Air Pollution and Rent Prices: Evidence from Wildfire Smoke Plumes*

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Abstract

We leverage quasi-experimental wildfire smoke shocks to analyze the causal effect of air pollution exposure ($PM_{2.5}$) on the rent and prices of housing transactions, using satellite-based smoke plumes data and ambient air pollution data. Our results indicate that the rent of homes that are not directly affected by wildfires but exposed to wildfire plumes declines by about 0.7% per unit increase in $PM_{2.5}$, representing a net loss of $108.53 per year, per unit. The response of prices is more than three-fold highlighting a gap in the willingness to pay for high air quality between tenants and owners.

Keywords: Air Pollution, Rent Prices, Wildfire, Rental Housing.

JEL classification: Q52, Q53, R21

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1. Introduction

During June 2023, in the wake of 500 ongoing wildfire events in eastern Canada, heavy smoke and particulate emissions blanketed 122 million people across major parts of the northeast and north-central United States, resulting in some of the most polluted days on record. Wildfires are recognized as major contributors to air pollution, releasing about 15% of total particle emissions in the U.S. each year, with an increasing intensity and frequency (Xie et al., 2022). Wildfire smoke contains particulate matter contaminants with an aerodynamic diameter less than or equal to 2.5μm ($PM_{2.5}$), which have known health hazards that can impair labor productivity (Hanna and Oliva, 2015; Borgschulte et al., 2022; Zivin and Neidell, 2012) and procure long-term consequences on education and earnings (Case et al., 2002; Isen et al., 2017). Broadly speaking, air pollution represents a negative local dis-amenity affecting location choices of households that value access to clean air (Bento et al., 2015).

In this paper, we analyze the causal effect of air pollution on rent prices, using the natural occurrence of wildfire smoke to create exogenous shocks. This type of smoke increases pollution levels in ways that vary widely across different areas due to factors such as wind and rain patterns. Although there is an extensive literature exploring the effect of exposure to air pollution on house prices (e.g. Sager and Singer, 2022), less is known about how air pollution affects rent prices, which is surprising, considering the informativeness of rental rates about location demand and household preferences (Sonstelie and Portney, 1980; Howard and Liebersohn, 2021).

To identify the effect of air pollution on rent, we combine high-frequency rental data from the Las Vegas Realtor's Multiple Listing Service (MLS) that contain novel administrative details about lease covenants and contract terms with daily data on ambient air pollution from the U.S. Environmental Protection Agency's (EPA) Air Quality System. We then test whether rental rates respond to the daily variation in pollution that the property was exposed to while on the market using comprehensive hedonic models on repeat rental contracts that account for differences in lease covenants, property characteristics, neighborhood attributes, and temporal trends. Our identification strategy exploits the variation in the pollution within Clark County, NV where wildfires were not a direct threat but exposed households to large shocks in wildfire smoke and pollution.

Our study makes five key contributions. First, we document the relation between daily pollution levels and market rents from individual lease contracts, whereas prior studies commonly focus on the impact of monthly, quarterly, or yearly average pollution levels on aggregated survey-based housing values and exclude the revealed preferences of tenants who make up a large share of the population. We find that a one-unit increase in $PM_{2.5}$ observed on the lease date is associated with a 0.02% decline in the negotiated monthly rent. This result is consistent across time and between most neighborhoods. Moreover, the negative relation is robust to alternate functional forms, various rent-pollution date matching schemes, and the pollution measure from a leading reanalysis project that uses ground monitors, satellite data, and chemical transport models to improve the precision of $PM_{2.5}$ measures (Van Donkelaar et al., 2021). We also replicate our analysis using CoreLogic Rent data for Chicago, Illinois and the Bay Area in California.

Second, we feature wildfire smoke as an instrument to address the potential concerns that pollution could be endogenous to locations of lower property values or rents and variation in the daily $PM_{2.5}$ measures may not perfectly reflect fluctuations from wildfire smoke as other air pollutant factors may exist. This approach allows us to depart from relying on policy shocks for identification (e.g., Amini et al., 2022; Bento et al., 2015; Grainger, 2012), which are prone to measurement errors (see Sager and Singer, 2022). To do so, we link the MLS lease data to a novel dataset of wildfire smoke plumes from an operational group of experts at the National Oceanic and Atmospheric Administration (NOAA) who use satellite images to identify the location and the movements of every wildfire smoke plume in the US. These data allow us to determine the daily smoke exposure status for all tracts in our sample, and exploit quasi-random variations in air quality triggered by drifting smoke plumes.[1] Specifically, we instrument pollution with the count of smoke days for the past year from thirty days before the date of rental signing for each transaction.[2] We consider this instrument to be relevant and meet the exclusion restriction as smoke particles contribute to the composition of $PM_{2.5}$, and the 30-day lag period rules out a direct effect on the rent. Adjusting the model for location endogeneity using a smoke instrument raises the magnitude of the marginal response of rents to a unit increase of $PM_{2.5}$ to about -0.7%. This point estimate indicates that the average effect of pollution on rent translates into a loss of approximately \$108.53 per year.[3] To add context, Bayer et al. (2009) estimated an elasticity of willingness to pay (WTP) with respect to the air quality of 0.34–0.42, implying that the median household would pay \$149–\$185 (in constant 1982–1984 dollars) for a one-unit reduction in average ambient concentrations of particulate matter.

Third, we explore the direct effect of smokey days on the contract rent. Our results indicate that the rent is about 3% lower when the tract is covered by smoke during the closing date, upon instrumenting the wildfire smoke indicator with the daily $PM_{2.5}$ level in the same tract. Intuitively, wildfire smoke is visible while $PM_{2.5}$ levels are not but both are related to each other, implying that this instrument meets the relevance and exclusion criteria. The results are consistent with estimates of the indirect smoke pollution effect on rental prices.

Fourth, to understand the mechanisms influencing the results, we examine the effect of pollution on liquidity factors including the number of days on the market, the likelihood of successfully leasing, and the quarterly quantity of listings. This analysis includes listings that were withdrawn from the market by landlords. Pollution seems to impact liquidity measures by economically meaningful levels. For instance, excess pollution measured by the $PM_{2.5}$ above 12 units delays the days on the market by 3.33% and reduces the likelihood that a property is leased. Likewise, each day of excess pollution decreases the quarterly number

[1] A similar approach was taken by Borgschulte et al. (2022) to explore the effect of air pollution on the labor market.

[2] A smoke day is defined if more than 50 percent of the area is covered by smoke.

[3] $\$108.53 = \$1,292 \times 0.7\% \times 12$.

of listings on the market by about 1.6%. However, accounting for these search frictions does not affect estimates of the rent response to pollution, and the quantity of lease contracts signed over a quarter is independent of fluctuations in pollution levels. One interpretation is that pollution is considered by tenants a transitory environmental condition with minor short-term consequences even though the negative health externalities may be much greater.

Fifth, we explore the effect of air pollution on house prices using a two-stage, repeat-transactions approach and housing deeds from the CoreLogic Real Estate data. We find a much larger response in house prices than rental rates. A unit increase in $PM_{2.5}$ is associated with a 4% decline in home prices, on average. The magnitude of this effect is similar to those reported by Sullivan (2016), and much larger than those from earlier studies (see Smith and Huang, 1995). Our findings suggest that tenants are less sensitive to air pollution and wildfire smoke exposure than homeowners, which is consistent with related work by Amini et al. (2022), Bento et al. (2015), Lang (2015), and Grainger (2012). Put differently, the marginal WTP for high air quality reflects tenure expectations at particular locations as tenants typically have a 1-year lease contract while homeowners often have a 30-year mortgage.

Our paper contributes to the literature that has sought to find evidence that air quality is capitalized in housing values (e.g., Sager and Singer, 2022; Zhang et al., 2021; Bayer et al., 2009; Smith and Huang, 1995; Chay and Greenstone, 2005).[4] For instance, Sager and Singer (2022) analyze the effect of the U.S. Clean Air Act standards for fine particulate matter and find that $PM_{2.5}$ reductions following nonattainment designation were associated with significant house price increases, representing an elasticity of around -1.4. Similarly, Chay and Greenstone (2005) estimate an elasticity of housing values with respect to particulates concentrations ranging from -0.2 to -0.35, while Smith and Huang (1995) estimate an elasticity of -0.04 to -0.07.

[4]In a related strain of literature, Hanna (2007) examines the response of house values to proximity to polluting manufacturing plants, while Davis (2011) investigates the impact of proximity to power plants on home values and rents. Meanwhile, Brasington and Hite (2005) and Mínguez et al. (2013) measure the impact of perceived pollution on property prices.

