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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 (PM2.5) on rent prices, 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 -2.4% per one standard deviation increase in PM2.5. The response of home prices is more than threefold highlighting a gap in the tolerance of poor air quality, which we find is driven by age-related differences between tenants and homeowners. We further show evidence that air pollution affects liquidity and search frictions in the rental market.

Keywords: Air Pollution, Rental Housing, House Prices, Wildfire Smoke

JEL Classification: Q52, Q53, R21

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During the summer of 2023, more than 122 million people across the United States were exposed to heavy smoke and high pollution levels as a result of extreme wildfires in Canada. Releasing about 15% of total particle emissions in the U.S. each year, with an increasing intensity and frequency (Xie et al., 2022), wildfires are becoming a major concern. Wildfire smoke contains particulate matter ($PM_{2.5}$), which has 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). In a Rosen-Roback model, poor air quality attributable to wildfire smoke pollution would represent a negative local dis-amenity affecting the location choices of households that value access to clean air (Bento et al., 2015; Roback, 1982; Rosen, 1974).

In this paper, we examine the capitalization of air pollution in rents and home prices, using the natural occurrence of wildfire smoke to create exogenous shocks. This type of smoke increases pollution 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, despite the informativeness of rental rates about location demand and household preferences (Sonstelie and Portney, 1980; Howard and Liebersohn, 2021). We document that renters respond less negatively to air pollution shocks than homeowners and show that the differential responses may be attributed to age-related factors or differences in tolerance and not expectations about the exposure duration to air pollutants.

Our identification strategy exploits the variation in the ground-level pollution at locations where wildfires were not a direct threat but exposed households to wildfire smoke and pollution shocks. We combine high-frequency rental data from Multiple Listing Services (MLS) with daily data on ambient air pollution from the U.S. Environmental Protection Agency's (EPA) Air Quality System and then test whether rental rates respond to the variation in pollution that the property is 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. Likewise, we estimate the response of home prices to air pollution. Although we examine rents and prices in multiple cities, we focus on transactions in the Las Vegas MSA, which offers the perfect testing platform as wildfires were not a direct threat in the area but exposed households to large shocks in wildfire smoke and pollution. Additionally, as we have access to unique and detailed information on lease covenants, contract terms, and neighborhood restrictions in Las Vegas, we explore the salient role of individual expectations and behaviors.

Our study makes three key contributions. First, we document the relation between daily pollution and market rents from individual lease contracts. We find that a one standard deviation increase in $PM_{2.5}$ observed on the lease date is associated with a 0.08% decline in the monthly rent. This 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 monthly $PM_{2.5}$ measures by census tracts (Van Donkelaar et al., 2021). We also find similar results using CoreLogic Rent data for Chicago, Illinois, and the Bay Area in California.

Second, we propose using the variation in wildfire smoke plumes as an instrumental variable to measure the causal effects of air pollution on rent prices.[1] The challenge in identifying the causal effects of air pollution on rent prices is that air quality is correlated with local economic factors. For example, locations with lower-income households and low growth, i.e., with low rent prices that are closer to industrial centers, could suffer from high levels of pollution. In contrast, wildfire smoke plumes are uncorrelated with unobserved determinants of rent prices, as the movement of the smoke is determined by exogenous factors, such as wind and rain, and not related to the economic factors in the area. For this reason, we link the lease data to daily satellite images of the location and movements of wildfire smoke plumes captured by the National Oceanic and Atmospheric Administration

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

(NOAA) and set the annual smoke days (with a one-month lag) as our instrument, which raises the magnitude of the $PM_{2.5}$ effect on rents to about -2.4% per standard deviation increase in pollution. This point estimate indicates that the average effect of a pollution shock on rent translates into a loss of approximately $372 per year in operating income. This loss could reduce the appraised value of affected income-producing property by as much as $7,000, given an average capitalization rate of 5.33%.

Our third contribution is to demonstrate that tenants are less sensitive to air pollution and wildfire smoke exposure than homeowners and show that differences in their tolerance to low air quality are likely influencing the differential response. Focusing on repeat-transactions and housing deeds from the CoreLogic Real Estate data, we find that a unit increase in $PM_{2.5}$ reduces the average house prices by approximately 9%, which is statistically significant at the 1% level.[2] 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).[3] We hypothesize that homeowners and renters have different demographic characteristics, which make their tolerance to air pollution or willingness to pay for clean air differ. Indeed, using the Federal Reserve Bank of New York Consumer Credit Panel/Equifax data (CCP), we show that, on average, renters in Las Vegas are younger and have lower Equifax Risk Scores, compared to the local homeowners. Supporting this hypothesis, we find that the response to air pollution in rents is statistically stronger during the earlier years (2008-2011) when tenants are older than in the latter years (2016-2019) when tenants are younger, on average. Rental rates also react more negatively to air pollution shocks in 55+ communities than in neighborhoods that do not have any age restrictions.

One alternative hypothesis is that pollution is considered by tenants a transitory envi-

[2] Sager and Singer (2022), who analyze the effect of the fine particulate matter standards set forth by the U.S. Clean Air Act, estimate that $PM_{2.5}$ reductions following nonattainment designation drove house price increases with a price-pollution elasticity of -1.4. Chay and Greenstone (2005) estimate price-pollution elasticity between -0.2 and -0.35, while Smith and Huang (1995) estimate an elasticity that ranges from -0.04 to -0.07.

[3] Our findings are consistent with related work (i.e., Amini et al., 2022; Bento et al., 2015; Lang, 2015; Grainger, 2012). One potential mechanism for the effect of smoke pollution on the demand for housing is through out-migration and residential sorting, as shown in (Bayer et al., 2009; Lopez et al., 2024).

ronmental condition with minor short-term consequences even though the negative health externalities may be much greater. However, we find no evidence that tenants with short-term contracts vs long-term contracts react less negatively to pollution shocks. This suggests that expectations about how long a tenant will be living in the property and be exposed to the area's air pollution do not explain the gap.

Lastly, we provide an analysis of how landlords respond to air pollution. Specifically, we examine the effect of pollution on pricing decisions and liquidity factors including the days-on-the-market, the likelihood of successfully leasing, and the quarterly listings. This analysis brings into consideration listings that were withdrawn from the market. Pollution appears to impact liquidity measures by economically meaningful levels. For instance, excess pollution measured by the $PM_{2.5}$ above 12 $\mu g/m^3$ (or about one standard deviation beyond the average pollution level) delays the days-on-the-market by 3.4% and reduces the likelihood that a property is leased. Likewise, each day of excess pollution appears to decrease the quarterly 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 pollution shocks. The initial pricing of a rental property is also not sensitive to pollution shocks. The findings suggest that landlords strategically consider the air quality when advertising properties for lease.

Our paper contributes to the literature on the capitalization of air quality in housing values (e.g., Sager and Singer, 2022; Chay and Greenstone, 2005; Smith and Huang, 1995). This literature includes only a handful of studies. For instance, Amini et al. (2022) examine the impact of nitrogen dioxide (NO_2) pollutants on house 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 tract-level rent estimates from the U.S. decennial census survey. 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, Cvijanović et al. (2024) study the impact of $PM_{2.5}$ on commercial property returns. While most of the related work focuses on changes in air quality because of a new policy or relies on aggregated measures, we exploit natural variation in surface air pollution, wildfire smoke plumes, and rental transactions using high-frequency data. We highlight the mechanisms influencing differences between renters and homeowners in the reaction to air pollution shocks, and that the heterogeneity response to air pollution is not only across homeowners and tenants but also landlords.

1. Data

1.1. 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.[4] 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 Zillow. After finding a tenant and executing a rental contract, the real estate agent updates the lease listing with information about the lease terms. The 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).[5]

Table 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

[4]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.

[5]We employ similar filters on the rent data as Lopez and Yoshida (2022) and Lopez (2022).

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 1(a) reports the kernel density of the monthly rent per square, illustrating a normal distribution with a slight skew to the right. Figure 1(b) shows the average rent per square foot and the total lease contracts by year. More than 95% of the rental contacts were successfully matched to a pollution record.

1.2. 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 location attributes such as the address and geo-coordinates, details about the transaction like the transaction date, and property characteristics (e.g., year built and square footage). The corresponding summary statistics are shown in Table A.1.

