	0.807	0.419	0.793	0.833
N	1,474,624	1,474,771	1,474,771	1,474,771
Tract FEs	Y	Y	Y	Y
Month-Year FEs	Y	Y	Y	Y
Tract-Month Clustering	Y	Y	Y	Y

Table 6: Long-term effect of Smoke exposure on Real estate markets

This table presents the longer-term effect of total smoke on real estate market. Total Smoke T_{t-6}, T_{t-12}, T_{t-18}, and T_{t-24} are the lagged 6-, 12-, 18-, and 24-month of smoke occurrence. Days Closed in Columns (1) and (2) is the number of days a listing outstands in the market. Price Difference in Columns (3) and (4) is the percentage of difference between opening and closing prices.. Net listing in Columns (5) and (6) is the difference between the number of opening and closed listings within a month. Standard errors are clustered at tract level. The test statistics are included in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable					
Total Smoke Days	**Days closed**		**Price Difference**		**Net listing**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Total Smoke Days T_{t-6}	0.010	0.061***	-0.008**	-0.003*	-0.032	-0.035
	(0.036)	(0.016)	(0.003)	(0.001)	(0.191)	(0.082)
Total Smoke Days T_{t-12}	0.116**	0.041**	-0.009***	-0.002	-1.478***	0.051
	(0.052)	(0.014)	(0.002)	(0.002)	(0.197)	(0.069)
Total Smoke Days T_{t-18}	-0.062	0.129***	0.001	0.000	-0.441***	-0.471***
	(0.041)	(0.029)	(0.002)	(0.003)	(0.139)	(0.118)
Total Smoke Days T_{t-24}	0.101**	0.053*	-0.001	-0.005**	-0.247	-0.113
	(0.039)	(0.024)	(0.002)	(0.002)	(0.160)	(0.073)
Constant	456.698***	372.055***	-1.839***	-2.140***	591.128***	175.166***
	(0.426)	(7.911)	(0.036)	(0.038)	(2.246)	(8.003)
Adj-R2	0.824	0.767	0.438	0.442	0.715	0.906
N	882,306	887,790	882,407	887,853	882,353	887,708
Lagged Y_{t-1}		Y		Y		Y
Tract FEs	Y	Y	Y	Y	Y	Y
Month-Year FEs	Y	Y	Y	Y	Y	Y
Tract Clustering	Y	Y	Y	Y	Y	Y

Table 7: How Climate change belief intervenes the impact of smoke on real estate for Total Smoke Days

This table presents the effect of how worry about climate change meditate the effect of smoke on real estate market in the U.S. since June 2010 to December 2019. Worry is an indicator variable that takes value of 1 if the proportion of population worrying about climate change is happening is higher than the country's median, and zero otherwise. Column (1), (4), and (7) include full sample. Columns (2), (5), and (8) include observations with first-time exposing to smoke. Columns (3), (6), and (9) include properties with more than one time coming into contact with smoke. All regressions include Tract FEs and Month-Year FEs. The test statistics are included in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively

		Days closed			Price Difference			Net listing	
Total Smoke Days	**Full**	**First-time**	**Multiple**	**Full**	**First-time**	**Multiple**	**Full**	**First-time**	**Multiple**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Total Smoke Days	0.080*	-0.385	0.031	-0.001	0.015	-0.000	-0.100	2.307	-0.312
	(0.044)	(1.338)	(0.042)	(0.001)	(0.038)	(0.001)	(0.366)	(2.045)	(0.356)
Total Smoke Days # Worry	0.004	1.165	0.096**	-0.010***	-0.010	-0.012***	0.085	-1.564	0.160
	(0.033)	(1.614)	(0.042)	(0.001)	(0.034)	(0.001)	(0.264)	(1.975)	(0.266)
Constant	465.079***	446.253***	468.307***	-2.027***	-2.068***	-2.043***	559.980***	493.270***	565.671***
	(0.164)	(0.204)	(0.204)	(0.007)	(0.005)	(0.008)	(1.281)	(0.186)	(1.314)
Adj-R2	0.809	0.872	0.798	0.421	0.385	0.435	0.727	0.872	0.726
N	1,415,157	179,535	1,065,271	1,415,303	179,578	1,065,342	1,415,158	179,540	1,065,276
Tract FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month-Year FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Tract & Month Clustering	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 8: Migration Channel for Total Smoke Days

This table presents the effect of smoke on population migration patterns within the U.S. covering 2010-2019 period. Smoke measure is the number of smoke days occurring in previous year. Ln(Population) is the natural logarithm of total county population in year t. Population Change is the annual change between year t and year (t-1) of population in a county. Net migration is the difference between in-migration and out-migration in a county in year t. Net migration rate is the difference between the number of migrants entering and those leaving a country in a year over 1,000 people. Standard errors are clustered at county level. The test statistics are included in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively

	Dependent Variable				
Total Smoke Days	**Ln(Population)**	**Ln(Population)**	**Population Change**	**Net Migration**	**Net Migration Rate**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Total Smoke Days	-0.009***	-0.002**			
	(0.002)	(0.001)			
ΔTotal Smoke Days			-274.364***	-1.275*	-0.003
			(101.594)	(0.716)	(0.006)
Lagged Y_{t-1}		0.942***			
		(0.005)			
Constant	1027.302***	60.077***	64006.215***	267.928***	-0.143
	(0.104)	(4.976)	(5475.760)	(41.460)	(0.133)
Adj-R2	0.999	0.999	0.084	0.092	0.122
N	31,420	31,420	28.278	28.278	28,278
County FEs	Y	Y			
State -Year FEs	Y	Y	Y	Y	Y
County Clustering	Y	Y	Y	Y	Y

Appendix C:

Table 1: Non-linear effect of Smoke on Real Estate Market

This table presents the non-linear effect of smoke on real estate market. Panel A uses Days with Medium-Heavy Smoke Density, Panel B uses all smoke levels. Column (1), (4), and (7) include number of smoke days and its quadratic value. Column (2), (5), and (8) include number of smoke days, its quadratic and cubic value. Columns (3), (6), and (9) include number of smoke days, its quadratic value, cubic value, and lagged one-month of the explained variable. All regressions include Tract FEs and Month-Year FEs. The test statistics are included in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively

Pane A: Medium-Heavy	**Days closed**			**Price Difference**			**Net listing**		
Smoke Days	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Medium-Heavy Smoke Days	0.405***	0.477***	0.335**	-0.053***	-0.065***	-0.059***	-0.096	0.268	-1.860***
	(0.104)	(0.146)	(0.108)	(0.006)	(0.009)	(0.008)	(0.950)	(1.156)	(0.511)
Medium-Heavy Smoke Days ^2	-0.001	-0.013	-0.006	0.001***	0.003***	0.003***	-0.068*	-0.126	0.060
	(0.004)	(0.016)	(0.012)	(0.000)	(0.001)	(0.001)	(0.037)	(0.125)	(0.046)
Medium-Heavy Smoke Days ^3		0.000	0.000		-0.000**	-0.000**		0.002	-0.001
		(0.000)	(0.000)		(0.000)	(0.000)		(0.004)	(0.001)
Constant	465.084***	465.060***	307.491***	-2.041***	-2.036***	-1.837***	560.643***	560.523***	134.825***
	(0.092)	(0.097)	(15.539)	(0.005)	(0.005)	(0.021)	(0.841)	(0.840)	(7.949)
Adj-R2	0.809	0.809	0.840	0.421	0.421	0.432	0.727	0.727	0.891
Lagged Y_{t-1}			Y			Y			Y
Tract FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month-Year FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Tract & Month Clustering	Y	Y	Y	Y	Y	Y	Y	Y	Y

Panel B: Total Smoke Days	**Days closed**			**Price Difference**			**Net listing**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Total Smoke Days	-0.026	-0.099	-0.076	-0.018***	-0.025***	-0.023***	0.542	1.309	-0.753
	(0.039)	(0.078)	(0.065)	(0.002)	(0.003)	(0.003)	(0.442)	(0.853)	(0.498)
Total Smoke Days ^2	0.003***	0.008	0.007	0.000***	0.001***	0.001***	-0.015	-0.066	0.015
	(0.001)	(0.005)	(0.004)	(0.000)	(0.000)	(0.000)	(0.009)	(0.040)	(0.026)
Total Smoke Days ^3		-0.000	-0.000		-0.000***	-0.000***		0.001	-0.000
		(0.000)	(0.000)		(0.000)	(0.000)		(0.001)	(0.000)
Constant	465.390***	465.506***	307.635***	-2.007***	-1.995***	-1.799***	558.369***	557.157***	135.743***
	(0.179)	(0.171)	(15.596)	(0.009)	(0.009)	(0.022)	(1.831)	(2.392)	(8.111)
Adj-R2	0.809	0.809	0.840	0.421	0.421	0.432	0.727	0.727	0.891
N	1,415,157	1,415,157	1,300,520	1,415,303	1,415,303	1,300,733	1,415,158	1,415,158	1,300,517
Lagged Y_{t-1}			Y			Y			Y
Tract FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month-Year FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Tract & Month Clustering	Y	Y	Y	Y	Y	Y	Y	Y	Y