Our paper is among the first to explore the effect of air pollution on rental market prices and liquidity. This literature includes only a handful of studies. For instance, Amini et al. (2022) examine the impact of nitrogen dioxide (NO_2) pollutants on transaction-level housing prices and rents in Tehran, Iran following the passage of the Comprehensive Iran Sanctions, Accountability, and Divestment Act by the U.S. Congress. Bento et al. (2015) and Grainger (2012) quantify the value in the reduction of suspended particulate matter (PM_{10}) due to the 1990 Clean Air Act Amendments using rent estimates from the U.S. decennial census survey data at the tract level. Lang (2015) conduct a similar analysis on PM_{10} but using restricted data from the American Housing Survey. Wang and Lee (2022) explore the capitalized benefits of an air quality index in city-average prices and rents in China. Lastly, Cvijanovic et al. (2023) study the impact of $PM_{2.5}$ on commercial property returns. While the most related work focus on changes in air quality because of a new policy or rely on aggregated measures, we exploit natural variation in wildfire smoke plumes and rental transactions using high-frequency data.

2. Data

2.1. Lease Contracts

Our data source for rental contracts is the Las Vegas Realtors' (LVR) MLS, which contains information on fully executed lease contracts in Clark County, NV that were arranged by Realtors from August 2008 to December 2019.[5] Real estate agents who are members of the LVR association use the MLS to help landlords find a tenant and create lease listings that stream information about the property and desired rental contract terms to other real estate agents with access to the MLS and online platforms like Trulia or Zillow that subscribe to MLS feeds. After finding a tenant and executing a rental contract, the real estate agent

[5]Given 950,874 housing units in Clark County, NV of which 45% are non-owner occupied (according to the 2022 U.S. Census Bureau), the LVR-MLS database accounts for roughly a third of all renters.

updates the lease listing with information about the rent and lease terms.

We exclude data on rental contracts where the monthly lease rate is more than $10,000 or less than $300, the property has a living area greater than 6,000 square feet or less than 400 square feet, the lot size is more than 50,000 square feet, the number of bedrooms or bathrooms is more than five, the garage fits more than three cars, the number of fireplaces exceeds three, the property's structure age is greater than 60 years, and the referral commission amount is more than $7,000. We also exclude properties that do not clearly identify the lease term and observations where any of the relevant fields are missing. Lastly, we remove rental contracts for manufactured homes. The final sample consists of 308,082 executed leases for non-commercial residential properties, representing 138,898 unique rental properties, which account for approximately 96% of all the rental properties in the LAR-MLS (as of December 2019).

Table A.1 provides summary statistics on key characteristics of the rental contract in Panel A, the rental property's neighborhood in Panel B, and the rental property's structure in Panel C. The average rental contract has a lease rate of $1,292 per month. The average rental contract starts within a week of signing and most have a term length of 12 months (85%). Figure A.1(a) reports the kernel density of the monthly rent per square, illustrating a normal distribution with a slight skew to the right. Figure A.1(b) shows the average rent per square foot for each year from 2008 to 2019 and the total quantity of fully executed lease contracts by year. About 96% of the rental contacts were successfully matched to a record on pollution.

2.2. CoreLogic Real Estate data

Our source for property-level information is the CoreLogic Real Estate data. These data come from public records, MLS platforms, and local government tax assessment files, and contain information on both transactions and home characteristics for almost all houses in Clark County, NV. Key variables we observe include the precise site address; latitude and longitude coordinates of the property; transaction date and type; year built; and building and land square footage. The corresponding summary statistics are show in Table A.2.

We also use the CoreLogic Real Estate data to explore the effect of pollution on rent prices in Chicago and the Bay Area in California, and report summary statistics in Table A.3. We limit our attention to listings that provided a closing rent. A potential issue with these rent data is that they lack information about the lease contract such as the contract term and type (e.g, net, gross, full service). Therefore, we only use the CoreLogic Real Estate data as a robustness test, not the main specification.

2.3. Air Pollution

We obtain ambient air pollution data from the Environmental Protection Agency's (EPA) Air Quality System. We use daily ground monitor readings for EPA "criteria pollutants" including a measure of particulate matter ($PM_{2.5}$). To measure air pollution for a tract, we take the distance-weighted average of two valid readings for each pollutant from monitors that are the closest to the tract's centroid. We spatially intersect these data with tract boundary files and link them to individual-level administrative records. Figure A.2 shows the location of the pollution monitors (the blue dots) in 2019. Table A.4 shows the number of monitors by year from 2008 to 2019. Figure A.3 shows the variation in pollution levels in July of each year, where the black borders are tracts. Tables A.5 and A.6 show the rich variation in smoke and pollution patterns.

The EPA's air quality monitoring network is spatially sparse, and more than 80 percent of U.S. counties do not contain a $PM_{2.5}$ monitor. In Clark County, NV, there are only 6 monitors prior to 2017 and 5 monitors prior to 2012 (see Table A.4). Recent advances in satellite technology, combined with advances in prediction techniques (e.g., machine learning) have helped researchers to better identify the effects of exposure to high levels of air pollution. For instance, a growing suite of satellite observations of aerosol optical depth makes it possible to estimate ground-level concentrations of $PM_{2.5}$ at fine spatial resolutions (<1km). Social scientists are increasingly using these satellite-based estimates of $PM_{2.5}$ concentrations to analyze the health and economic impacts of ambient pollution exposure (e.g., Di et al., 2017; Fowlie et al., 2019).

Thus, we also use an alternative measure of $PM_{2.5}$, produce by Van Donkelaar et al. (2021) (version V5.GL.03), that includes various auxiliary variables like meteorological or geographical factors that have been adopted into the Geographically Weighted Regression (GWR) model. This measure offers a spatial resolution of 1-km $\times$ 1-km cells, opposed to tract boundaries, which allow us to assign precise pollution levels to all housing units in Clark County, NV between 2008 and 2019.[6] The GWR dataset is publicly available on a monthly time scale.[7]

2.4. Wildfire Smoke

We collect the daily smoke exposure data that were developed by Miller et al. (2021) using wildfire smoke analysis produced by the National Oceanic and Atmospheric Administration's Hazard Mapping System (HMS), which are available from September 2005 onward.[8] The HMS uses observations from the Geostationary Operational Environmental Satellite, which produces imagery at a 1-km resolution for visual bands and a 2-km resolution for infrared bands, to identify fire and smoke emissions over the contiguous United States (Ruminski et al., 2006). Smoke analysts process the satellite data to draw georeferenced polygons that represent the spatial extent of wildfire smoke plumes detected each day. Plumes are typically drawn twice per day, once shortly before sunrise and once shortly after sunset. We use the HMS smoke plume data from 2008 to 2019 to construct smoke exposure at the tract level for each day in the sample period.

[6] Version V5.GL.03 combines Aerosol Optical Depth retrievals from the NASA MODIS, MISR, and SeaWIFS instruments with the GEOS-Chem chemical transport model and is calibrated to regional ground-based observations of both total and compositional mass using GWR.

[7] https://wustl.app.box.com/v/ACAG-V5GL03-GWRPM25/folder/183627598190.

[8] These data come from an operational group of NOAA experts who rely on satellite imageries to identify the location and the movements of every wildfire smoke plume in the US.

3. Pollution and Rent

3.1. *Baseline Analysis*

We examine the effect of air pollution on rent using a standard hedonic model:

$$Y_{it} = \delta PM_{zt} + X_{it}\beta + \tau_t + \zeta_i + \varepsilon_{it} \tag{1}$$

where Y_{it} is the monthly rent of property i at time t in the natural log form, PM_{zt} is the average pollution observed at time t in tract z, and δ is the coefficient of interest to be estimated. X_{it} stands for an array of a lease contract, property, and neighborhood characteristics; and β is a vector of corresponding coefficients. We also include fixed effects for the year-quarter of lease contract execution date τ_t and individual property ζ_i. Lastly, ε_{it} stands for an error term. The property fixed effects allow us to exploit the repeated rental contracts to measure the change in rent relative to the change in the pollution level from one deal to the next (excluding unobserved renewals) while holding all invariant property and location-specific factors constant.

Table 1 reports the results of ordinary least squares (OLS) estimates of the $PM_{2.5}$ effect on the natural log of contract rents using various specifications. The t-statistics used for statistical inference are based on standard errors clustered at the property level. Column (1) does not include any control variables, showing that a unit increase in the $PM_{2.5}$ level is associated with a decrease in the monthly rent by about 0.78%, on average. After adding year-quarter fixed effects, column (2) shows that the magnitude of the $PM_{2.5}$ effect on rent decreases to 0.46%. However, column (3) highlights the importance of the property fixed effects. When calibrating the model for property fixed effects the explained variation described by the adjusted R^2 increases from about 8.4% to 95.9%, while the $PM_{2.5}$ effect diminishes to -0.02%. Adding controls to the model as shown in Equation (1) that account for differences in rental contracts such as what utilities the tenant must pay and changes to the property's structural features or neighborhood's amenities does not have a major impact on the result of $PM_{2.5}$ on rent. However, in all the specifications, the relation between pollution and rent is negative and statistically significant at the 1% level.