We also use the CoreLogic Real Estate data to explore the effect of pollution on rent in Chicago and the Bay Area in California, and report summary statistics in Table A.2. We limit our attention to listings that provide a closing rent. A potential issue with these rent data is that they lack information about the lease contract, such as the contract term.[6] Therefore, we only use the CoreLogic Real Estate data as a robustness test, not the main specification.

1.3. FRBNY Consumer Credit Panel/Equifax Data (CCP)

To better understand the different responses of homeowners and renters to exposure to pollution, we bring an additional database into the analysis called FRBNY Consumer Credit

[6] Only 12 percent of rental properties nationwide are listed using a Realtor; those properties are considered to be of a higher quality than the average rental unit (Loewenstein and Willen, 2023).

Panel/Equifax data set (CCP). The CCP data are a nationally representative anonymous random sample of Equifax credit report data. This dataset tracks all consumers with a US credit file residing in the same household from a random, anonymous sample of 5% of US consumers with a credit file.[7] Although the CCP data does not classify if a consumer is a homeowner or renter, we use the panel nature of the data and its richness to observe the consumer's address over time and their mortgage balance to classify housing tenure. We define a homeowner if they have a positive mortgage balance and if they live at the same address for more than three years.

1.4. Air Pollution

We obtain publicly available daily ground monitor readings of $PM_{2.5}$ measure of particulate matter from the Environmental Protection Agency (EPA)'s Air Quality System.[8] According to the EPA Quality Assurance Guidance Document, the "EPA stores data from over 10,000 monitors, 5,000 of which are currently active." These monitors tend to be located in highly populated areas.[9] To measure air pollution by census tract, we take the distance-weighted average of the two closest EPA monitors to the census tracts in Las Vegas. Figure 2 shows the location of the pollution monitors in 2019. Table A.3 shows the number of monitors by year from 2008 to 2019. Figure 3 shows the tract-level variation in pollution in July of each year. Tables A.4 and A.5 show the rich variation in pollution patterns.

The EPA's air quality monitoring network does not cover all tracts within a county Fowlie et al. (2019), and fewer than 20 percent of U.S. counties have a $PM_{2.5}$ monitor (Xu et al., 2020). In Clark County, NV, there are six monitors prior to 2017 and 5 monitors prior to 2012 (see Table A.3), which reduces concerns about pollution data coverage. However, we additionally use a satellite-based measure of $PM_{2.5}$, produced by Van Donkelaar et al. (2021)

[7] Although this paper categorizes census tracts based on racial composition; it does not use any individual-level racial information from the CCP data. Equifax consumer credit reports and Equifax data assets do not contain information about consumer's race or gender. For more information, see https://newyorkfed.org.

[8] Data source: https://www.epa.gov/outdoor-air-quality-data/download-daily-data.

[9] `https://www3.epa.gov/ttnamti1/files/ambient/pm25/qa/fieldsoppm.pdf`

(version V5.GL.03), which accounts for various meteorological and geographical factors and calibrates using a "Geographical Weighted Regression model." This measure offers a spatial resolution of 1-km × 1-km cells, as opposed to tract boundaries, which allows us to assign more precise monthly pollution estimates to all housing units in our analysis.[10]

1.5. *Wildfire Smoke*

We collect the daily smoke exposure data that were developed by Miller et al. (2021) using wildfire smoke analyses produced by NOAA's Hazard Mapping System (HMS), which are available from September 2005 onward. [11] According to Borgschulte et al. (2022):

> "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 focus on the 2008-2019 HMS smoke plume data to identify smoke days at the tract-level for each day in the sample. Figure 4 illustrates the variation in the smoke days in July by year, while Tables A.4 and A.5 report temporal patterns in the average smoke days.

[10] Version V5.GL.03 is available at https://wustl.app.box.com/v/ACAG-V5GL03-GWRPM25/folder/183627598190. Satellite-based estimates of $PM_{2.5}$ concentrations have been used in other studies including those in health and social sciences (e.g., Di et al., 2017; Fowlie et al., 2019).

[11] 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 (see An et al. (2023)).

2. Pollution and Rent

2.1. *Baseline Analysis*

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

$$Y_{it} = f(P_{zt}, C_i) + X_{it} \cdot \beta + \tau_t + \zeta_i + \varepsilon_{it} \tag{1}$$

where Y_{it} is the monthly rent of property i at time t in the natural log form, and $f(P_{zt}, C_i)$ is a pollution function. For our baseline specification, the pollution function is defined as:

$$f(P_{zt}, C_i) \equiv P_{zt} \cdot C_i \cdot \delta \tag{2}$$

where P_{zt} is the average monitor-based pollution measure of $PM_{2.5}$ readings observed at time t in tract z, C_i is a vector that we initially define as a constant 1 ($C_i^1 = [1]$), and δ is the coefficient (vector) of interest to be estimated. X_{it} stands for an array of lease contract, property, and neighborhood characteristics, and β is a vector of corresponding coefficients. We also include fixed effects for the year-month 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 pollution between transactions (excluding unobserved renewals) while holding all invariant property and location-specific factors constant.

Table 2 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 Huber/White/sandwich robust variance estimators. For ease of interpretation, we standardize the pollution measure into z-scores by demeaning the monitor-based $PM_{2.5}$ estimate and dividing it by the sample standard deviation. Column (1) does not include any control variables, showing that a one-standard-deviation increase in $PM_{2.5}$ is associated with a decrease in the rent by about 3.3%, on average. After adding year-month fixed effects, column (2) shows that the $PM_{2.5}$ effect on rent changes to -2.1%. 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 adjusts to -0.07%. Adding controls to the model (column (4)) 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 $PM_{2.5}$ effect on rent. However, in all the specifications, the relation between pollution and rent is negative and statistically significant at the 1% level.[12]

To visualize the effects differently, we relax assumptions of the functional form. Figure 5 shows the marginal effect of air pollution on rent when modeling $PM_{2.5}$ as a categorical variable. The effect is insignificant when $PM_{2.5}$ is below 6.6 $\mu g/m^3$ but greatest when between 12.2 and 15 $\mu g/m^3$. The effect declines slightly but remains negative for pollution levels above 15 $\mu g/m^3$.[13] In Table 3, we examine the effect of pollution on rent using two other functional forms. First, $PM_{2.5}$ is measured as the average $PM_{2.5}$ using rolling 30-day windows from the rental contract date in column (1). Second, a dummy variable that toggles from 0 to 1 when $PM_{2.5}$ on the contract date exceeds 12 $\mu g/m^3$ 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 the satellite-based 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 × 1-km cells, which introduces geographic variation but at the cost of temporal variation in pollution. Column (3) of Table 3 shows that the measure has a negative effect on rent that is significant at the 1% level. The effect size using the

[12] We find similar results when using year-month fixed effects, year-month-zip code fixed effects, year-week fixed effects, year-week and day-of-year fixed effects, which account for unobserved factors like a change in the neighborhood supply of housing (Table A.6). There is also a negative and statistically significant response to pollution across property types (see Table A.7).

[13] Alternatively, we add the squared value of the standardized pollution measure to the baseline model (Table A.8). We observe that the relation between rent and pollution is convex.

V5.GL.03 measure is about 62% greater than the baseline estimates. The difference may reflect differences between how daily and monthly pollution is perceived.

Lastly, we explore other cities in the U.S. that were not directly affected by wildfires but were exposed to wildfire smoke plumes. Table A.9 in the appendix 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. We examine the underlying mechanisms in Section 3.

