Smoked Out: Impact of Wildfire Smoke on Labour and Buildings

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PRELIMINARY AND INCOMPLETE. COMMENTS WELCOME.

Abstract

We investigate how air pollution impacts office buildings and workers by analyzing the effect of far reaching transient wildfire smoke on rent, lease term length and worker productivity. Combining satellite smoke plume data with office rents and lease term length on new contracts, we find that increased exposure to heavy smoke leads to lower rents and shorter lease terms. Building quality (new, high quality) mitigates some of the negative effect on rents associated with wildfire smoke exposure. We find that buildings exposed to lower levels of heavy smoke historically also see significant declines in rent and lease term length with increased heavy smoke exposure. No effect is found for buildings exposed to higher levels of heavy smoke historically. We additionally find evidence that the negative effect of smoke exposure on worker productivity is a significant channel for our findings. In general, the effect on rents and term length occurs in the short to medium term—within 6 months of exposure. However, given that office lease contracts range from 5 to 10 years, the downward pressure on rent is long-lasting.

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1 Introduction

Recent empirical work finds that air pollution exposure can produce a range of negative health and economic outcomes. Air pollution reduces labour supply and productivity in various settings and locations (Aguilar-Gomez, Dwyer, Zivin and Neidell, 2022; Zivin and Neidell, 2012), and additionally impacts cognitive performance, human capital accumulation and multiple forms of decision making. However, less is known about the potential downstream effects on the built environment. In this paper, we turn our attention to the economic consequences of air pollution on the built environment by studying the effects of transitory air pollution shocks on commercial real estate (CRE) markets with specific attention towards the office rental market.

A key empirical challenge for analyzing the causal effect of air pollution on the CRE market outcomes is finding geographically widespread variation in pollution that is not itself driven by factors that directly impact economic activity. To address the potential bias coming from air quality and economic activity being jointly determined by an omitted variable, our analysis leverages variation in air quality induced by wildfire smoke. The use of wildfire smoke as an air pollution source goes beyond its attractive exogenous features. Understanding the effect wildfire smoke in and of itself is increasingly important as the frequency, intensity, and geographic scope of wildfire smoke is now a significant source of $PM_{2.5}$-related air pollution nationwide (Borgschulte, Molitor and Zou, 2022).

From 2000 to 2020, national annual levels of $PM_{2.5}$ declined by 35%—largely due to the Clean Air Act, the Cross-State Air Pollution Rule, the Regional Haze Rule, and various motor vehicle emission standards across many states (E.P.A., 2023; Sarangi, Qian, Leung, Zhang, Zou and Wang, 2023). However, there has been a significant increase in $PM_{2.5}$ post-2016. This increase is likely due to increased economic activity, declining enforcement of the Clean Air Act, and an increase in wildfire smoke (Clay, Muller and Wang, 2021). The increased level of wildfire activity in terms of size and length of the wildfire season present worrying trends that may wipe out the substantial progress in the reduction of $PM_{2.5}$ seen in the past two decades.[1] Further, while wildfire burn-areas in North America are predominately located in the western part of Canada and the US, prevailing westerly winds during much of wildfire season carries significant levels of smoke across the United States (Sarangi et al., 2023). Additionally, recent research shows that wildfire smoke is a particularly toxic form $PM_{2.5}$ as compared to other sources of the pollutant (Aguilera, Corringham, Gershunov and Benmarhnia, 2021).

In focusing on the US office market in the research presented here, we aim to understand how extant observations of declining health and productivity at the worker-level might influence tenants' and building owners' reactions to these adverse shocks. We begin by identifying whether—and over what time frame—wildfire smoke exposure impacts rents for newly signed leases. Given the heterogeneity in office real estate, we hypothesize certain building characteristics (age, quality) may be protective against possible downward rent pressure. Lastly, we investigate whether declines in worker productivity due to wildfire smoke exposure may be a mechanism through which rent declines.

In general, we find that increased exposure to wildfire smoke leads to lower rents and shorter lease terms in the office market. For rent, the effect primarily occurs in the short run where an additional 10 days of heavy smoke exposure in 1 to 60 days and 61 to 120 days since a lease was signed results in a 2.2% to 3% drop in rent respectively. We find that lease term length declines roughly 5% to 8% given an additional 10 days of heavy smoke exposure in the past 8 months.

Our investigation into potential heterogeneous effects yields several important insights.

[1] Climate change-induced increases in rainfall anomalies, soil moisture evaporation, global wind speeds, frequency and severity of heat waves, and lightning strikes have all contributed to the increased frequency of *fire triangle* conditions—the presence of fuel, oxygen, and an ignition source (Xu, Yu, Abramson, Johnston, Samet, Bell, Haines, Ebi, Li and Guo, 2020)

First, we observe a heterogeneous effect of heavy smoke exposure with respect to building quality. Newer developments and class A buildings are somewhat shielded from the decline in rents. The effect of exposure on lease term lengths is not significantly different across age or building class. Second, the negative effects on rent and lease length are predominately associated with buildings that have historically lower levels of smoke exposure. This implies any increase in smoke exposure days represents more of a shock to these buildings than buildings historically exposed to higher levels of smoke. We view this difference as a somewhat adaptive response on behalf of the more exposed buildings. Importantly, given that office lease contracts are typically long term (e.g. 5 to 10 years), recent wildfire smoke exposure prior to lease signing will exert significant long-lasting downward pressure on rents.