We visualize the economic meaning of these statistics using the direct capitalization concept that the value of an asset is proportional to its annual cash flows. Hence, an extreme increase in the $PM_{2.5}$ level from the 1st percentile to the 99th percentile (approximately 22 units) is associated with an average decrease in the negotiated rent by about 0.44%, which is an average loss of approximately \$68 per year.[9] If the rental return to housing in the U.S. is approximately 5.33% (according to Jordà et al., 2019), such a reduction of $PM_{2.5}$ is valued at about \$1,276.[10] This estimate is a lower bound for the aversion of wildfire smoke pollution, as pollution levels may reach extreme heights during wildfire episodes, exceeding $PM_{2.5}$ levels of 100 units compared to the average $PM_{2.5}$ levels, typically between 6 and 8 units (see Tables A.5 and A.6). Furthermore, we show in the next section that the average economic effect is much greater when estimated using an alternative modeling approach.

3.2. Robustness

We examine whether the effect of air pollution varies across time and between neighborhoods. Table A.7 shows the daily $PM_{2.5}$ effect on rent from 2008 to 2014 is similar to that from 2015 to 2019. Table A.8 illustrates the daily $PM_{2.5}$ effect by the neighborhood racial composition. For simplicity based on the American Community Survey (5-year estimates, as of the closing end year), Black neighborhoods are where 20% or more of the residents are Black; Hispanic neighborhoods are those where 42% or more of the residents are Hispanic; Asian neighborhoods have at least 23% of the residents identify as Asian or Pacific Islander; Lastly, White neighborhoods are those where more than 72% identify as White.[11] We find that the effects are driven by Black, Hispanic, and White neighborhoods but not

[9] 0.44%=exp(-0.0002*22)-1; $\$68 = 0.44\% \times 1,292 \times 12$; 1,292 is the monthly average rent.

[10] $\$1,276 = \$68/0.0533$.

[11] The neighborhood thresholds represent the 90th percentile mark for the Black share, Hispanic share, Asian share, and White share.

Asian neighborhoods.[12]

We next relax assumptions of the functional form. We standardized $PM_{2.5}$ into a z-statistic using the sample mean and standard deviation and then added this term and the squared value of this term to the baseline model. Table A.10 shows that the effect of pollution on rent prices is nonlinear. Figure A.4 shows the marginal effect of air pollution on rent when modeling the $PM_{2.5}$ level as a categorical variable. In Table A.11, we examine the effect of pollution on rent using two other functional forms for $PM_{2.5}$. First, $PM_{2.5}$ is measured as the average $PM_{2.5}$ level using rolling 30-day windows from the rental contract date in column (1). Second, a dummy variable that toggles from 0 to 1 when the $PM_{2.5}$ level on the contract date exceeds 12 units is set as the explanatory variable in column (2). Both specifications allow us to draw a similar interpretation.

Additionally, as the $PM_{2.5}$ measure we employ relies on the average pollution measure from the nearest pollution meters, we examine an alternative pollution measure from Van Donkelaar et al. (2021) (Version V5.GL.03). This is a monthly $PM_{2.5}$ estimate at a spatial resolution of 1-km $\times$ 1-km cells. Column (3) of Table A.11 shows that the measure has a negative effect on rent that is significant at the 5% or higher level. The effect size using the V5.GL.03 measure is similar to the baseline estimates.

We also consider the robustness of our findings to the date at which the pollution observation is matched. Given that the rent price is usually defined through negotiation between visiting and signing, we differ between three dates: (1) The Contract Date, which is the day that the lease contract is fully executed by both parties to the transactions, including landlords and tenants; (2) The Off-Market Date, which is when the property is removed from the market as the listing is under contract, withdrawn, or expired; and (3) The Listing Date, which is the day the property is first put on the market for lease. Table A.12 shows that the rents respond to pollution levels observed on the contract date and off-market date but not the listing date. We find similar results when using indicators of extreme pollution

[12]We find similar results when splitting the sample by property type (see Table A.9).

or a rolling window that captures the 30 days preceding the off-market date. This suggests that pollution affects the tenants' decisions but not necessarily the landlords' when putting up a property for rent.

Lastly, we also explore other cities in the U.S. that were not directly affected by wildfires but were exposed to wildfire smoke plumes. Table A.13 presents two panels: for Chicago, Illinois (Panel A) and cities in California (Panel B) using CoreLogic Real Estate data and a similar specification but with no information about lease covenants. The results are in line with those presented earlier, though there is some variation between areas.

4. Indirect Effects of Wildfire Smoke Pollution

We examine the effect of pollution on rent using a two-stage least squares (2SLS) approach, as pollution could be endogenous to locations where rents tend to be relatively low. To do so, we fit the following model:

$$Y_{it} = \delta \hat{PM}_{zt} + X_{it}\beta + \tau_t + \zeta_i + \varepsilon_{it}. \tag{2}$$

$\hat{PM}_{zt}$ is the pollution level predicted using the following model:

$$\hat{PM}_{zt} = \lambda Smoke_{zt} + X_{it}\theta + \tau_t + \zeta_i \tag{3}$$

where $Smoke_{zt}$ is the count of smoke days over the last year from the contract date, lagged by 30 days. Equation (3) includes the same control variables and set of fixed effects as Equation (2), except for the smoke instrument. An adequate instrument must be relevant and meet the exclusion restriction. Conceptually, areas that are prone to more smoke will likely have higher levels of pollution as smoke matter particles make up a part of the $PM_{2.5}$ composition. Furthermore, the smoke instrument should not have a direct effect on the rent. If smoke is sufficiently dense and visible, it could influence the decisions of potential tenants.

However, by lagging the smoke measure, we rule out the direct effect of visible smoke on rent. Thus, the smoke instrument meets both criteria.

Table A.14 reports the 2SLS first stage results and Table 1 features the second stage results in column (5). The effect of the lagged annual smoke days on $PM_{2.5}$ is positive and statistically significant, bolstering the relevance criteria. Ten days of smoke increases the average $PM_{2.5}$ level by approximately 0.169 units. Meanwhile, the instrumented effect of $PM_{2.5}$ on rent has an effect size greater than previously estimated with the baseline model. A unit increase in $PM_{2.5}$ reduces the average rent level by approximately 0.69%, which is statistically significant at the 10% level. In terms of the economic magnitude, a reduction from the 99th to 1st $PM_{2.5}$ percentile is valued at $2,305 in annual rent.

5. Direct Effects of Wildfire Smoke

One concern is that landlords and tenants are unlikely to keep track of day-to-day changes in pollution, especially since doing so requires specialized knowledge and the pollution levels are normally not visible. By contrast, wildfire smoke is visible to the average individual. Hence, we examine the impact of wildfire smoke on the rent price. To do so, for each rental transaction, we identify whether the tract was covered by wildfire smoke on the lease contract date. However, one challenge is that wildfire smoke covers a wide range of tracts simultaneously limiting variation. Hence, we instrument the effect of wildfire smoke on rent using the $PM_{2.5}$ level under the assumption that $PM_{2.5}$ does not directly affect rent as it is invisible and not a tangible neighborhood attribute. This meets the exclusion restriction. Furthermore, we exploit the correlation between $PM_{2.5}$ levels and smoke to meet the relevance condition.

Our two-stage model is as follows:

$$Y_{it} = \Delta \hat{S}_{zt} + X_{it}\beta + \tau_t + \zeta_i + \varepsilon_{it}. \tag{4}$$

where $\hat{S}_{zt}$ is the linear prediction of wildfire smoke estimated using the following model:

$$S_{zt} = \Lambda PM_{zt} + X_{it}\theta + \tau_t + \zeta_i + \epsilon_{it} \tag{5}$$

and S_{zt} is an indicator for whether the rental property in tract z at time t is covered by wildfire smoke. PM_{zt} is the daily measure of pollution.

Table 2 shows the results using different measures of pollution to instrument for the wildfire smoke indicator. Column (1) uses the daily $PM_{2.5}$ pollution monitors measure and Column (2) uses the Van Donkelaar et al. (2021) V5.GL.03 pollution measure. The two columns indicate that the rent is about 3% lower on days that the neighborhood is covered by wildfire smoke. The effects are statistically significant at the 5% level or higher. A day of wildfire smoke lowers the rent by about $38.76 per year as rental contracts are typically annual. These results are consistent with our earlier findings.