2.2. Endogeneity

Although the repeat rent specification reduces concerns that poor air quality could be endogenous to locations of lower property values or rents, variation in the daily $PM_{2.5}$ measures may reflect air pollution shocks that may correlate with neighborhood trends. Just as Borgschulte et al. (2022) argue that the quasi-random movement of wildfire smoke plumes is a natural instrument to estimate the air pollution effect on labor market outcomes in an IV framework, we use smoke plumes to identify the causal effect of air pollution on rent. To allow for non-linear specifications, we modify the pollution function as follows:

$$f(P_{zt}, C_i) \equiv (\hat{f}_{i,1} + \hat{f}_{i,2} + \cdots + \hat{f}_{i,k}) \cdot \delta \tag{3}$$

where $\hat{f}_{i,k}$ represents the predicted value for the k^{th} endogenous regressor in $P_{zt} \cdot C_i$. The first stage model(s) is

$$f_{i,k} = Smoke_{zt} \cdot C_i \cdot \lambda_k + X_{it}\theta_k + \tau_{t,k} + \zeta_{i,k} + \varepsilon_{it,k}. \tag{4}$$

where $Smoke_{zt}$ is the count of smoke days over the last year from the contract date (lagged by 30 days), C_i is a vector as before, and λ is a parameter vector capturing the effect(s) of the instrument(s) on pollution. Equation (4) includes the same control variables and fixed effects as Equation (1) except for the instrument(s) defined by $(Smoke_{zt} \cdot C_i)$. We consider the smoke instrument to 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 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.

Table 4 reports the first stage and the second stage results of the IV analysis. The effect of the lagged annual smoke days on $PM_{2.5}$ is positive and statistically significant, bolstering the relevance criteria (Columns (1)). Meanwhile, the instrumented effect of $PM_{2.5}$ on rent, in Columns (2), has an effect size greater than previously estimated with the baseline model. A unit increase in $PM_{2.5}$ reduces the average rent by approximately 2.25%, which is statistically significant at the 1% level. In Columns (3) to (6) of Table 4, we show that the results are robust to using different lagged days of the instrument (i.e., 90 days and 360 days).

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, one standard deviation increase in $PM_{2.5}$ concentrations (approximately 4.2 $\mu g/m^3$) is associated with an average decrease in the rent by about 2.4%, which is an average loss of approximately \$372 per year.[14] 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 \$7,000.[15]

[14] $\$372 = 2.4\% \times \$1,292 \times 12$; \$1,292 is the monthly average rent.
[15] $\$6,979.36 = \$372/0.0533$.

3. Homeowners vs Renters

3.1. *Pollution and Home Prices*

Here we document the effect of air pollution on house prices obtained from the CoreLogic Real Estate data. Table 7 reports OLS and IV estimates of the monthly average $PM_{2.5}$ (observed two months behind the closing month) on the natural log of house prices using various specifications. We standardize the pollution measure into z-scores by demeaning the monitor-based PM2.5 estimate and dividing it by the sample standard deviation. Column (1) shows that when not accounting for any controls, a unit increase in $PM_{2.5}$ is correlated with an average decrease in house prices of approximately 3.3%. The relation is statistically significant at the 1% level. After adding year-month fixed effects, column (2) shows that the $PM_{2.5}$ effect on house prices adjusts to -9.99% and remains statistically significant. Columns (3) and (4) reveal that the pollution effect is robust to additional controls such as bedrooms, bathrooms, year built, and unobservable characteristics captured by parcel fixed effects. A unit increase in $PM_{2.5}$ reduces the average house prices by approximately 3%, which is statistically significant at the 1% level. In column (5), we show the second stage results of the IV analysis, using the lagged annual smoke days on $PM_{2.5}$ as the first stage. The instrumented effect of $PM_{2.5}$ on house prices has an effect size greater than estimated using the OLS model (column (4)). A unit increase in $PM_{2.5}$ reduces the average house prices by approximately 9%, which is statistically significant at the 1% level. The size of the effect on house prices is more than three times the effect size observed with rent. Overall, the results are consistent with Sager and Singer (2022) and demonstrate a gap in the response to pollution between homeowners and tenants.

3.2. *Tolerance to Pollution*

One reason that tenants respond less to pollution than owner-occupied homeowners is that they may differ in their tolerance to pollution. To investigate this claim, we compare the age and Equifax Risk Score profile of households using the Federal Reserve Bank of New York Consumer Credit Panel/Equifax data (CCP). The FRBNY CCP/Equifax provides information on household liability over time for a 5% random sample of individuals in the United States that have a social security number and an Equifax credit report. Figure 6 shows that tenants have lower Equifax Risk Scores and are younger than homeowners.

We examine the age factor by testing the impact of pollution on rents over time since the gap in the age of homeowners and tenants has grown over time. Whereas renters and homeowners were roughly of the same age in early 2008, homeowners are more likely to be over 50 than renters as of 2019 (Figure 6). If age is a driving factor, then the response to air pollution should decline over time, given that the health of young tenants may be more resilient to fluctuations in air quality than the health of older tenants. Thus, we expand our IV model (equations (1) and (4)) by setting the characteristics vector, C_i, in the pollution function to

$$C_i = [1[Before2012]\ 1[2012to2015]\ 1[After2016]],$$

where $1[Before2012]$ is one if the property was leased before 2012, $1[2012to2015]$ is one if the property was leased between 2012 and 2015, and $1[After2015]$ is one if the property was leased on or after 2016. All three variables are zero if false. Subsequently, our IV model features three endogenous regressors and three instruments. Table 5, Column (1), shows the daily $PM_{2.5}$ effect on rent during (1) 1/2008 to 12/2011, (2) 1/2012 to 12/2015, and (3) 1/2016 to 12/2019. We find that the response to pollution among renters is stronger during the earlier years than in the latter years in terms of either magnitude or statistical significance. However, a set of Wald tests indicates that the marginal effects are not statistically different from each other, suggesting that the effect of pollution does not change over time.

More formally, we test the response to air pollution by whether the rental property is in an age-restricted community. An age-restricted community is a neighborhood in which the association requires all residents to be 55 years or older. To do so, we modify our IV model by setting the characteristics vector, C_i, in the pollution function to

$$C_i = [1 \; 1[AgeRistriction]_i] \, ,$$

where 1 is a constant, and $1[AgeRestriction]$ is a dummy variable that equals one if the property i is located in a community that imposes a 55+ age restriction, and zero if otherwise. The second column of Table 5 reports the effects on a community with an age restriction and a community without an age restriction. We observe that the response to air pollution is twice as in an age-restricted community than the effect in a community without any age restrictions (i.e., 4.5% vs 1.94%). The marginal difference is statistically significant at the 5% level. Combined, the results suggest that age-related differences in tolerance to air pollution between tenants and homeowners may be driving a differential response to pollution between the two groups.

3.3. Tenure Length Expectations

One alternative reason that tenants respond to pollution at a rate less than homeowners is that a homeowner may anticipate living at the property much longer than a tenant. Hence, we test whether the effects vary depending on the rental contract length. If expectations about the exposure duration to local air pollution is a factor in location choice, then sensitivity to pollution may increase with the lease term. As we observe rental contracts that are 1-3 months, 4-6 months, 7-11 months, 12 months, and 12+ months, we set the pollution function to

$$C_i = [1[ShortLease] \; 1[YearLease] \; 1[LongLease]] \, ,$$

where $ShortLease$ is one if the lease term is less than 12 months, $YearLease$ is one if the lease term is 12 months, and $LongLease$ is one if the lease term is longer than 12 months.

These dummy variables are zero if false. Table 6 reports the results. However, we find no evidence that the response to pollution lessens or strengthens by a significant amount with expectations about how long the tenant will be living at the property. We observe that the pollution effects are statistically significant for year-long leases but not for short-term or long-term leases.

4. Landlords vs Tenants

4.1. *Pricing Choices*

Are landlords indifferent about air pollution at the rental property since they likely live elsewhere? To infer the differential response to pollution between landlords and tenants, we consider the date at which the pollution is observed. Given that the rent 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.10 shows that rents respond to pollution observed on the contract date and off-market date but not the listing date. We find similar results when using indicators of extreme pollution or a rolling window that captures the 30 days preceding the off-market date. This suggests that pollution affects the tenants' decisions at the extensive margin but not the landlords' pricing when advertising a property for rent.

4.2. *Liquidity and Search Frictions*

Bringing into the sample observations of failed listings that expired or were withdrawn by the landlord, we measure how excessive $PM_{2.5}$ influences 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:

$$L_{it} = \gamma \cdot 1[PM > 12]_{zt} + X_{it} \cdot \beta + \tau_t + \zeta_i + \varepsilon_{it} \tag{5}$$

where L_{it} is a liquidity factor, and $1[PM > 12]_{zt}$ is a function that equals 1 if the $PM_{2.5}$ exceeds 12 $\mu g/m^3$, 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 8 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 $PM_{2.5}$ above 12 $\mu g/m^3$ 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. 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. One implication is that landlords react to pollution by timing when to advertise a property for rent.