Lastly, we identify productivity as a significant channel through which our results are generated. Using county-level office employment, we show that exogenous shocks to air quality through wildfire smoke exposure puts downward pressure on office employment counts. These declines in employment generate an exogenous negative shock to office space demand with rents on newly signed leases declining as a result. Comparing old versus new office buildings, we find the effect of smoke-induced employment decline significantly dampens rents for older buildings only.

Existing literature is limited in its exploration of the effect of air pollution exposure on commercial real estate. Cvijanovic, Rolheiser and Van de Minne (2024) analyze the impact of air pollution (acute fine particulate matter) exposure on the commercial real estate (CRE) market. By instrumenting for air pollution using changes in local wind direction, the authors find that an increase in fine particulate matter exposure leads to a contemporaneous decrease in CRE market values and (net) income as well as an increase in capital expenditures. Focusing on housing rental data in Las Vegas, Lopez and Tzur-Ilan (2023) document that increases in acute fine particulate matter induced by transient wildfire smoke lead to significant reduction in housing rents and values. We add to this literature by considering the near population of office real estate for rent in the United States along with a rich set of building and lease observables with a specific focus on the effect of smoke exposure on rents and lease term length.

The remainder of the paper is organized as follows: Section 2 presents existing literature and our conceptual framework. Section 3 discusses our methodologies. Section 4 describes the data and sample construction. In Section 5 we present the empirical results, and in Section 6 we conclude.

2 Background and Conceptual Framework

2.1 Existing Literature

Existing literature shows significant impact of air pollution, as measured by exposure to fine particulate matter $PM_{2.5}$ and/or wildfire smoke, both on health and non-health related outcomes affecting both people and places.[2]

Wildfire smoke, similar to other air pollutants, contains particulate matter that can enter human respiratory system and bloodstream. In addition, it carries other pollutants like ozone, carbon monoxide, atmospheric mercury, etc. While wildfire smoke affects health in ways similar to other air pollutants, its specific composition may result in varying levels of harm to human health per unit of measured particulate matter.

Existing work on the health impact of wildfire smoke have linked exposure to increases in adult mortality (Miller, Molitor and Zou, 2021), increases in infant mortality (Jayachandran, 2009), elevated risk of low birth weight (Mccoy and Zhao, 2021), and reductions in lung capacity (Pakhtigian, 2022).

[2] We do not summarize health-related outcomes here but see Aguilar-Gomez et al. (2022) for a summary of the effect of air pollution exposure on the heart, lungs, and brain.

2.1.1 Air Pollution, Labor Supply and Productivity

For worker-focused outcomes—the intensive margin—empirical findings confirm exposure to air pollution does indeed impact productivity and labor supply. Physically demanding jobs such as outdoor agricultural work, indoor garment production, and professional sports show decreases in productivity with exposure to pollutants such as ozone and $PM_{2.5}$ (Zivin and Neidell, 2012; Chang, Graff Zivin, Gross and Neidell, 2016; He, Liu and Salvo, 2019; Lichter, Pestel and Sommer, 2017; Guo and Fu, 2019; Mullins, 2018). Cognitively demanding occupations with monitored productivity show similar results (Archsmith, Heyes and Saberian, 2018; Chang, Graff Zivin, Gross and Neidell, 2019; Huang and Du, 2022). Additionally, more acute side effects related to air pollution exposure can decrease productivity to zero when a worker calls in sick, thus affecting labour supply (Aguilar-Gomez et al., 2022). Hanna and Oliva (2015); Holub, Hospido and Wagner (2021) find evidence that an increase in $PM_{2.5}$ and SO_2 reduces hours of labour supplied per week and increases the number of workers taking at least one sick day.

The reduction in labour supplied and declines in productivity can have far reaching effects on workers. Borgschulte et al. (2022) show that temporary disruptions in the labor market caused by transient wildfire smoke can have long-term impacts on earnings and welfare. Workers' wages may be affected both directly and indirectly (through their family members falling ill) by serious illnesses, leading to lasting changes in productivity or employment.[3] By exploiting variation in $PM_{2.5}$ induced by changes in wind directions at the postcode level Leroutier and Ollivier (2023) find an increase in workers' absenteeism and decrease in firms' monthly sales in manufacturing, construction, and professional services in France from 2009 to 2015. Addoum, Gounopoulos, Gustafson, Lewis and Nguyen (2023) find significant declines in the number of workers per establishment for consumer-facing industries

[3] The Family Medical Leave Act covered 59% of workers in 2012 and allowed them to take up to 12 weeks of unpaid leave for their serious health condition, or that of a spouse, parent, or child (Klerman, Daley and Pozniak, 2012).