6. Pollution and Home Prices

Here we explore the effect of changes in pollution levels on house prices obtained from the CoreLogic Real Estate data. Table 3 reports OLS estimates of the monthly average $PM_{2.5}$ level (observed two months behind the closing month) on the natural log of house prices using various specifications of Equation (1). Column (1) does not include any control variables, showing that a unit increase in the $PM_{2.5}$ level is associated with an average decrease in house prices by more 1.9%. The relation is statistically significant at the 1% level. After adding year-month fixed effects, column (2) shows that the magnitude of the $PM_{2.5}$ effect on house prices increases to 3.3%. When we include additional controls such as the number of bedrooms or bathrooms and year built and parcel fixed effects (column 4), the effect of $PM_{2.5}$ remains statistically significant. In terms of the economic magnitude, a one-standard-deviation increase in pollution level (2.8 $PM_{2.5}$ units) is associated with a decline in house prices of about 6%. Lastly, in column (5), we estimate a 2SLS model (Equations (2) and (3) using the same annual smoke days instrument as in Table 1, column 5) and find a slightly larger effect of approximately -4%, which is statistically significant at the 1% level.

7. Liquidity and Search Frictions

7.1. Local Liquidity

Bringing into the sample observations of failed listings that expired or were withdrawn by the landlord, we measure how excessive $PM_{2.5}$ levels influence the length of time a property spends on the rental market and whether the property is leased to understand the effect of pollution events on market liquidity factors and search frictions. We also test the impact of excess $PM_{2.5}$ on the list price.

The market liquidity model is defined as follows:

$$Y_{it} = \gamma 1[PM \geq 12]_{zt} + X_{it}\beta + \tau_t + \zeta_i + \varepsilon_{it} \tag{6}$$

where $1[PM \geq 12]_{zt}$ is a function that equals 1 if the $PM_{2.5}$ level exceeds 12, and 0 if otherwise. We measure excess pollution at either the off-the-market date or the listed date, ensuring that failed listings are included in the sample.

Table 4 reports the effect of excess $PM_{2.5}$ on liquidity factors. The sample is set to properties listed on the market on or before 2020. Excess pollution above 12 $PM_{2.5}$ units increases the days on the market by about 3.3%, while it decreases the likelihood of a lease by about 1.29%. Both effects are statistically significant at the 1% levels. However, we find no evidence that excess pollution influences the list price that the landlord sets. We also examine the impact of pollution on the final rental rate in log form while controlling for the days on the market but find that the impact of pollution on rent remains negative and statistically significant at the 1% level.

7.2. Aggregated Liquidity

We aggregate the number of listings at the tract year-quarter level such that for each tract we observe the quarterly count of rental properties advertised on the market. We then match these data with pollution statistics detailing for each quarter the number of days that the $PM_{2.5}$ pollution level registered above 12 and the average $PM_{2.5}$ level in the same tract. As the statistics are aggregated at the quarterly level and we no longer may use repeat transactions to identify the effect of pollution on the outcome variable, we implement a two-stage procedure with a measure of smoke days as an instrument.

We estimate the following panel model:

$$Y_{jt} = \Psi \hat{PM}_{jt} + X_{jt}\beta + \tau_t + \zeta_j + \varepsilon_{jt}. \tag{7}$$

where Y_{jt} is the natural log of the number of listings in quarter j or the natural log of leases completed in quarter j for each tract t.[13] $\hat{PM}_{jt}$ is the linear prediction of a $PM_{2.5}$ related variable estimated using the following model:

$$PM_{jt} = \Gamma SmokeDays_{jt} + X_{jt}\theta + \tau_t + \zeta_j + \epsilon_{it}. \tag{8}$$

We examine two pollution variables: 1) the number of days in the quarter during which the $PM_{2.5}$ level exceeded 12 units, and 2) the average $PM_{2.5}$ level over the quarter. The $SmokeDays$ instrument is the number of smoke days registered in the same tract during the same quarter. X_{jt} contains time-varying tract-level statistics from the American Community Survey, 5-year estimates, including the Hispanic share, Black share, Asian and Pacific Islander share, capitalization rate, and log median gross rent.[14] We also control for the median asking rent (and the total number of listings when examining signed leases) during the quarter in each tract.

[13]We add one to the count of listings and leases to avoid undefined log values.
[14]The capitalization rate is the ratio of the median gross rent divided by the median home value.

Table 5 reports the effect of excess $PM_{2.5}$ on liquidity factors, aggregated to the number of listings at the tract year-quarter level. Each day of excess pollution above 12 $PM_{2.5}$ units decreases the quarterly number of listings in a tract by about 1.6%, whereas the quarterly average $PM_{2.5}$ level decreases the quarterly number of listings in a tract by about 3.5%. Both effects are statistically significant at the 5% levels. However, we find no evidence that excess pollution influences the conditional, total leases signed.

8. Conclusion

Over the last decade, wildfire activity has become more extreme and destructive. Wildfires emit large amounts of smoke that contain harmful pollutants and can drift for hundreds or thousands of miles, regularly affecting populations far from the fires themselves. We leverage plausibly exogenous variation in smoke exposure to produce estimates of the causal effects of air pollution on rent prices and home prices. We find that a one-unit increase in $PM_{2.5}$ leads to a 0.7% decrease in the average monthly rent level and a 4% decline in housing prices. The results suggest that the aggregated value of a 50% reduction in the area's pollution (or 3.5 $PM_{2.5}$ units) is approximately $22.97 billion.[15] The value of aversion to an extreme wildfire event may be much greater.

We also find that during heavy smoke days, there is a sharp decline in the number of listings and a delay in transactions, probably because renters are less able to visit the property during those days. Landlords also avoid listing properties on the market during the most polluted days. However, the effects of pollution on search frictions and liquidity do not explain the price response gap between the housing and rental market. Our findings suggest that tenants are not fully internalizing the price of pollution into the rent because perhaps exposure to pollution is temporary.

[15] $22.97B=(1-0.554)*950,874*(exp(-0.0069*3.5)-1)*12*1292.26/.0533+(0.554)*950,874*(exp(-0.040*3.5)-1)*12*1292.26/.0533; 0.554 is the owner-occupancy rate; 950,874 is the households in the area; 5.33% is the capitalization rate; and 1,292.26 is the monthly average rent.

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Table 1: The Effect of Daily Average $PM_{2.5}$ on Log(Rent)

VARIABLES	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) 2SLS
$PM_{2.5}$ (daily)	-0.0078***	-0.0046***	-0.0002***	-0.0002***	-0.0069*
	(-43.8980)	(-25.5634)	(-4.4615)	(-4.3346)	(-1.7636)
Observations	269,902	269,902	215,061	214,138	209,672
Adjusted R-squared	0.0087	0.0838	0.9591	0.9614	-0.0771
Constant	✓	✓	✓	✓	✓
Controls	x	x	x	✓	✓
Year-Quarter FE	x	✓	✓	✓	✓
Parcel FE	x	x	✓	✓	✓

This table presents the regression estimates of the $PM_{2.5}$ effect on log rents using a sample of rental housing transactions from August 2008 to December 2019. Controls include log living area square footage, log lot square footage, bedrooms, bathrooms, fireplaces, private pool, private spa, garage car spaces, heating fuel type, cooling fuel type, washer/dryer indicators (both, dryer only, washer only), dishwasher, occupancy type indicators (owner, tenant, vacant), property type indicators (single family, condominium, 2-3 unit single family), log commission, log start time in days, log deposit, tenant pays indicators, age restriction, gated community, community pool, community spa, community park, community golf, community basketball, community clubhouse, community gym, and community rules. Robust t-statistics based on standard errors clustered at the property level are noted in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively. Sources: Las Vegas Realtors' (LVR) MLS, EPA's Air Quality System, and smoke data from Miller et al. (2021) and NOAA's Hazard Mapping System (HMS).

Table 2: The Impact of Wildfire Smoke on Rent

VARIABLES	(1) Monitors	(2) V5.GL.03
Wildfire Smoke	-0.0292***	-0.0280**
	(-4.3118)	(-2.0642)
Observations	214,138	241,789
Adjusted R-squared	0.0501	0.0516
Constant	✓	✓
Controls	✓	✓
Year-Quarter FE	✓	✓
Parcel FE	✓	✓

This table presents the IV regression estimates of the wildfire smoke effect on log rents using a sample of rental housing transactions from August 2008 to December 2019. Wildfire Smoke is an indicator for whether the tract is covered by smoke on the lease contract date that is instrumented with the daily monitor-based $PM_{2.5}$ level in Column (1), and the monthly 1-k $\times$ 1-k $PM_{2.5}$ estimate from Van Donkelaar et al. (2021) - V5.GL.03 in Column (2). Controls include log living area square footage, log lot square footage, bedrooms, bathrooms, fireplaces, private pool, private spa, garage car spaces, heating fuel type, cooling fuel type, washer/dryer indicators (both, dryer only, washer only), dishwasher, occupancy type indicators (owner, tenant, vacant), property type indicators (single family, condominium, 2-3 unit single family), log commission, log start time in days, log deposit, tenant pays indicators, age restriction, gated community, community pool, community spa, community park, community golf, community basketball, community clubhouse, community gym, and community rules. Robust t-statistics based on standard errors clustered at the property level are noted in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively. Sources: Las Vegas Realtors' (LVR) MLS, EPA's Air Quality System for air pollution monitors data, and V5.GL.03 from Van Donkelaar et al. (2021).