4.3. Market-wide Liquidity

We aggregate the 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 quarterly pollution statistics and estimate the following panel model:

$$Y_{jt} = \Psi \cdot \hat{PM}_{jt} + X_{jt} \cdot \beta + \tau_t + \zeta_j + \varepsilon_{jt}. \tag{6}$$

where Y_{jt} is the natural log of listings in quarter j or the natural log of leases in quarter j for each tract t.[16] $\hat{PM}_{jt}$ is the linear prediction of a $PM_{2.5}$ related variable estimated using

[16]We add one to the count of listings and leases to avoid undefined log values.

the following model:

$$PM_{jt} = \Gamma \cdot SmokeDays_{jt} + X_{jt} \cdot \theta + \tau_t + \zeta_j + \epsilon_{it}. \tag{7}$$

We examine two pollution variables: (1) the number of days in the quarter during which $\mathrm{PM}_{2.5}$ exceeded 12 $\mu g/m^3$, and (2) the average $\mathrm{PM}_{2.5}$ over the quarter. The *SmokeDays* instrument is the 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.[17] We also control for the quarterly tract-level median asking rent (and total listings when examining leases).

Table 9 reports the effect of excess $\mathrm{PM}_{2.5}$ on liquidity factors, aggregated to the listings at the tract year-quarter level. Each day of excess pollution above 12 $\mu g/m^3$ decreases listings in a tract by about 1.6%, whereas increases in the average $\mathrm{PM}_{2.5}$ decrease the 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 quarterly leases signed. Thus, landlords appear to withdraw properties from the market or delay advertisements during polluted days.

5. Conclusion

Wildfires are becoming more frequent and destructive over time. This is concerning because their smoke plumes can travel far away and carry harmful pollutants affecting populations far from the fires themselves. We estimate the impact of air pollution on rent and home prices using monitor-based pollution measures and quasi-random variation in the annual smoke days observed from satellite images of moving wildfire smoke plumes. We find that a one standard deviation increase in air pollution leads to a 0.8% decrease in the average

[17] The capitalization rate is the ratio of the median gross rent divided by the median home value.

monthly rent and a 3% decline in house prices. When using the annual smoke days as an instrument, we observe that the effect of pollution is -2.4% on the monthly rent and -9% on house prices, highlighting a differential response between renters and homeowners. To understand the differential response, we examine the cross-section response to air pollution by whether the property is in an age-restricted community and over time. The results suggest that differences in tolerance to air pollution between tenants and homeowners are driving a differential response between the two groups.

References

Amini, A., K. Nafari, and R. Singh (2022). Effect of air pollution on house prices: Evidence from sanctions on iran. *Regional Science and Urban Economics 93*, 103720.

An, X., S. A. Gabriel, and N. Tzur-Ilan (2023). Extreme wildfires, distant air pollution, and household financial health.

Bayer, P., N. Keohane, and C. Timmins (2009). Migration and hedonic valuation: The case of air quality. *Journal of Environmental Economics and Management 58*(1), 1–14.

Bento, A., M. Freedman, and C. Lang (2015). Who benefits from environmental regulation? Evidence from the clean air act amendments. *Review of Economics and Statistics 97*(3), 610–622.

Borgschulte, M., D. Molitor, and E. Y. Zou (2022). Air pollution and the labor market: Evidence from wildfire smoke. *Review of Economics and Statistics*, 1–46.

Case, A., D. Lubotsky, and C. Paxson (2002). Economic status and health in childhood: The origins of the gradient. *American Economic Review 92*(5), 1308–1334.

Chay, K. Y. and M. Greenstone (2005). Does air quality matter? Evidence from the housing market. *Journal of Political Economy 113*(2), 376–424.

Cvijanović, D., L. Rolheiser, and A. Van de Minne (2024). Commercial real estate and air pollution. *Real Estate Economics 52*(3), 951–989.

Di, Q., L. Dai, Y. Wang, A. Zanobetti, C. Choirat, J. D. Schwartz, and F. Dominici (2017). Association of short-term exposure to air pollution with mortality in older adults. *Jama 318*(24), 2446–2456.

Fowlie, M., E. Rubin, and R. Walker (2019). Bringing satellite-based air quality estimates down to earth. In *AEA Papers and Proceedings*, Volume 109, pp. 283–288. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Grainger, C. A. (2012). The distributional effects of pollution regulations: Do renters fully pay for cleaner air? *Journal of Public Economics 96*(9-10), 840–852.

Hanna, R. and P. Oliva (2015). The effect of pollution on labor supply: Evidence from a natural experiment in mexico city. *Journal of Public Economics 122*, 68–79.

Howard, G. and J. Liebersohn (2021). Why is the rent so darn high? the role of growing demand to live in housing-supply-inelastic cities. *Journal of Urban Economics 124*, 103369.

Isen, A., M. Rossin-Slater, and W. R. Walker (2017). Every breath you take—every dollar you'll make: The long-term consequences of the clean air act of 1970. *Journal of Political Economy 125*(3), 848–902.

Jordà, Ò., K. Knoll, D. Kuvshinov, M. Schularick, and A. M. Taylor (2019). The rate of return on everything, 1870–2015. *The Quarterly Journal of Economics 134*(3), 1225–1298.

Lang, C. (2015). The dynamics of house price responsiveness and locational sorting: Evidence from air quality changes. *Regional Science and Urban Economics 52*, 71–82.

Loewenstein, L. and P. S. Willen (2023). House prices and rents in the 21st century. Technical report, National Bureau of Economic Research.

Lopez, L. A. (2022). Is there a principal-agency problem with real estate agents in rental markets? *The Journal of Real Estate Finance and Economics*, 1–41.

Lopez, L. A., D. Murphy, N. Tzur-Ilan, and S. Wilkoff (2024). Up in smoke: The impact of wildfire pollution on healthcare municipal finance. *Available at SSRN 5040273*.

Lopez, L. A. and J. Yoshida (2022). Estimating housing rent depreciation for inflation adjustments. *Regional Science and Urban Economics 95*, 103733.

Miller, N., D. Molitor, and E. Zou (2021). A causal concentration-response function for air pollution: Evidence from wildfire smoke.

Roback, J. (1982). Wages, rents, and the quality of life. *Journal of Political Economy 90*(6), 1257–1278.

Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy 82*(1), 34–55.

Ruminski, M., S. Kondragunta, R. Draxler, and J. Zeng (2006). Recent changes to the hazard mapping system. In *Proceedings of the 15th International Emission Inventory Conference*, Volume 15, pp. 18.

Sager, L. and G. Singer (2022). Clean identification? The effects of the clean air act on air pollution, exposure disparities and house prices. Grantham Research Institute on Climate Change and the Environment Working Paper, 376, http://eprints.lse.ac.uk/id/eprint/115528.

Smith, V. K. and J.-C. Huang (1995). Can markets value air quality? A meta-analysis of hedonic property value models. *Journal of Political Economy 103*(1), 209–227.

Sonstelie, J. C. and P. R. Portney (1980). Gross rents and market values: Testing the implications of tiebout's hypothesis. *Journal of Urban Economics 7*(1), 102–118.

Sullivan, D. M. (2016). The true cost of air pollution: Evidence from house prices and migration.

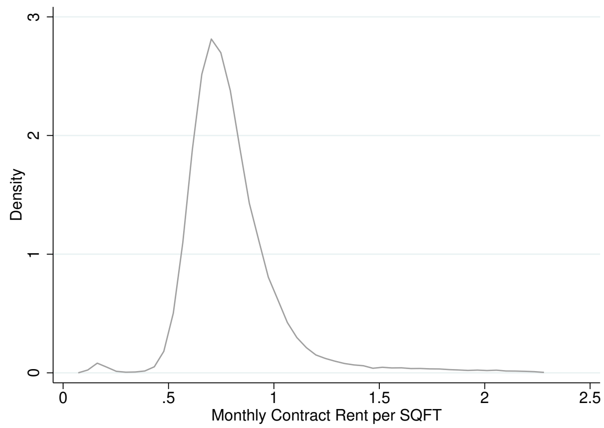
Van Donkelaar, A., M. S. Hammer, L. Bindle, M. Brauer, J. R. Brook, M. J. Garay, N. C. Hsu, O. V. Kalashnikova, R. A. Kahn, C. Lee, et al. (2021). Monthly global estimates of fine particulate matter and their uncertainty. *Environmental Science & Technology 55*(22), 15287–15300.