(retail/restaurant/entertainment), where this effect continues for 2-3 years after exposure.

Additional findings on wildfire smoke exposure highlights various behavioral responses beyond missed work such as increased indoor time and extended use of air conditioners (Jones, Thacher, Chermak and Berrens, 2016). Further, Burke, Heft-Neal, Li, Driscoll, Baylis, Stigler, Weill, Burney, Wen, Childs and Gould (2022) observed changes in awareness and behavior, including health-protective measures, mobility adjustments, and shifts in sentiment in response to rising wildfire pollution.

On the extensive margin, in response to increased exposure to individuals, Addoum et al. (2023) document an increase in county-level establishment churn, as well as a decline in establishment-level cash flows and store visits (for retail industry) in the short run. Similarly, Leroutier and Ollivier (2023) find a significant decline in sales for manufacturing/construction/professional service industries in France. These findings suggest that overall declines in productivity/sales might be pushing some establishments to exit heavily exposed areas. Some establishments may also be updating the perceived climate risk of their current location in response to these shocks.

While the existing literature has mainly focused on the impact of increased air pollution on labor supply and productivity, research on tenants' (establishments') location choice and willingness to pay for a set of hedonic/location characteristics following an increase in air pollution exposure is scarce. We make headway on this question by studying how air pollution-driven changes in (office) worker productivity (or declines in employment) impact lease contracts (at the building level). In a departure from the existing literature, we assume that both tenants (establishments) and landlords (property owners) *react* to the exogenous changes in location value stemming from increases in air pollution.

Following an increase in air pollution, establishments experience a reduction in labor supply and/or productivity, and might decide that the location is no longer worth the prevailing rent. They may decide to (1) negotiate a lower rent, (2) ask the landlord to improve the quality of the building such that the negative labour effects are mitigated, or they may decide to (3) leave the property altogether. At the same time, faced with this negative shock, the landlord may decide to: (1) reduce rents; (2) invest in building improvements in order to minimise tenant turnover (and improve the quality of the building), or they can decide to (3) replace the tenant with a new one, who would be willing to pay the prevailing market rent. However, if the negative pressure on rents stemming from increased air pollution is an office market-wide effect (in our case at the county level), the latter remains no longer an option for the landlord. We hypothesize that to incentivize the tenants to stay, landlords will thus reduce rents and/or invest in building improvements. Faced with location-specific preferences, some tenants may have to bargain more intensely to achieve lower rents (or building improvements) in order to avoid having to go through a costly relocation. An additional hypothesis stemming from the analysis above is that buildings with characteristics that mediate the negative labour effects would not be as affected in terms of the downward pressure on rents.

3 Methodology

3.1 Effect of wildfire smoke on office leases

Our main log-linear specification is provided by;

$$\begin{aligned}\ln Y_{ntpmi} =&\alpha_0 + \sum_{k=1}^{K} \lambda^{l,k}\mathbf{light}_{np,k} + \sum_{k=1}^{K} \lambda^{med,k}\mathbf{medium}_{np,k} + \sum_{k=1}^{K} \lambda^{h,k}\mathbf{heavy}_{np,k} + \\ &\sum_{k=1}^{K} \phi^{k} T_{n,k} + \mu L_n + \rho_{tp} + \omega_m + \theta_i + \eta_{ntpmi}, \qquad (1)\end{aligned}$$

where dependent variable Y represents effective rents or lease terms for lease n located in property i in year t in county p in month m. The main coefficients of interest represent the effect of *light*, *medium*, and *heavy* smoke on effect rents or lease term length. We consider various bins of days leading up to the signing of the lease. Note that we use the date of signing, not the date of commencement of the lease. Parameter k denotes a bin of days prior to signing. We use 6 (k) bins; 1 – 60 days, 61 – 120 days, 121 – 180, 181 – 240, 241 – 300, and 300 – 365 days period to signing. The set of smoke variables *light*, *medium*, and *heavy* represent the amount of smoke days of the corresponding category in those k bins of days leading up to the signing of the lease. Matrix T contains climate variables including average maximum day temperature, average minimum night temperature, average precipitation (mm), and average wind speed where the averages are measured over the k bins leading up to the signing of the lease. Climate variables are observed on a daily basis and are aggregated up to the county level.

We control for tenant and lease characteristics (L) including dummy variables for who pays for the OpEx (Gross, Hybrid, Net, NN, and NNN) and dummy variables for tenant industry.[4] ρ is a county $\times$ year fixed effect which controls for time-varying local economic factors that could be correlated with an increase in forest fires at the county level. To control for within-year cyclically we also include within-year month-fixed effects ω. The property level fixed effects are provided by θ. Note that the unit of measurement is an individual lease contract (n); hence, we can identify both lease/tenant characteristics, *and* include a building fixed effect (θ) without multicollinearity issues. We include error term η, and constant α_0.