Table 3: The Effect of $PM_{2.5}$ on Log(House Prices)

VARIABLES	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) 2SLS
$PM_{2.5}$ (monthly)	-0.019***	-0.033***	-0.034***	-0.036***	-0.040***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.010)
Observations	357,729	357,729	332,101	314,677	302,890
Adjusted R-squared	0.001	0.115	0.608	0.710	0.074
Constant	✓	✓	✓	✓	✓
Controls	x	x	x	✓	✓
Year-Quarter FE	x	✓	✓	✓	✓
Parcel FE	x	x	✓	✓	✓

This table presents the regression estimates of the $PM_{2.5}$ effect on log house prices using a sample of housing transactions from August 2008 to December 2019. Controls include bedrooms, bathrooms, and year built (age of the building). In column (5), we estimate a 2SLS model (using Equations (2), (3), using the annual smoke days in a tract as an instrument. Robust t-statistics based on standard errors clustered at the property level are noted in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively. Source: CoreLogic Real Estate data, EPA's Air Quality System, and smoke data from Miller et al. (2021) and NOAA's Hazard Mapping System (HMS).

Table 4: $PM_{2.5}$ Effects on Market Liquidity

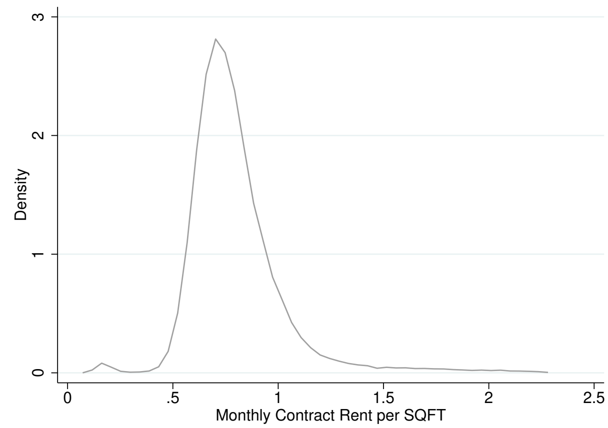
VARIABLES	(1) ln(DOM+1)	(2) 1[Leased]	(3) ln(LP)	(4) ln(Rent)
$1[PM_{2.5} \geq 12]_{off}$	0.0437***	-0.0161***		-0.0016***
	(5.6958)	(-6.3343)		(-2.6387)
$1[PM_{2.5} \geq 12]_{list}$			0.0001	
			(0.1524)	
ln(DOM+1), Winsorized				-0.0030***
				(-13.0626)
Observations	290,536	290,551	290,643	245,199
Adjusted R-squared	0.2490	0.1260	0.9638	0.9615
Constant	✓	✓	✓	✓
Controls	✓	✓	✓	✓
List Year-Quarter FE	✓	✓	✓	✓
Parcel FE	✓	✓	✓	✓

This table presents the regression estimates of the $PM_{2.5}$ effect on liquidity factors using a sample of rental housing listings from August 2008 to December 2019. The column headers indicates whether the estimates are from an OLS or 2SLS model. $PM_{2.5}$ is measured as the observed pollution level by the nearest monitors at the day of contract signing. Controls include log living area square footage, log lot square footage, bedrooms, bathrooms, fireplaces, private pool, private spa, garage car spaces, heating fuel type, cooling fuel type, washer/dryer indicators (both, dryer only, washer only), dishwasher, occupancy type indicators (owner, tenant, vacant), property type indicators (single family, condominium, 2-3 unit single family), log commission, log start time in days, log deposit, tenant pays indicators, age restriction, gated community, community pool, community spa, community park, community golf, community basketball, community clubhouse, community gym, and community rules. The first stage 2SLS results are reported in Table A.14 in the appendix. Robust t-statistics based on standard errors clustered at the property level are noted in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively. Sources: Las Vegas Realtors' (LVR) MLS, EPA's Air Quality System for air pollution monitors data, and smoke data from Miller et al. (2021) and NOAA's Hazard Mapping System (HMS).

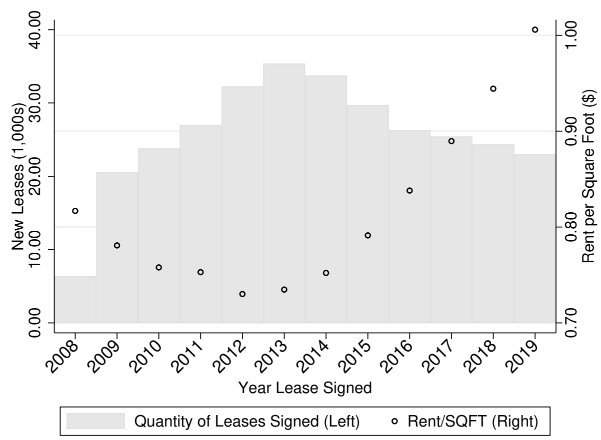
Table 5: $PM_{2.5}$ Effects on Quantity of Listings and Sales

VARIABLES	(1) ln(Listings+1)	(2) ln(Listings+1)	(3) ln(Leases+1)	(4) ln(Leases+1)
Days $PM_{2.5} \geq 12$	-0.0156**		-0.0009	
	(-2.1047)		(-0.2564)	
$PM_{2.5}$ (quarterly)		-0.0348**		-0.0019
		(-2.1736)		(-0.2565)
ln(Listings +1)			0.9295***	0.9294***
			(175.5216)	(173.1221)
ln(Median Asking Rent)	-0.0880***	-0.0900***	-0.0906***	-0.0907***
	(-3.2067)	(-3.3013)	(-4.6435)	(-4.6595)
Hispanic Share	-0.1282	-0.1322	-0.0828**	-0.0830**
	(-1.2888)	(-1.3442)	(-2.1318)	(-2.1526)
Black Share	0.0244	0.0469	-0.0218	-0.0205
	(0.1868)	(0.3664)	(-0.4345)	(-0.4195)
API Share	0.0728	0.0850	-0.0014	-0.0007
	(0.5026)	(0.5925)	(-0.0242)	(-0.0124)
Cap Rate	0.0202	0.0859	-0.2029***	-0.1992***
	(0.0662)	(0.3019)	(-4.0557)	(-4.0337)
ln(Median Gross Rent)	0.1186	0.1334*	-0.0310	-0.0302
	(1.5388)	(1.8394)	(-1.0978)	(-1.1259)
Observations	18,527	18,527	18,527	18,527
Adjusted R-squared	-0.0954	-0.0218	0.7378	0.7381
Constant	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓
Tract FE	✓	✓	✓	✓

This table presents the 2SLS regression estimates of the $PM_{2.5}$ effect on the log quantity of listings or sales using a sample of rental housing listings from August 2008 to December 2019. The instrument for PM25 in all columns is the number of smoke days in the same quarter and tract. Robust t-statistics based on standard errors clustered at the tract level are noted in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively.Sources: Las Vegas Realtors' (LVR) MLS, EPA's Air Quality System for air pollution monitors data, and smoke data from Miller et al. (2021) and NOAA's Hazard Mapping System (HMS).



(a) Rent Distribution



(b) Market Conditions

Fig.A.1. Rental Market Activity

This figure reports the kernel density of monthly rents per square foot in Panel (a) and the quantity of leases signed and average rent per square foot by year in Panel (b). The statistics are based on lease contracts recorded in the Las Vegas Realtors' MLS from August 2008 to December 2019.