Wang, J. and C. L. Lee (2022). The value of air quality in housing markets: A comparative study of housing sale and rental markets in China. *Energy Policy 160*, 112601.

Xie, Y., M. Lin, B. Decharme, C. Delire, L. W. Horowitz, D. M. Lawrence, F. Li, and R. Séférian (2022). Tripling of western us particulate pollution from wildfires in a warming climate. *Proceedings of the National Academy of Sciences 119*(14), e2111372119.

Xu, R., P. Yu, M. J. Abramson, F. H. Johnston, J. M. Samet, M. L. Bell, A. Haines, K. L. Ebi, S. Li, and Y. Guo (2020). Wildfires, global climate change, and human health. *New England Journal of Medicine 383*(22), 2173–2181.

Zivin, J. G. and M. Neidell (2012). The impact of pollution on worker productivity. *American Economic Review 102*(7), 3652–3673.



(a) Rent Distribution

(b) Market Conditions

Fig.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.

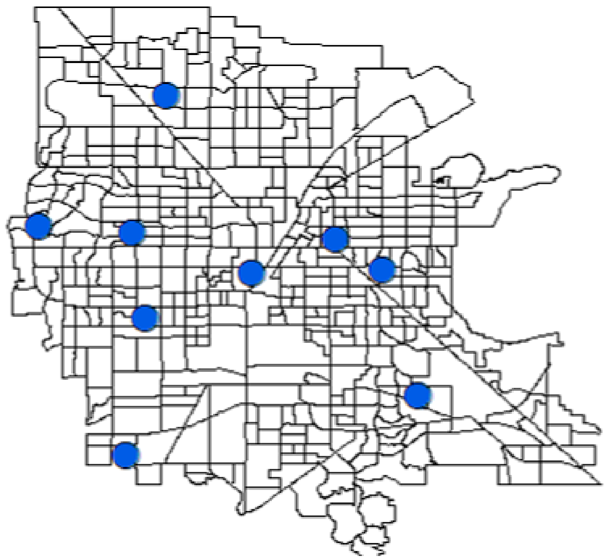
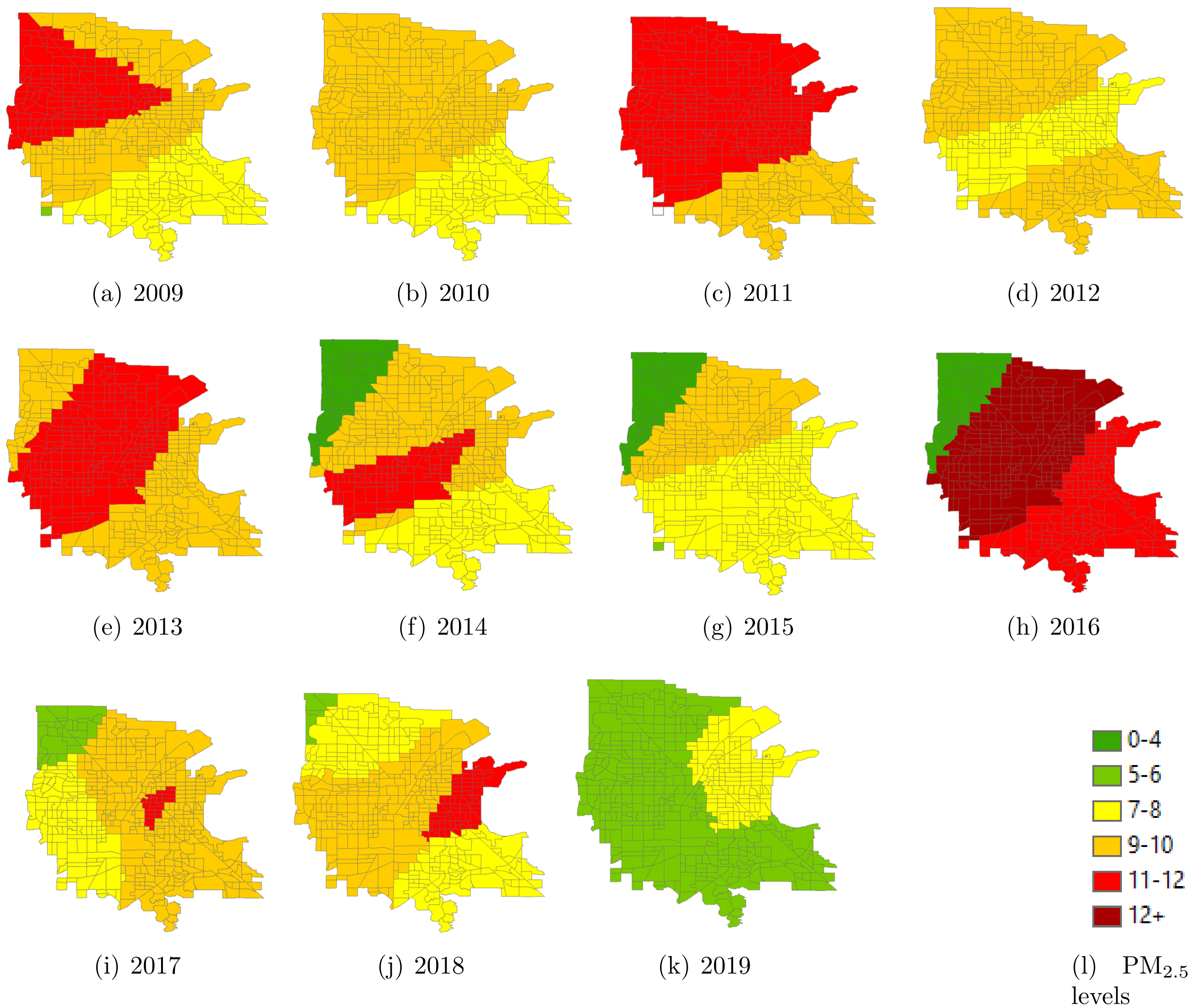


Fig.2. Location of the Pollution Monitors in Las Vegas city

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.



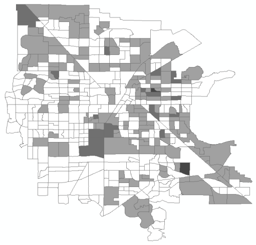
(a) 2009 (b) 2010 (c) 2011 (d) 2012

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

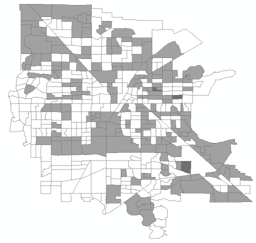
(i) 2017 (j) 2018 (k) 2019 (l) $PM_{2.5}$ levels

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

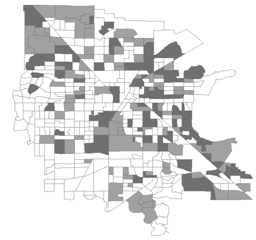
This figure shows the variation in pollution level as a measure of $PM_{2.5}$ overtime in July, between 2009 and 2019. Source: EPA's Air Quality System.