Following Sager and Singer (2022) and Cvijanovic et al. (2024) we use a county-level unit of measurement for smoke days. Only when a county is *fully* covered in light smoke (or medium/heavy) do we designate it as a "light smoke day" for that county for that specific day. The λ coefficients are interpreted as the change in log Y given an additional day of (light/medium/heavy) smoke in the past k bin of days. λs are identifiable given the variation in the days leases are signed; thus, there is no perfect collinearity with the county$\times$year

[4] See Figure 3 for breakdown of lease type and tenant industry.

fixed effects (ρ). The model is estimated via OLS, and standard errors are clustered at the county$\times$year level.

We also consider an alternative specification that uses a cumulative window of time rather than the binned windows used in Equation 1 and focus only on heavy smoke. We use cumulative windows of 60, 120, 180, 365 days with separate specifications for each window.

$$\ln Y_{ntpmi} = \alpha_0' + \lambda \mathbf{heavy}_{np\tau} + \gamma' T_{n\tau} + \mu' L_n + \rho_{tp}' + \omega_m' + \theta_i' + \varepsilon_{ntpmi}' \tag{2}$$

where $\mathbf{heavy}_{np\tau}$ is the number of heavy smoke days within the past τ days with respect to lease n in county p where smoke days are measured at the county level. The set of controls remain the same as in Equation 1.

To explore heterogeneity that might be driving our results, we additionally employ an interacted version of the main specification as follows:

$$\begin{aligned}\ln Y_{ntpmi} =& \alpha_0 + \sum_{k=1}^{K} \lambda^{l,k} \mathbf{light}_{n,k} + \sum_{k=1}^{K} \lambda^{m,k} \mathbf{medium}_{n,k} + \sum_{k=1}^{K} \lambda^{h,k} \mathbf{heavy}_{n,k} + \\ & \sum_{k=1}^{K} \beta^{l,k} (\mathbf{light}_{n,k} \times \Gamma_n) + \sum_{k=1}^{K} \beta^{m,k} (\mathbf{medium}_{n,k} \times \Gamma_n) + \sum_{k=1}^{K} \beta^{h,k} (\mathbf{heavy}_{n,k} \times \Gamma_n) + \\ & \zeta \Gamma_n + \sum_{k=1}^{K} \phi'^{k} T_{n,k} + \mu' L_n + \rho_{tp}' + \omega_m' + \theta_i' + \epsilon_{ntpmi},\end{aligned} \tag{3}$$

where Γ is an indicator variable (1/0 dummy) that exploits heterogeneity within the data. Specifically, we explore 3 different sources of heterogeneity: (1) newer developments, (2) class A buildings, and (3) whether the county has above-average smoke days in our data. The first two variables explore building quality heterogeneity. We categorize newer developments as buildings built within the five years before the signing of the lease or had an extensive renovation in the last five years. The reference category contains building built more than five years before the signing of the lease that lack extensive renovation. The reference category for class A buildings is class B/C buildings. The third heterogeneity test investigates whether buildings within counties that have experienced high levels of smoke days historically have adjusted to this exposure; and thus, have minimal reactions to new exposure shocks. Both tenants and buildings via large-scale capital expenditures may adapt to high levels of exposure. Currently, we cannot distinguish between the two possible sources of adaptation. We identify low versus high historical exposure as follows. Beginning with the average number of smoke days per county, we then take the average of those averages. Counties above this average are considered to have high historical exposure.

3.2 Wildfire-induced changes in employment and subsequent lease effects

Lastly, we investigate whether wildfire smoke-induced changes in county-level office employment provides a channel through which we can observe changes in rent. Following our conceptual framework, we hypothesize that wildfire smoke exposure negatively impacts employment through productivity channels. Note that we do not directly observe productivity; instead, we observe office employment counts at the county-level on a quarterly basis.The important linkage here between productivity and employment is that when establishments are faced with productivity declines they may opt to downsize or leave the market. Both events result in a decline in office employment. A shock to employment levels in a given market results in a decline in the demand for space in that market—holding space per worker constant in the short-run. This decline in demand subsequently puts upward pressure on vacancies and downward pressure on rent.

With these relationships in mind, we employ a two-step specification procedure. First, we identify exogenous changes in employment due to wildfire smoke exposure. Next, we regress rent on predicted employment from the first stage where the variation in employment is now only due to variation in smoke exposure. This setting allows us to identify whether employment is a potential channel through which wildfire smoke effects rents.

The first stage is as follows:

$$\ln Emp_{ntpqi} = \alpha_0' + \lambda \mathbf{heavy}_{np\tau} + \gamma' T_{n\tau} + \mu' L_n + \rho_{tp}' + \omega_m' + \theta_i' + \varepsilon_{ntpmi}' \tag{4}$$

We assign county-level quarterly (q) office employment counts (Emp) to each lease observation n in property i in year t in county p in month m. Given an observed lease, we predict employment in the quarter the lease is observed based on a past window of county-level heavy smoke days where the window varies from 60, 120, 180, to 365 days. The heavy smoke variable and controls are the same as in Equation 2. Again, we consider separate regressions varying the window of smoke observation prior to the lease being signed.