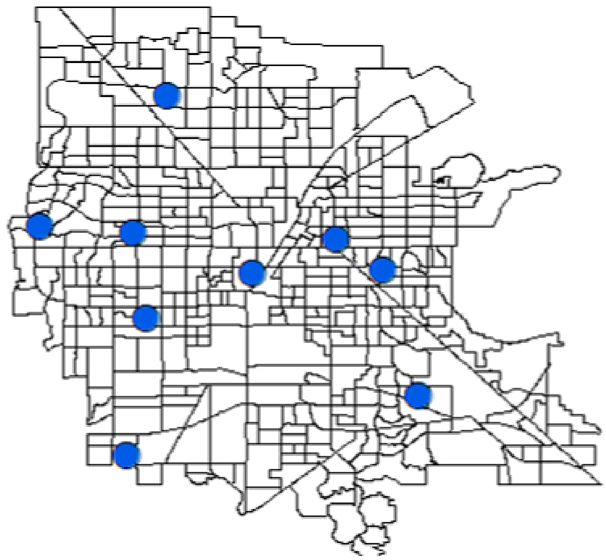
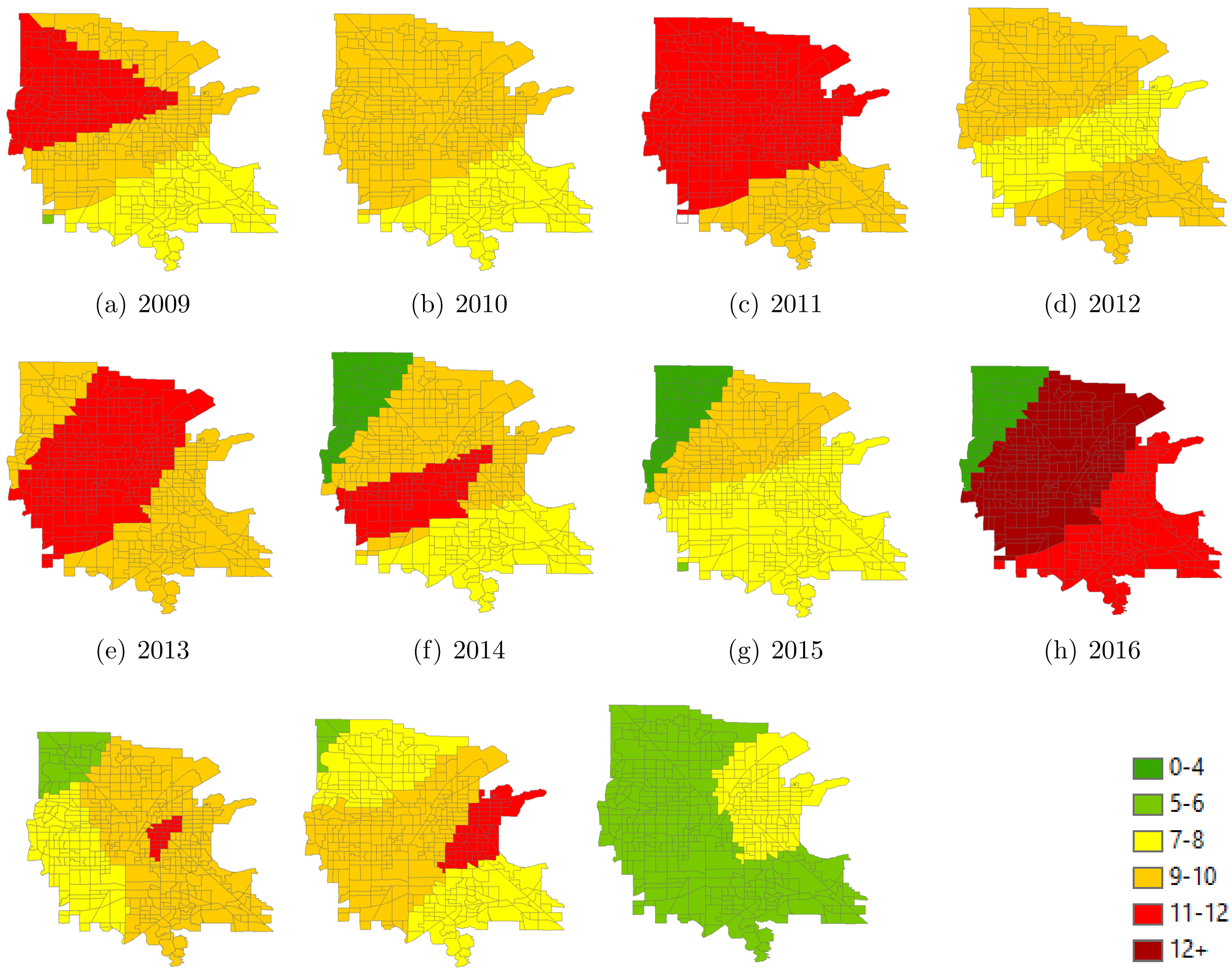


Fig.A.2. Location of the Pollution Monitors in Las Vegas city
This figure shows the variation in the location of the pollution monitors in Clark County, NV (the blue dots), in 2019. The black boarders are tracts. Source: EPA's Air Quality System.



(a) 2009 (b) 2010 (c) 2011 (d) 2012

(e) 2013 (f) 2014 (g) 2015 (h) 2016

(i) 2017 (j) 2018 (k) 2019 (l) $PM_{2.5}$ levels

Fig.A.3. The Distribution of $PM_{2.5}$ Over Time in July

This figure shows the variation in pollution level over time in July, between 2009 to 2019. Source: EPA's Air Quality System.

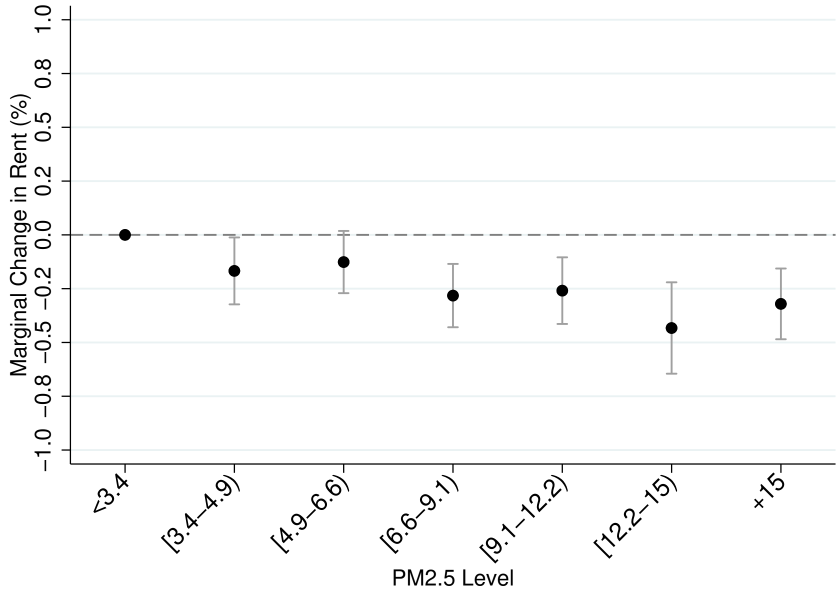


Fig.A.4. Discrete Effect of Air Pollution on Rent

This figure shows the marginal effect of air pollution on rent when modeling the $PM_{2.5}$ level as a categorical variable. Source: EPA's Air Quality System and Las Vegas Realtors' (LVR) MLS data.

Table A.1: Summary Statistics of Rental Contracts

Panel A: Contract Characteristics

Variables	Mean	SD
Contract Rent ($)	1292.26	555.85
Total Deposit ($)	1753.91	886.02
Commission ($)	319.47	116.14
Term: 1-3 Months	0.01	0.10
Term: 4-6 Months	0.02	0.14
Term: 7-11 Months	0.01	0.12
Term: 12 Months	0.85	0.35
Term: 12+ Months	0.10	0.30
Start Time (days)	7.38	71.08
Tenant Pays: Cable	0.79	0.41
Tenant Pays: Gas	0.89	0.31
Tenant Pays: Power	0.97	0.17
Tenant Pays: Sewer	0.54	0.50
Tenant Pays: Water	0.76	0.43
Tenant Pays: Garbage Pickup	0.61	0.49
Tenant Pays: Other Services	0.62	0.49

Panel B: Neighborhood Characteristics

Variables	Mean	SD
Age Restriction	0.06	0.23
Gated Community	0.29	0.45
Community Pool	0.36	0.48
Community Spa	0.19	0.39
Community Park	0.07	0.25
Community Golf	0.04	0.19
Community Basketball	0.03	0.16
Community Clubhouse	0.16	0.36
Community Gym	0.13	0.34
Community Rules (HOA)	0.75	0.43

Panel C: Property Characteristics

Variables	Mean	SD
Building Age	15.74	10.43
Living Area Square Footage	1680.50	691.38
Lot Square Footage	3891.48	3432.70
Bedrooms	2.93	0.94
Bathrooms	2.50	0.73
Fireplaces	0.45	0.58
Private Pool	0.09	0.28
Private Spa	0.06	0.24
Garage Car Spaces	1.60	0.93
Heating Fuel: Electric	0.12	0.32
Heating Fuel: Gas	0.88	0.33
Heating Fuel: Mixed	0.00	0.06
Heating Fuel: Other	0.00	0.03
Cooling Fuel: Electric	0.99	0.12
Cooling Fuel: Gas	0.01	0.12
Cooling Fuel: Other	0.00	0.02
W/D: Washer and Dryer	0.87	0.34
W/D: Dryer Only	0.00	0.05
W/D: None	0.13	0.34
W/D: Washer Only	0.00	0.04
Dishwasher	0.98	0.14
Occupancy: Owner	0.02	0.15
Occupancy: Tenant	0.06	0.24
Occupancy: Vacant	0.92	0.27
Property Type: Single Family	0.68	0.47
Property Type: 2-3 Unit Single Family	0.09	0.29
Property Type: Condominium	0.23	0.42
Observations	308,082	

This table reports summary statistics on a sample of rental housing listings from August 2008 to December 2019 obtained from the Las Vegas Realtors' MLS. SD stands for standard deviation.