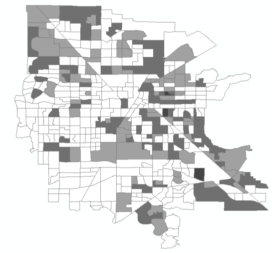
(a) 2009



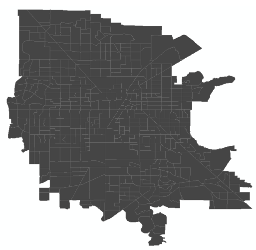
(b) 2010



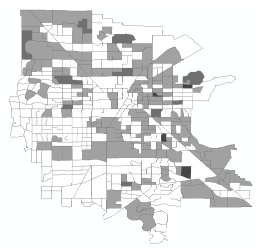
(c) 2011



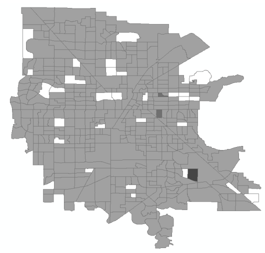
(d) 2012



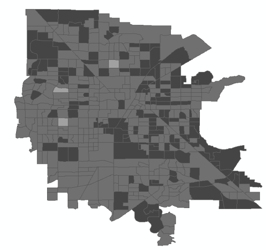
(e) 2013



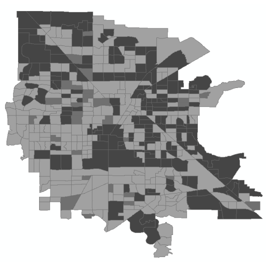
(f) 2014



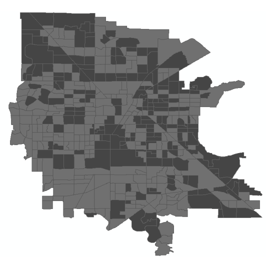
(g) 2015



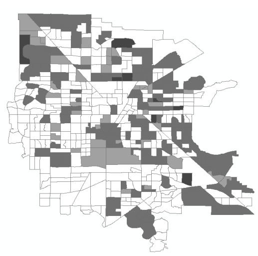
(h) 2016



(i) 2017



(j) 2018



(k) 2019

(l) Smoke Days

Fig.4. The Distribution of the Smoke Days per Month Over Time in July

This figure shows the variation in the smoke days per month in July between 2009 and 2019. Source: the National Oceanic and Atmospheric Administration's Hazard Mapping System (HMS).

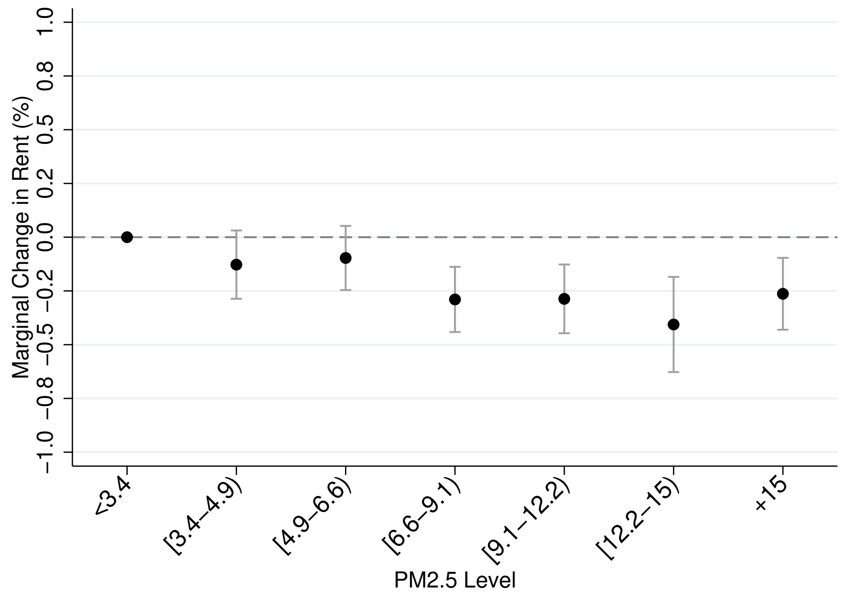


Fig.5. Discrete Effect of Air Pollution on Rent

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

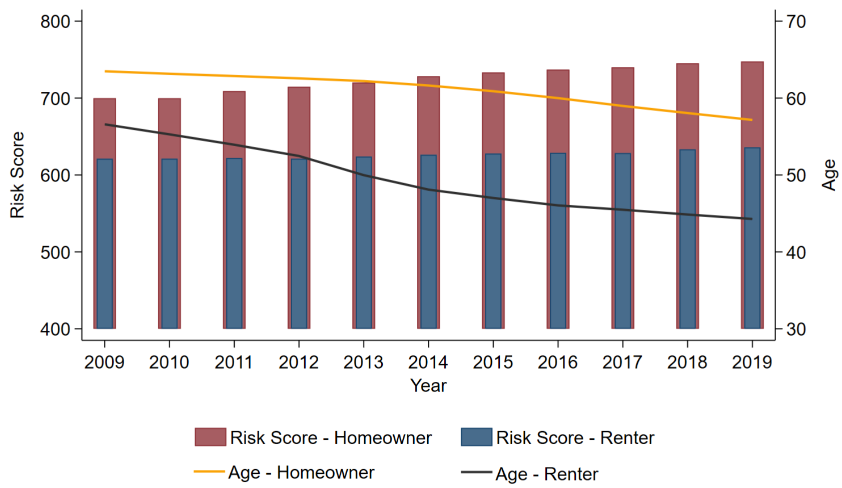


Fig.6. Demographic Characteristics of Owners and Renters in Las Vegas, 2009-2019

This figure shows the demographic characteristics of homeowners and renters in Las Vegas between 2009 and 2019. We measure demographic characteristics of households using the Federal Reserve Bank of New York Consumer Credit Panel/Equifax data (CCP). The CCP is a nationally representative anonymous random sample of Equifax credit report data. This data tracks all consumers with a US credit file residing in the same household from a random, anonymous sample of 5% of US consumers with a credit file. Equifax consumer credit reports and Equifax data assets do not contain information about consumer's race or gender. We use Risk Score to refer to Equifax Risk Score thereafter. We define consumers with a positive mortgage balance and who have been living at the same address for more than three years as homeowners. Source: Authors' calculations using Consumer Credit Panel/Equifax data (CCP), EPA's Air Quality System data, and Las Vegas Realtors' (LVR) MLS data.

Table 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 2: The Effect of $PM_{2.5}$ on Log(Rent Prices)

	(1)	(2)	(3)	(4)
Dep. Var.:	ln(Rent)	ln(Rent)	ln(Rent)	ln(Rent)
Pollution	-0.0329***	-0.0209***	-0.0007***	-0.0008***
	(-46.8055)	(-28.7486)	(-3.2240)	(-3.6226)
Observations	268,922	268,922	214,138	214,138
Adjusted R-squared	0.0086	0.0840	0.9593	0.9615
Constant	✓	✓	✓	✓
Controls	x	x	x	✓
Year-Month FE	x	✓	✓	✓
Parcel FE	x	x	✓	✓

This table presents the regression estimates of the air pollution effect on log rents. *Pollution* is the $PM_{2.5}$ registered on the contract date, standardized into z-score using the sample mean and standard deviation. Controls include lease term indicators, 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. In parentheses, t-statistics based on Huber/White/sandwich robust variance estimators are provided. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively. Sources: Authors' calculations using Las Vegas Realtors' (LVR) MLS, CoreLogic Real Estate data, EPA's Air Quality System, smoke data from Miller et al. (2021), and NOAA's Hazard Mapping System (HMS).

Table 3: Effect of Various $PM_{2.5}$ Measures on Log(Rent)

	(1)	(2)	(3)
Dep. Var.:	ln(Rent)	ln(Rent)	ln(Rent)
Pollution:	30 Day Avg	1[Above 12]	V5.GL.03
Pollution	-0.0006**	-0.0021***	-0.0013***
	(-2.4593)	(-3.1938)	(-4.2093)
Observations	241,968	241,968	252,131
Adjusted R-squared	0.9623	0.9623	0.9625
Constant	✓	✓	✓
Controls	✓	✓	✓
Year-Month FE	✓	✓	✓
Parcel FE	✓	✓	✓