There is one complicating feature of this set-up due to variation in the frequency of data. First, for a lease observed in the beginning of a quarter, the window of the past 60 days is likely more predictive of the previous quarter of employment that the current. The next version of this draft will consider applying a weighted employment count based on where a lease signing occurs within a given quarter.

Predicted values of $\ln Emp$ for a give cumulative window τ from the first stage are used in the second stage with bootstrapped standard errors:

$$\ln Rent_{ntpmi} = \alpha_0' + \lambda \widehat{\ln EMP}^{\tau}_{ntpmi} + \gamma' T_{n\tau} + \mu' L_n + \rho_{tp}' + \omega_m' + \theta_i' + \varepsilon_{ntpmi}' \tag{5}$$

Note that in future drafts we will consider building heterogeneity in this setting as well.

4 Data and Descriptive Statistics

Data on wildfire smoke plumes in the United States is available through the National Oceanic and Atmospheric Administration (NOAA). Similar to Miller, Molitor and Zou, we build a daily panel of wildfire smoke exposure based on NOAA's Hazard Mapping System.[5] We construct mutually exclusive polygons of the three density levels of smoke density: light, medium, heavy.[6]

Figure 1 plots the number of smoke days per year for the three levels of smoke exposure we observe. Notably, all levels of exposure increase after 2019 with light smoke exposure jumping to an average of more than 60 days in 2022.

[Place Figure 1 About Here]

Climate data (mean temperature and precipitation) is retrieved from the PRISM climate group.[7] PRISM data is available daily for 481,631 16-sq-km (or 4×4 km) grid-locations covering the continental United States. Wind speed data comes from the North American Regional Reanalysis (NARR) daily reanalysis data. NARR incorporates raw data from land-based weather stations, aircraft, satellites, radiosondes (weather balloons), dropsondes (weather instruments dropped from aircraft), and other meteorological datasets. Wind conditions are reported on a 100x100 kilometer grid. We map these grid cells to counties.

Commercial lease level data comes from CompStak Inc. which provides detailed information on individual commercial leases across the US. We observe 484,055 leases covering all commercial real estate segments (i.e. office, retail, industrial) signed between 2008 and mid-2022 across the U.S. (Figure 2). The CompStak data include information on the amount of space leased, rent per square foot, lease term, street address, latitude and longitude of

[5] https://satepsanone.nesdis.noaa.gov/pub/FIRE/web/HMS/Smoke Polygons/Shapefile/

[6] The original form of the shapefile provides overlapping layers where heavy smoke polygons overlap with medium and light and medium overlaps with light. We construct mutually exclusive polygons for each density type.

[7] https://prism.oregonstate.edu/

the building, building quality (Class A, B and C), and tenant composition (Figure 3). In our empirical analysis, we work with effective rent, a standard measure in the CRE industry that includes monthly rent and other payments between landlord and tenant converted to a monthly basis.

[Place Figure 2 About Here]

[Place Figure 3 About Here]

Quarterly county-level office employment data is retrieved from the US Census Quarterly Workforce Indicators time series. We use NAICS codes starting with 5 to identify office employment counts. The Bureau of Labor Statistics provides the monthly unemployment rate for all sectors at the county level.

Table 1 present summary statistics for the lease characteristics, smoke days, and climate variables 365 days prior to the signing of the lease. Variable means remain consistent across the two samples apart from the number of smoke days. Effective rent is just under $30/sqft, average lease term is just over 4.5 years, buildings are about 22 years old (accounting for renovation dates), half of the sample is class A office, 30% of the sample consists of local tenants, and about 22% of the leases are renewals. On average there is roughly a 10-degree Celsius difference between minimum and maximum temperatures, 2.6mm of precipitation, and wind speed of 4.6 miles per hour. There are respective 1.5 and 17 light smoke days in the 30 days and 365 days prior to signing a lease. There are 0.3 and 3.2 medium smoke days in the 30 days and 365 days prior to signing a lease. And lastly, there are 0.1 and 1.1 heavy smoke days in the 30 days and 365 days prior to signing a lease.

[Place Table 1 About Here]

5 Results

5.1 Main Results

Our main results are plotted in Figure 4.[8][9] In general, increased light or medium smoke exposure at any point over a one year period has minimal effect on rents and lease terms with the exception of light smoke exposure in the 61-120 day interval for rent. There, we see a somewhat significant, but small positive effect—10 additional light smoke days 2 to 4 months ago results in a roughly 0.8% increase in rent per square foot. This effect is not significant at the 1% level, however. These insignificant results for light and medium smoke carry through our other results. Thus, we refrain from presenting them in the main text.

We find larger, negative and more significant effects when considering heavy smoke exposure. For rent, the effect primarily occurs in the short run—i.e. exposure within the past 4 months. The magnitude of the effect ranges from about a 2.2% drop to a 3% drop in rents with an additional 10 days of heavy smoke exposure in days 1 to 60 and 61 to 120 respectively. Exposure to increases further back in time do not appear to impact rent. The negative effect of heavy smoke on lease term lingers over a longer period of time as additional smoke days in the previous 1-60, 61-120, 121-180, 181-240 windows all result in significantly lower lease term length. The magnitudes here are large with declines in lease term length ranging from roughly 5% to 8% given an additional 10 days of heavy smoke exposure in the past 8 months.[10]

Tables 2 and 3 present the results for the cumulative window setting where we consider heavy smoke days only (Eq. 2). This specification serves as a reference for our specifications considering $PM_{2.5}$ and employment discussed below. For rent, we find a fairly consistent

[8] Estimated control variable coefficients for the full model are shown in Appendix Table A1.