Table A.2: Summary Statistics of Housing Transactions Data

Variable	Obs	Mean	Std. dev.
ln(Price)	357,729	12.35	1.14
Bedrooms	339,686	3.17	0.94
Bathrooms	340,442	2.57	0.76
Number of Rooms	340,381	6.09	1.68
Lot Acres	313,964	0.25	2.50
Effective Year Built	342,235	1998	14.06
$PM_{2.5}$ monitor	357,754	7.46	2.72

This table presents summary statistics of CoreLogic Real Estate data from August 2008 to December 2019. This dataset contains property-level information as originally electronically keyed at county registries (or recorders) of deeds. This data set contains information on both transactions and home characteristics for almost all houses in Clark County, NV. Source: CoreLogic Real Estate data and EPA's Air Quality System for air pollution monitors data.

Table A.3: Summary Statistics of Rental Transactions Data

Panel A - Chicago			
Variable	Obs	Mean	Std. dev.
ln(Price)	216,678	7.65	0.89
Bedrooms	216,678	1.85	0.98
Bathrooms	216,678	1.52	0.64
Number of Rooms	216,678	4.89	1.59
Effective Year Built	173,596	1970.7	36.72
$PM_{2.5}$ monitor	217,560	6.80	2.97
Panel B - San Francisco, Oakland, and San Jose			
Variable	Obs	Mean	Std. dev.
ln(Price)	197,670	12.49	2.00
Bedrooms	197,310	2.49	1.14
Bathrooms	197,670	1.76	0.89
Number of Rooms	197,310	3.38	3.18
Effective Year Built	190,608	1953.7	33.90
$PM_{2.5}$ monitor	197,670	8.27	5.86

This table presents summary statistics of CoreLogic Real Estate data from August 2008 to December 2019 in Chicago, San Francisco, Oakland, and San Jose. Sources: CoreLogic Real Estate data and EPA's Air Quality System for air pollution monitors data.

Table A.4: The number of air pollution monitors in Las Vegas

Year	Number of Monitors in City Center	Number of Monitors in Clark County, NV
2009	4	6
2010	5	7
2011	4	5
2012	4	5
2013	4	6
2014	4	6
2015	4	6
2016	4	6
2017	6	8
2018	6	8
2019	6	7

This table presents the number of pollution monitors in Las Vegas city center over time, between 2009-2019. Source: EPA's Air Quality System.

Table A.5: Summary Statistics of Pollution and Smoke Over Months

Month	Num of Days with PM Above 15	Num of Days with PM Above 12	Num of Days with PM Above 10	Average Number of Smoke Days
1	10.9	15	18.4	0
2	2.71	6.9	10.6	0
3	1.07	4.2	8.4	0
4	2.21	5	8.4	0.2
5	1.35	3.5	8.6	0.4
6	2.14	5.1	10.1	2.8
7	4.52	7.7	11.9	3.3
8	3.7	7.1	13	5.7
9	3.42	7.35	14.1	4.3
10	4.3	9.9	16.1	1.7
11	12	15.8	19.1	0.2
12	13.4	17.8	20.2	0.0

This table presents summary statistics of pollution and smoke over months, on average between 2009-2019. Sources: EPA's Air Quality System and smoke data from Miller et al. (2021) and NOAA's Hazard Mapping System (HMS).

Table A.6: Summary Statistics of Pollution and Smoke Over Time

Month	Mean Pollution	Max Daily Pollution	Num of Days with PM>12	Num of Days with $PM_{2.5}$>10	Num of Days with $PM_{2.5}$>15	Average Number of Smoke Days
2009	6.9	82	102	161	40	14.4
2010	6.4	43	68	110	33	1.2
2011	6.9	61	70	119	34	1.0
2012	7.6	104	103	174	54	5.0
2013	7.4	100	121	188	77	17.9
2014	7.4	104	110	185	66	1.0
2015	6.5	83	99	158	49	14.7
2016	7.2	103	126	199	69	18.7
2017	6.9	78	90	152	58	14.6
2018	6.8	70	101	132	71	21.5
2019	6.1	52	75	101	51	4.3

This table presents summary statistics of pollution and smoke over time, between 2009-2019. Sources: EPA's Air Quality System and smoke data from Miller et al. (2021) and NOAA's Hazard Mapping System (HMS).

Table A.7: The Effect of $PM_{2.5}$ on Log(Rent) by Time Period

VARIABLES	(1) 2008-2014	(2) 2015-2019
$PM_{2.5}$ (daily)	-0.0002**	-0.0002***
	(-2.1686)	(-2.6719)
Observations	96,775	71,506
Adjusted R-squared	0.9627	0.9723
Constant	✓	✓
Controls	✓	✓
Year-Quarter FE	✓	✓
Parcel FE	✓	✓

This table presents the regression estimates of the $PM_{2.5}$ effect on log rents using a sample of rental housing transactions from 2009-2014 in column (1) and from 2015-2019 in column (2). Controls include log living area square footage, log lot square footage, bedrooms, bathrooms, fireplaces, private pool, private spa, garage car spaces, heating fuel type, cooling fuel type, washer/dryer indicators (both, dryer only, washer only), dishwasher, occupancy type indicators (owner, tenant, vacant), property type indicators (single family, condominium, 2-3 unit single family), log commission, log start time in days, log deposit, tenant pays indicators, age restriction, gated community, community pool, community spa, community park, community golf, community basketball, community clubhouse, community gym, and community rules. Robust t-statistics based on standard errors clustered at the property level are noted in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively. Sources: EPA's Air Quality System and Las Vegas Realtors' (LVR) MLS data.

Table A.8: The Effect of $PM_{2.5}$ on Log(Rent) by Racial Neighborhood

VARIABLES	(1) Asian	(2) Black	(3) Hispanic	(4) White
$PM_{2.5}$ (daily)	-0.0001	-0.0003**	-0.0003**	-0.0003**
	(-0.4838)	(-2.1882)	(-2.0114)	(-1.9700)
Observations	19,112	19,300	17,424	18,699
Adjusted R-squared	0.9623	0.9586	0.9482	0.9685
Constant	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓
Parcel FE	✓	✓	✓	✓

This table presents the regression estimates of the $PM_{2.5}$ effect on log rents using a sample of rental housing transactions from 2009-2019 by the tract racial composition. Controls include log living area square footage, log lot square footage, bedrooms, bathrooms, fireplaces, private pool, private spa, garage car spaces, heating fuel type, cooling fuel type, washer/dryer indicators (both, dryer only, washer only), dishwasher, occupancy type indicators (owner, tenant, vacant), property type indicators (single family, condominium, 2-3 unit single family), log commission, log start time in days, log deposit, tenant pays indicators, age restriction, gated community, community pool, community spa, community park, community golf, community basketball, community clubhouse, community gym, and community rules. Robust t-statistics based on standard errors clustered at the property level are noted in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively. Sources: EPA's Air Quality System and Las Vegas Realtors' (LVR) MLS data.

Table A.9: The Effect of $PM_{2.5}$ on Log(Rent) by Property Type

VARIABLES	(1) SFR	(2) CONDO
$PM_{2.5}$ (daily)	-0.0002***	-0.0003***
	(-3.2154)	(-2.8738)
Observations	144,026	51,379
Adjusted R-squared	0.9519	0.9575
Constant	✓	✓
Controls	✓	✓
Year-Quarter FE	✓	✓
Parcel FE	✓	✓

This table presents the regression estimates of the $PM_{2.5}$ effect on log rents using a sample of rental housing transactions from 2009-2019 by the tract racial composition. Controls include log living area square footage, log lot square footage, bedrooms, bathrooms, fireplaces, private pool, private spa, garage car spaces, heating fuel type, cooling fuel type, washer/dryer indicators (both, dryer only, washer only), dishwasher, occupancy type indicators (owner, tenant, vacant), property type indicators (single family, condominium, 2-3 unit single family), log commission, log start time in days, log deposit, tenant pays indicators, age restriction, gated community, community pool, community spa, community park, community golf, community basketball, community clubhouse, community gym, and community rules. Robust t-statistics based on standard errors clustered at the property level are noted in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively. Sources: EPA's Air Quality System and Las Vegas Realtors' (LVR) MLS data.