This table presents the regression estimates of the air pollution effect on log rents using a sample of rental housing transactions from August 2008 to December 2019. In Column (1), *Pollution* is the z-score of the average monitored-based $PM_{2.5}$ level over the 30 days leading up to the contract date. In Column (2), *Pollution* is an indicator for whether the monitor-based $PM_{2.5}$ reading is above 12 $\mu g/m^3$ on the contract date. In Column (3), *Pollution* is the z-score of the monthly pollution estimate (called V5.GL.03) from Van Donkelaar et al. (2021) at the 1-k $\times$ 1-k level (smaller than census tracts). Controls include lease term indicators, 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. In parentheses, t-statistics based on Huber/White/sandwich robust variance estimators are provided. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively. Sources: Authors' calculations using 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 4: IV Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
Stage:	First	Second	First	Second	First	Second
Dep. Var.:	Pollution	ln(Rent)	Pollution	ln(Rent)	Pollution	ln(Rent)
Instrument:	Lag 30	Lag 30	Lag 90	Lag 90	Lag 365	Lag 365
Pollution		-0.0241***		-0.0320***		-0.0362***
		(-2.6831)		(-3.5095)		(-4.4661)
Smoke Instrument	0.1141***		0.1187***		0.1378***	
	(9.3196)		(9.5940)		(10.7351)	
Observations	210,494	210,494	208,874	208,874	197,403	197,403
Adjusted R-squared	0.2402		0.2406		0.2440	
Kleibergen-Paap Wald F statistic	.	69.11	.	91.25	.	114.84
Constant	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓
Parcel FE	✓	✓	✓	✓	✓	✓

This table presents the instrumental variable estimates of the air pollution effect on log rents using a sample of rental housing transactions from August 2008 to December 2019. The even columns report the first stage regression estimates, while the odd columns report the second stage regression estimates. *Pollution* is the monitor-based $PM_{2.5}$ reading on the contract lease date, demeaned and divided by the sample standard deviation. The *Smoke Instrument* is the annual smoke days lagged by 30 days in columns (1) and (2), 90 days in columns (3) and (4), and 365 days in columns (5) and (6). All versions of the smoke instrument are demeaned and divided by the sample 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. In parentheses, t-statistics based on Huber/White/sandwich robust variance estimators are provided. The stars *, **, *** denote statistical significance at the 10, 5, and 1 percent level, respectively. Sources: Authors' calculations using Las Vegas Realtors' (LVR) MLS, CoreLogic Real Estate data, EPA's Air Quality System, smoke data from Miller et al. (2021), and NOAA's Hazard Mapping System (HMS).

Table 5: IV Analysis Over Time and Across Age Communities

	(1)	(2)
Dep. Var.:	ln(Rent)	ln(Rent)
Pollution		-0.0194**
		(-2.0918)
Pollution × Before 2012	-0.0447***	
	(-3.6784)	
Pollution × 2012 to 2015	-0.0255***	
	(-5.3825)	
Pollution × After 2015	-0.0462	
	(-1.4596)	
Pollution × 55+ Community Age Restriction		-0.0261**
		(-2.5450)
Observations	210,494	210,494
Adjusted R-squared	-0.7462	-0.5683
Constant	✓	✓
Controls	✓	✓
Year-Month FE	✓	✓
Parcel FE	✓	✓

This table presents the instrumental variable estimates of the air pollution effect on log rents using a sample of rental housing transactions from August 2008 to December 2019. The even columns report the first stage regression estimates, while the odd columns report the second stage regression estimates. *Pollution* is the monitor-based $PM_{2.5}$ reading on the contract lease date, demeaned and divided by the sample standard deviation. *Before 2012* is an indicator for whether the contract date is before 2012, *2012 to 2015* is an indicator for whether the contract date is between those two years, and *After 2015* is an indicator for whether the contract date is after 2015. *55+ Community Age Restriction* is an indicator of whether the property is in a community with an age restriction. In column (1), the three interaction terms are instrumented with interactions of our smoke instrument with each of the respective time indicators. In column (2), *Pollution* is instrumented with our smoke instrument, and *Pollution × 55+ Community Age Restriction* is instrumented with the interaction of our smoke instrument and the 55+ community indicator. Our smoke instrument is the annual smoke days lagged by 30 days from the contract lease date, demeaned and divided by the sample 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. In parentheses, t-statistics based on Huber/White/sandwich robust variance estimators are provided. The stars *, **, *** denote statistical significance at the 10, 5, and 1 percent level, respectively.

Table 6: The Effect of $PM_{2.5}$ on Log(Rent) and Lease Term

	(1)
Dep. Var.:	ln(Rent)
Pollution × 12-Month Lease	-0.0474***
	(-4.6044)
Pollution × Short Term Leases (1-11 Months)	0.1293
	(1.4640)
Pollution × Long Term Lease (12+ Months)	0.0172
	(0.7776)
Lease Term: 1-3 Months	0.0666***
	(9.2794)
Lease Term: 4-7 Months	0.0171**
	(2.3177)
Lease Term: 8-11 Months	0.0101**
	(2.0885)
Lease Term: 12+ Months	0.0038***
	(4.4161)
Observations	197,403
Adjusted R-squared	-1.2136
Constant	✓
Controls	✓
Year-Month FE	✓
Parcel FE	✓

This table presents the instrumental variable estimates of the air pollution effect on log rents by lease term using a sample of rental housing transactions from August 2008 to December 2019. *Pollution* is the monitor-based $PM_{2.5}$ reading on the contract lease date, demeaned and divided by the sample standard deviation. *12-Month Lease* is an indicator variable for whether the contract term is 12 months. *Short Term Lease* is an indicator for whether the lease term is less than 12 months. *12+ Months* is an indicator of whether the lease term is longer than 12 months. *Lease Term* is a categorical variable for the lease term length in months, as noted in the variable name. The interaction terms with pollution are instrument with interactions of our smoke instrument with the lease term indicators. Our smoke instrument is the annual smoke days lagged by 30 days from the contract lease date, demeaned and divided by the sample 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: Authors' calculations using EPA's Air Quality System and Las Vegas Realtors' (LVR) MLS data.

Table 7: The Effect of $PM_{2.5}$ on Log(House Prices)

	(1)	(2)	(3)	(4)	(5)
Dep. Var.:	ln(Price)	ln(Price)	ln(Price)	ln(Price)	ln(Price)
Model:	OLS	OLS	OLS	OLS	IV
Pollution	-0.0332***	-0.0999***	-0.0267***	-0.0301***	-0.0897***
	(-18.912)	(-44.943)	(-9.043)	(-12.642)	(-4.458)
Observations	357,729	357,729	319,911	302,908	298,921
Adjusted R-squared	0.0008	0.1409	0.7501	0.8224	
Constant	✓	✓	✓	✓	✓
Controls	x	x	x	✓	✓
Year-Month FE	x	✓	✓	✓	✓
Parcel FE	x	x	✓	✓	✓

This table presents the regression estimates of the air pollution effect on log house prices. *Pollution* is the 30-day average $PM_{2.5}$ monitor-based reading, two months prior to the close date, standardized into a z-score using the sample mean and standard deviation. 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. Column (5) uses an IV analysis and only shows the second stage. The smoke instrument is the annual smoke days lagged by 30 days from the close date, demeaned and divided by the sample standard deviation. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively. Sources: Authors' calculations using CoreLogic Real Estate data, EPA's Air Quality System, and smoke data produced by NOAA's Hazard Mapping System (HMS) Miller et al. (2021).

Table 8: $PM_{2.5}$ Effects on Market Liquidity

	(1)	(2)	(3)	(4)
Dep. Var.:	ln(DOM+1)	1[Leased]	ln(LP)	ln(Rent)
$1[PM_{2.5} > 12]$ (Off Market Date)	0.0341***	-0.0155***		-0.0013**
	(4.3558)	(-5.9600)		(-2.0946)
$1[PM_{2.5} > 12]$ (Listing Date)			0.0004	
			(0.6571)	
ln(DOM+1), Winsorized				-0.0029***
				(-12.5957)
Observations	290,536	290,551	290,643	245,199
Adjusted R-squared	0.2523	0.1266	0.9639	0.9616
Constant	✓	✓	✓	✓
Controls	✓	✓	✓	✓
List Year-Month FE	✓	✓	✓	✓
Parcel FE	✓	✓	✓	✓

This table presents the regression estimates of the air pollution effect on liquidity factors using a sample of rental housing listings from August 2008 to December 2019. Approximately 12.7% of the rental listings in the sample were unsuccessful and did not result in a contract lease. The dependent variable is the natural log of the days on the market in column (1), an indicator for whether the listing resulted in a transaction in column (2), the natural log of the listing price in column (3), and the natural log of the contract rent price in column (4). $1[PM_{2.5}]_{off} > 12$ is one if $PM_{2.5}$ at the off-the-market date is greater than 12 $\mu g/m^3$, and is zero if otherwise. The off-market date is when the listing was withdrawn from the market or when a tenant was found. $1[PM_{2.5}]_{list} > 12$ is one if $PM_{2.5}$ at the listing date is greater than 12 $\mu g/m^3$, and is zero if otherwise. Controls include lease term indicators, 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: Authors' calculations using 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 9: $PM_{2.5}$ Effects on Quantity of Listings and Sales