[9] We additionally considered retail properties but find no significant effect. See Appendix Figure A1.

[10] A possible concern with our baseline result is that the observed patterns are driven by changes in office rents during Covid years. Re-estimating our baseline specification and excluding observations after 2020Q2 yields quantitatively similar results.

effect as the window of time increases from the previous 60 days to the previous 365 days with the effect being the largest in the previous 120 days. A ten day increase in smoke days during the past 120 days decreases rent by 1.8%. Compared to the binned window specification, the magnitude of the effects are lower. This is likely a result of the larger window picking up on potentially sporadic smoke days whereas the 61 to 120 day window is capturing a more concentrated observation period. In other words, 10 days of smoke at any point over 120 days may be qualitatively different than 10 days of smoke over the past 61 to 120 days.

[Place Figure 4 About Here]

[Place Table 2 About Here]

[Place Table 3 About Here]

5.1.1 Smoke and $PM_{2.5}$

Wildfire smoke contains particulate matter (PM) and various noxious gases, but the component of most concern—given its significant negative impact on human health—is $PM_{2.5}$. Wildfire smoke is often used as an instrument to identify exogenous shocks to $PM_{2.5}$ levels (see Cvijanovic et al. (2024) as an example). Here, our question is not specifically about identifying the causal effect of $PM_{2.5}$ exposure on rents and lease term lengths, but about identifying how much of the negative smoke effect we observe is due to increased $PM_{2.5}$. We employ the cumulative window specification in a two-stage setting: the first stage regresses local $PM_{2.5}$ levels on the number of smoke days in the given window along with relevant controls. Predicted values of $PM_{2.5}$ are then used in the second stage which mirrors Equation 5. For an in depth discussion, please see Appendix Section A1.

In general, we find that the corresponding rise in air pollution generated by heavy smoke accounts for the full negative effect of wildfire smoke on both rents and lease term length.

5.2 Heterogeneity

Figures 5 and 6 present the resulting coefficients of interest in our exploration of heterogeneous effects of heavy wildfire smoke exposure on rent and lease term length.[11] We consider possible sources of heterogeneity stemming from the structural characteristics of the buildings themselves as well as variation in historical wildfire smoke exposure of a given location.

5.2.1 Quality of the Building

Panels (a) and (b) of Figures 5 and 6 present the smoke exposure coefficients for older buildings versus newer developments for both the rent and lease term length specifications. The short-run negative effect of heavy smoke exposure present in the full sample appears to be driven by older buildings. The negative effect is sustained over the first three time intervals considered with coefficients implying around a 3% decline in rents with a 10 day increase in heavy smoke exposure during these earlier intervals. We find a somewhat noisy positive marginal effect of newer development rents for windows between 1 and 240 days. The composite effect for newer developments at all windows is not significantly different from zero. We do not find significantly different lease term effects for older versus newer developments (Figure 6, Panels (a) and (b)).

Comparing class B/C buildings with class A buildings, we see somewhat similar patterns. A significant negative effect on rents (Panels (c) and (d) of Figure 5) is found within the 61 to 120 and 121 to 180 day windows for class B/C buildings. The magnitude of the coefficients are similar to those found for older buildings—around a 3% decline in rent if the number

[11] Coefficients for light and medium smoke are insignificant. We do not present these results for space purposes.

of smoke days within the interval increases by 10. Conversely, the positive and significant marginal effect found in the 121 to 180 and 181 to 240 day windows for class A buildings implies an overall null effect of heavy smoke exposure on rents for this building class.

A negative effect on lease term length from heavy smoke exposure is found in the first four intervals (first 8 months) for class B/C buildings; there is no significant difference for class A buildings relative to class B/C (Panels (c) and (d) of Figure 6). The downward pressure on class B/C lease term length is fairly large—decline in term length given a 10 day increase in heavy smoke exposure ranges from just under 5% to roughly 7.5%. These results are similar to the full sample results.

In general, it appears that building quality (newer, class A) mitigates some of the negative effect on rents associated with wildfire smoke exposure. Conversely, building quality does not mitigate the decline in lease term length that results from smoke exposure.

5.2.2 Historical Exposure

Lastly, we consider whether buildings that have been exposed to more smoke throughout the time period considered are less reactive to changes in smoke exposure (Panels (e) and (f) of Figure 5 and Figure 6). Comparing buildings in locations with above and below historic smoke levels, we again find most of the impact coming from heavy smoke exposure. Interestingly, it is the buildings that have historically lower levels of smoke exposure that display significant declines in rent and lease term length as a result of increased heavy smoke exposure. The negative rent effect is most salient within the first four months. We find a rent decline of about 3% and 5% given a increase in heavy smoke days by 10 within 1 to 60 and 61 to 120 days respectively. For those same intervals, the marginal effect for buildings that have historically higher levels of smoke exposure are positive and indicate a composite null effect of exposure.