Table A.10: Nonlinear $PM_{2.5}$ Effects

VARIABLES	(1)
$PM_{2.5}$ z-score	-0.0015***
	(-4.3526)
($PM_{2.5}$ z-score)^2	0.0002**
	(2.5295)
Observations	214,138
Adjusted R-squared	0.9614
Constant	✓
Controls	✓
Year-Quarter FE	✓
Parcel FE	✓

This table presents the regression estimates of the nonlinear $PM_{2.5}$ effect on log rents using a sample of rental housing transactions from August 2008 to December 2019. The column headers indicate the subsample of rental transactions by racial neighborhood groups. $PM_{2.5}$ is standardized into a z-statistic using the sample mean and standard deviation. Controls include log living area square footage, log lot square footage, bedrooms, bathrooms, fireplaces, private pool, private spa, garage car spaces, heating fuel type, cooling fuel type, washer/dryer indicators (both, dryer only, washer only), dishwasher, occupancy type indicators (owner, tenant, vacant), property type indicators (single family, condominium, 2-3 unit single family), log commission, log start time in days, log deposit, tenant pays indicators, age restriction, gated community, community pool, community spa, community park, community golf, community basketball, community clubhouse, community gym, and community rules. Robust t-statistics based on standard errors clustered at the property level are noted in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively. Sources: EPA's Air Quality System and Las Vegas Realtors' (LVR) MLS data.

Table A.11: Effect of Various $PM_{2.5}$ Measures on Log(Rent)

VARIABLES	(1)	(2)	(3)
$PM_{2.5}$: window(30)	-0.0003***		
	(-3.9814)		
$PM_{2.5}$: above 12		-0.0027***	
		(-4.3405)	
$PM_{2.5}$: V5.GL.03			-0.0004**
			(-2.4545)
Observations	241,968	241,968	252,131
Adjusted R-squared	0.9622	0.9622	0.9624
Constant	✓	✓	✓
Controls	✓	✓	✓
Year-Quarter FE	✓	✓	✓
Parcel FE	✓	✓	✓

This table presents the regression estimates of the $PM_{2.5}$ effect on log rents using a sample of rental housing transactions from August 2008 to December 2019. $PM_{2.5}$: window(30) in Column (1) is the average monitored-based pollution level over the 30 days leading up to the contract date at the tract level. $PM_{2.5}$ above 12 in Column (2) is an indicator for whether the monitor-based $PM_{2.5}$ level is above 12 units. $PM_{2.5}$: V5.GL.03 in Column (3) is the 1-k $\times$ 1-k pollution estimate from Van Donkelaar et al. (2021). Controls include log living area square footage, log lot square footage, bedrooms, bathrooms, fireplaces, private pool, private spa, garage car spaces, heating fuel type, cooling fuel type, washer/dryer indicators (both, dryer only, washer only), dishwasher, occupancy type indicators (owner, tenant, vacant), property type indicators (single family, condominium, 2-3 unit single family), log commission, log start time in days, log deposit, tenant pays indicators, age restriction, gated community, community pool, community spa, community park, community golf, community basketball, community clubhouse, community gym, and community rules. Robust t-statistics based on standard errors clustered at the property level are noted in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively. Sources: Las Vegas Realtors' (LVR) MLS, EPA's Air Quality System for air pollution monitors data, and V5.GL.03 from Van Donkelaar et al. (2021).

Table A.12: $PM_{2.5}$ Levels at Various Dates

VARIABLES	(1)	(2)	(3)
$PM_{2.5}$ (Contract Date)	-0.0002***		-0.0001**
	(-2.7194)		(-2.4377)
$PM_{2.5}$ (Off Market Date)	-0.0001**		-0.0001*
	(-2.0684)		(-1.6806)
$PM_{2.5}$ (Listing Date)	-0.0001		
	(-1.3186)		
$1[PM_{2.5} \geq 12]$ (Contract Date)		-0.0025***	
		(-3.8035)	
$1[PM_{2.5} \geq 12]_{off}$ (Off Market Date)		-0.0006	
		(-0.8785)	
$1[PM_{2.5} \geq 12]_{list}$ (Listing Date)		-0.0000	
		(-0.0715)	
Average $PM_{2.5}$: window(30) off market date			-0.0001
			(-1.3881)
Observations	184,720	241,860	200,017
Adjusted R-squared	0.9620	0.9622	0.9618
Constant	✓	✓	✓
Controls	✓	✓	✓
Year-Quarter FE	✓	✓	✓
Parcel FE	✓	✓	✓

This table presents the regression estimates of the $PM_{2.5}$ effect on log rents using a sample of rental housing transactions from August 2008 to December 2019. $PM_{2.5}$ refers to the daily monitor-based pollution measure observed as of the contract date, off market date, or listing date. Contract Date is the day that the lease contract is fully executed by both parties to the transactions including landlords and tenants. Off market date is the day the property is removed from the market as the listing is under contract, withdrawn, or expired. Listing date is the day the property is first put on the market for lease. $[PM_{2.5} \geq 12]$ is an indicator for whether the pollution measure is above 12 units. "Average $PM_{2.5}$: window(30) off market date" measures the tract level pollution over the 30 days leading up to the off market date. Controls include log living area square footage, log lot square footage, bedrooms, bathrooms, fireplaces, private pool, private spa, garage car spaces, heating fuel type, cooling fuel type, washer/dryer indicators (both, dryer only, washer only), dishwasher, occupancy type indicators (owner, tenant, vacant), property type indicators (single family, condominium, 2-3 unit single family), log commission, log start time in days, log deposit, tenant pays indicators, age restriction, gated community, community pool, community spa, community park, community golf, community basketball, community clubhouse, community gym, and community rules. Robust t-statistics based on standard errors clustered at the property level are noted in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively. Sources: EPA's Air Quality System and Las Vegas Realtors' (LVR) MLS data.

Table A.13: The Effect of Daily Average $PM_{2.5}$ on Log(Rent)

Panel A - Chicago	(1) OLS	(2) OLS	(3) OLS	(4) OLS
$PM_{2.5}$ (daily)	-0.0050***	-0.0052***	-0.0001	-0.0004**
	(0.0006)	(0.0006)	(0.0002)	(0.0002)
Observations	216,678	216,678	216,678	167,443
Adjusted R-squared	0.001	0.009	0.839	0.893
Constant	✓	✓	✓	✓
Controls	x	x	x	✓
Year-Quarter FE	x	✓	✓	✓
Parcel FE	x	x	✓	✓

Panel B - San Francisco, Oakland, and San Jose	(1) OLS	(2) OLS	(3) OLS	(4) OLS
$PM_{2.5}$ (daily)	-0.0108***	-0.0120***	-0.0003***	-0.0004***
	(0.0031)	(0.0033)	(0.0001)	(0.0001)
Observations	197,670	197,670	197,670	190,608
Adjusted R-squared	0.0002	0.0875	0.9933	0.9948
Constant	✓	✓	✓	✓
Controls	x	x	x	✓
Year-Quarter FE	x	✓	✓	✓
Parcel FE	x	x	✓	✓

This table presents the regression estimates of the $PM_{2.5}$ effect on log rents using a sample of rental housing transactions from August 2008 to December 2019. Controls include bedrooms, bathrooms, and year built (age of the building). Robust t-statistics based on standard errors clustered at the property level are noted in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively. Sources: CoreLogic Real Estate data and EPA's Air Quality System.

Table A.14: Relation between Annual Smoke Days and $PM_{2.5}$

VARIABLES	(1) $PM_{2.5}$
Annual Smoke Days Lagged	0.0169***
	(4.4555)
Observations	209,706
Adjusted R-squared	0.1686
Constant	✓
Controls	✓
Year-Quarter FE	✓
Parcel FE	✓

This table presents the first stage results of the IV regression estimates of the $PM_{2.5}$ effect on log rents using a sample of rental housing transactions from August 2008 to December 2019. $PM_{2.5}$ the daily monitor-based pollution measure at the tract level. $PM_{2.5}$ is instrumented with the smoke days over the last year from the lease contract date, lagged by 30 days. Controls include log living area square footage, log lot square footage, bedrooms, bathrooms, fireplaces, private pool, private spa, garage car spaces, heating fuel type, cooling fuel type, washer/dryer indicators (both, dryer only, washer only), dishwasher, occupancy type indicators (owner, tenant, vacant), property type indicators (single family, condominium, 2-3 unit single family), log commission, log start time in days, log deposit, tenant pays indicators, age restriction, gated community, community pool, community spa, community park, community golf, community basketball, community clubhouse, community gym, and community rules. Robust t-statistics based on standard errors clustered at the property level are noted in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively. Sources: EPA's Air Quality System and Las Vegas Realtors' (LVR) MLS data.