	(1)	(2)	(3)	(4)
Dep. Var.:	ln(Listings+1)	ln(Listings+1)	ln(Leases+1)	ln(Leases+1)
Days $PM_{2.5} > 12$	-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 instrumental variable estimates of the air pollution effect on the log quantity of listings using a sample of rental housing listings from August 2008 to December 2019, which were aggregated to the census tract year quarter level. Days $PM_{2.5} > 12$ is the count of days during the quarter in which $PM_{2.5}$ exceeded 12 $\mu g/m^3$. $PM_{2.5}$ (quarterly) is the quarterly average $PM_{2.5}$ level at the tract level. *ln(Listings + 1)* is the natural log of listings in a quarter, and *ln(Median Asking Rent)* is the median rental rent at the tract year quarter level that was observed in the MLS. *Hispanic Share*, *Black Share*, and *API Share* are the population share of the named racial group at the tract year level obtained from the American Community Survey. API stands for Asian and Pacific Islander. *Cap Rate* is the median gross rent (times 12) divided by the median home price at the year tract level. Lastly, *ln(Median Gross Rent)* is the natural log of median gross rent at the tract year level. We obtain the *Cap Rate* and *Median Gross Rent* from the American Community Survey, 5-year estimates. The instrument for the pollution measures (of $PM_{2.5}$) 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: Authors' calculations using Las Vegas Realtors' (LVR) MLS, EPA's Air Quality System for air pollution monitors data, smoke data from Miller et al. (2021) and NOAA's Hazard Mapping System (HMS), and the U.S. Census American Community Survey 5-year estimates.

Table A.1: 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
Smoke Days per Month	309,648	3.58	3.19

This table presents summary statistics of CoreLogic Real Estate data from August 2008 to December 2019. This dataset contains property-level information from county registries (or recorders) of deeds. The data include both transactions and home characteristics for virtually all residential properties in Clark County, NV. Source: CoreLogic Real Estate data and EPA's Air Quality System for air pollution monitors data.

Table A.2: 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: Authors' calculations using CoreLogic Real Estate data and EPA's Air Quality System for air pollution monitors data.

Table A.3: 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 the Las Vegas city center over time between 2009 and 2019. Source: EPA's Air Quality System.

Table A.4: 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: Authors' calculations using EPA's Air Quality System and smoke data from Miller et al. (2021) and NOAA's Hazard Mapping System (HMS).

Table A.5: 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 and 2019. Sources: Authors' calculations using EPA's Air Quality System and smoke data from Miller et al. (2021) and NOAA's Hazard Mapping System (HMS).

Table A.6: The Effect of $PM_{2.5}$ on Log(Rent) with High Dimensional Time Fixed Effects

	(1)	(2)	(3)	(4)
Dep. Var.:	ln(Rent)	ln(Rent)	ln(Rent)	ln(Rent)
Pollution	-0.0008***	-0.0008***	-0.0008***	-0.0006***
	(-3.6226)	(-3.1225)	(-3.0801)	(-2.5867)
Observations	214,138	214,138	214,138	213,990
Adjusted R-squared	0.9615	0.9615	0.9615	0.9633
Constant	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Parcel FE	✓	✓	✓	✓
Year-Month FE	✓			
Year-Week FE		✓	✓	
Year-Month-ZIP code FE				✓
Day of Year FE			✓	

This table presents the regression estimates of the air pollution effect on log rents using a sample of rental housing transactions from August 2008 to December 2019. *Pollution* is the monitor-based $PM_{2.5}$ reading on the contract lease date, demeaned and divided by the sample standard deviation. Controls include lease term indicators, 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: Authors' calculations using EPA's Air Quality System and Las Vegas Realtors' (LVR) MLS data.

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

	(1)	(2)
Dep. Var.:	ln(Rent)	ln(Rent)
Subsample:	SFR	CONDO
Pollution	-0.0007***	-0.0012**
	(-2.9568)	(-2.3309)
Observations	144,026	51,379
Adjusted R-squared	0.9520	0.9576
Constant	✓	✓
Controls	✓	✓
Year-Month FE	✓	✓
Parcel FE	✓	✓

This table presents the regression estimates of the air pollution effect on log rents using a sample of rental housing transactions from August 2008 to December 2019 by property type: single-family residences (SFR) and condominiums (CONDO). *Pollution* is the monitor-based $PM_{2.5}$ reading on the contract lease date, demeaned and divided by the sample standard deviation. Controls include lease term indicators, 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: Authors' calculations using EPA's Air Quality System and Las Vegas Realtors' (LVR) MLS data.

Table A.8: Nonlinear $PM_{2.5}$ Effects

	(1)
Dep. Var.:	ln(Rent)
Pollution	-0.0011***
	(-4.3259)
Pollution^2	0.0001**
	(2.3922)
Observations	214,138
Adjusted R-squared	0.9615
Constant	✓
Controls	✓
Year-Month FE	✓
Parcel FE	✓

This table presents the regression estimates of the nonlinear air pollution effects on log rents using a sample of rental housing transactions from August 2008 to December 2019. *Pollution* is the monitor-based $PM_{2.5}$ reading on the contract lease date, demeaned and divided by the sample standard deviation. *Pollution*^{2} is *Pollution* squared. Controls include lease term indicators, 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: Authors' calculations using EPA's Air Quality System and Las Vegas Realtors' (LVR) MLS data.

Table A.9: The Effect of Daily Average $PM_{2.5}$ on Log(Rent Prices)

Panel A - Chicago	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Pollution	-0.0152***	-0.0158***	-0.0013*	-0.0008
	(-7.4011)	(-7.7432)	(-1.9534)	(-1.3714)
Observations	216,678	216,678	210,918	210,918
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
Pollution	-0.0314***	-0.0324***	-0.0008*	-0.0007*
	(-7.9823)	(-8.5635)	(-1.9311)	(-2.0234)
Observations	197,670	197,670	197,670	197,310
Adjusted R-squared	0.0002	0.1416	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 air pollution effect on log rents using a sample of rental housing transactions from August 2008 to December 2019. $PM_{2.5}$ is standardized into a z-score using the sample mean and standard deviation. 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: Authors' calculations using CoreLogic Real Estate data and EPA's Air Quality System.

Table A.10: $PM_{2.5}$ Levels at Various Dates

Dep. Var.:	(1) ln(Rent)	(2) ln(Rent)	(3) ln(Rent)
Pollution (Contract Date)	-0.0006**		-0.0006**
	(-2.4426)		(-2.3072)
Pollution (Off Market Date)	-0.0004*		-0.0004
	(-1.7211)		(-1.6264)
Pollution (Listing Date)	-0.0003		
	(-1.1253)		
$1[PM_{2.5} > 12]$ (Contract Date)		-0.0021***	
		(-3.0041)	
$1[PM_{2.5} > 12]$ (Off Market Date)		-0.0001	
		(-0.1715)	
$1[PM_{2.5} > 12]$ (Listing Date)		0.0003	
		(0.4314)	
Average $PM_{2.5}$: window(30) off market date			-0.0002
			(-0.6978)
Observations	184,720	241,860	200,017
Adjusted R-squared	0.9621	0.9623	0.9619
Constant	✓	✓	✓
Controls	✓	✓	✓
Year-Month FE	✓	✓	✓
Parcel FE	✓	✓	✓

This table presents the regression estimates of the air pollution effect on log rents using a sample of rental housing transactions from August 2008 to December 2019. *Pollution* is the monitor-based $PM_{2.5}$ 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. The listing date is the day the property is first put on the market for lease. *$1[PM_{2.5} > 12]$* is an indicator for whether the pollution measure is above 12 $\mu g/m^3$. *"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 lease term indicators, 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: Authors' calculations using EPA's Air Quality System and Las Vegas Realtors' (LVR) MLS data.