The effect of heavy smoke on lease term length for buildings typically experiencing lower levels of smoke is persistently negative and significant across all time intervals considered. The largest effect size is found within the 6 to 8 month window with lease term lengths dropping by about 10% given an increase in the number of heavy smoke days by 10. The marginal effect on buildings with higher levels of historic smoke exposure are positive for all intervals but are fairly noisy.

[Place Figure 5 About Here]

[Place Figure 6 About Here]

5.3 Employment

Starting with the first stage of our two-step specification (Table 4), we find a significant negative relationship between prior smoke days and employment count. The largest effect occurs during the past 120 or 180 days of a lease being signed where ten more days of smoke decreases office employment by 1%.

The second stage shows the expected positive association between rising office employment and rents (Table 5). Given our concern is negative employment shocks we interpret the coefficients as follows. Focusing on the 120 day window, an increase in smoke days by 10 decreases employment by 1% which then implies a decrease in rents by 1.8%. This result is nearly identical to our findings in Table 2. Results for 180 and 365 day windows are qualitatively similar as well.[12] These results imply that much of the negative effect of smoke exposure on rents is flowing through general office market channels as represented by employment count.

We might be concerned that a quarterly measure of employment provides too coarse of variation. While office employment at the county level is not publicly available at a

[12] Note that for this specification the 60 day window is noisy due to the size of a quarter versus the 60 day length of smoke observation.

shorter frequency, we do observe the unemployment rate on a monthly basis for all sectors. Of course, having this measure for office employment only would be ideal; however, the general unemployment rate still provides a reasonable robustness check for concerns regarding county-level phenomena varying at a frequency smaller than yearly such that our county-by-year fixed affect cannot account for them. Results for the first and second stage are found in Appendix Tables A6 and A5. We find qualitatively similar effects to the quarterly employment specification where unemployment rate is positively associated with increasing smoke days with the resulting change in rents estimated to be between 1.5% and 1.8% depending on the window of observation.

Lastly, we stratify the main specification (Appendix Tables 4 and 5) by building age—new (less than 10 years old) and old (ten years and older). To simplify our assessment, we focus on a window of 180 days prior to the signing of a new lease. The first stage for each group is qualitatively identical to the first stage for the full sample, which is expected. Only the subsample of older buildings produces a significant coefficient on employment count in the second stage. Taking the first and second stage coefficients together, a 10 day increase in heavy smoke decreases employment by about 1% which then implies a 1.7% decline in rent for older buildings—with significance of 1%. We view these findings as suggestive evidence that younger buildings may contain structural and functional characteristics that are protective against negative smoke-induced labor shocks. We will investigate this hypothesis in detail in future drafts.

6 Conclusion

We examine the economic consequences of air pollution on buildings and workers by studying the effects of transitory air pollution shocks on office rents, lease term length, and worker productivity. To address the potential bias coming from air quality and economic activity being jointly determined by an omitted variable, our analysis leverages variation in air quality induced by wildfire smoke.

Combining satellite smoke plumes data with office rental market outcomes, we find that increased exposure to heavy wildfire smoke has a significant negative effect on office rents both in the short to medium term. This negative effect on rents appears to run through a productivity channel as wildfire smoke exposure puts downward pressure on productivity leading to declines in rent. We find a somewhat more persistent negative effect on lease term length. While the exposure effect on new leases is observed within a few months of exposure, the downward pressure on rents is in fact long-term given long lease terms for office (5-10 years).

Our investigation into potential heterogeneous effects yields three insights. First, we observe a heterogeneous effect of heavy smoke exposure with respect to building quality. Rents for older buildings and class B/C buildings are both negatively impacted by exposure to heavy smoke, with the effect most acute during the first six months after exposure. Newer developments and class A buildings are somewhat shielded from the decline in rents. Third, the negative effects on rent and lease length are predominately associated with buildings that have been exposed to historically lower levels of smoke. This implies any increase in smoke exposure days represents more of a shock to these buildings than buildings historically exposed to higher levels of smoke. We view this difference as a somewhat adaptive response on behalf of the more exposed buildings where the exposure effect may already be capitalized into rents.

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Tables and Figures

Tables

Table 1: Summary statistics of main variables

Statistic	N	Mean	St. Dev.
effective rent ($)	479,624	29.140	41.304
lease term (months)	480,916	56.618	39.006
size of space (sqft)	488,216	9,618	27,138
effective age	432,990	22.225	20.210
A-class office	469,249	0.504	0.500
Smoke days			
light	484,055	16.894	16.432
medium	484,055	3.156	4.591
heavy	484,055	1.144	2.980
Climate variables			
minimum temperature °C	484,055	9.784	3.917
maximum temperature °C	484,055	20.715	4.362
precipitation (mm)	484,055	2.664	1.368
wind speed	484,055	4.618	0.986
County variables			
Office employment	484,700	345,272	314,186
Unemployment (%)	491,162	0.0570	0.0245
$PM_{2.5}$ (μ/m^3)	454,867	9.44	2.30

Note: N is number of observations, St. Dev. is Standard deviation. Effective age is computed by subtracting the max(Year built, Year renovated) from the year that the lease was signed. *A-class* = 1/0 indicator variable for high-quality buildings. Smoke days and climate variables are given over the year preceding the signing of the lease. The county variables are based on 180 days of lags. The mean and missing amount of observations can change slightly accordingly.

Table 2: Direct impact of heavy smoke days on effective rents w/cumulative time window

Model:	(1)	(2)	(3)	(4)
Days:	60	120	180	365
Variables				
Heavy smoke (days)	-0.0015**	-0.0018***	-0.0016***	-0.0013**
	(0.0006)	(0.0006)	(0.0005)	(0.0006)
Max temperature (°C)	-0.0006	0.0000	0.0018	0.0019
	(0.0006)	(0.0010)	(0.0014)	(0.0043)
Min temperature (°C)	0.0000	-0.0008	-0.0027*	-0.0094*
	(0.0007)	(0.0010)	(0.0015)	(0.0055)
Precipitation (mm)	-0.0005	-0.0006	0.0010	-0.0023
	(0.0004)	(0.0008)	(0.0011)	(0.0033)
Wind speed (m/h)	0.0000	-0.0005	-0.0010	-0.0018
	(0.0015)	(0.0025)	(0.0030)	(0.0087)
log(Square foot)	-0.0206***	-0.0207***	-0.0209***	-0.0211***
	(0.0018)	(0.0018)	(0.0018)	(0.0019)
Fixed-effects				
Lease type	Yes	Yes	Yes	Yes
Year × county	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Property level	Yes	Yes	Yes	Yes
Tenant industry	Yes	Yes	Yes	Yes
Fit statistics				
Observations	486,497	484,578	481,916	475,465
R^2	0.836	0.837	0.837	0.838
Dependent Variable:	log(effective rent)			

Clustered (Year × County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3: Direct impact of heavy smoke days on effective lease term lengths w/cumulative time window

Model:	(1)	(2)	(3)	(4)
Days:	60	120	180	365
Variables				
Heavy smoke (days)	-0.0034**	-0.0031**	-0.0036***	-0.0041***
	(0.0014)	(0.0013)	(0.0010)	(0.0011)
Max temperature (°C)	-0.0017	0.0012	0.0040	-0.0191**
	(0.0016)	(0.0022)	(0.0029)	(0.0089)
Min temperature (°C)	0.0015	-0.0012	-0.0034	0.0070
	(0.0017)	(0.0024)	(0.0032)	(0.0097)
Precipitation (mm)	-0.0009	0.0015	0.0047**	0.0028
	(0.0012)	(0.0015)	(0.0023)	(0.0061)
Wind speed (m/h)	-0.0012	0.0007	0.0043	-0.0050
	(0.0028)	(0.0040)	(0.0053)	(0.0177)
log(Square foot)	0.2040***	0.2039***	0.2038***	0.2038***
	(0.0020)	(0.0020)	(0.0021)	(0.0021)
Fixed-effects				
Lease type	Yes	Yes	Yes	Yes
Year × county	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Property level	Yes	Yes	Yes	Yes
Tenant industry	Yes	Yes	Yes	Yes
Fit statistics				
Observations	487,897	485,972	483,288	476,799
R^2	0.548	0.548	0.548	0.550
Dependent Variable:	log(lease term)			

Clustered (Year × County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 4: First stage of the two-step procedure to isolate smoke-induced changes in (log) office employment. Office employment is measured on a county-by-quarter level using NAICS codes that start with a 5.

	(1)	(2)	(3)	(4)
Days:	60	120	180	365
Variables				
Heavy smoke (days)	-0.0005***	-0.0010***	-0.0010***	-0.0008***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Max temperature (°C)	-0.0001	0.0000	0.0003	0.0027*
	(0.0002)	(0.0004)	(0.0006)	(0.0015)
Min temperature (°C)	0.0000	0.0000	-0.0001	-0.0045***
	(0.0002)	(0.0004)	(0.0006)	(0.0017)
Precipitation (mm)	-0.0002	-0.0006**	-0.0006**	-0.0001
	(0.0001)	(0.0002)	(0.0003)	(0.0009)
Wind speed (m/h)	-0.0016***	-0.0005	0.0010	0.0018
	(0.0003)	(0.0006)	(0.0010)	(0.0029)
log(Square foot)	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Fixed-effects				
Lease type	Yes	Yes	Yes	Yes
Year × county	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Property level	Yes	Yes	Yes	Yes
Tenant industry	Yes	Yes	Yes	Yes
Fit statistics				
F-test	377	5,073	8,815	5,490
Wald	6.66	23.65	32.61	17.75
Dependent Variable:	log(office employment)			

Clustered (Year × County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

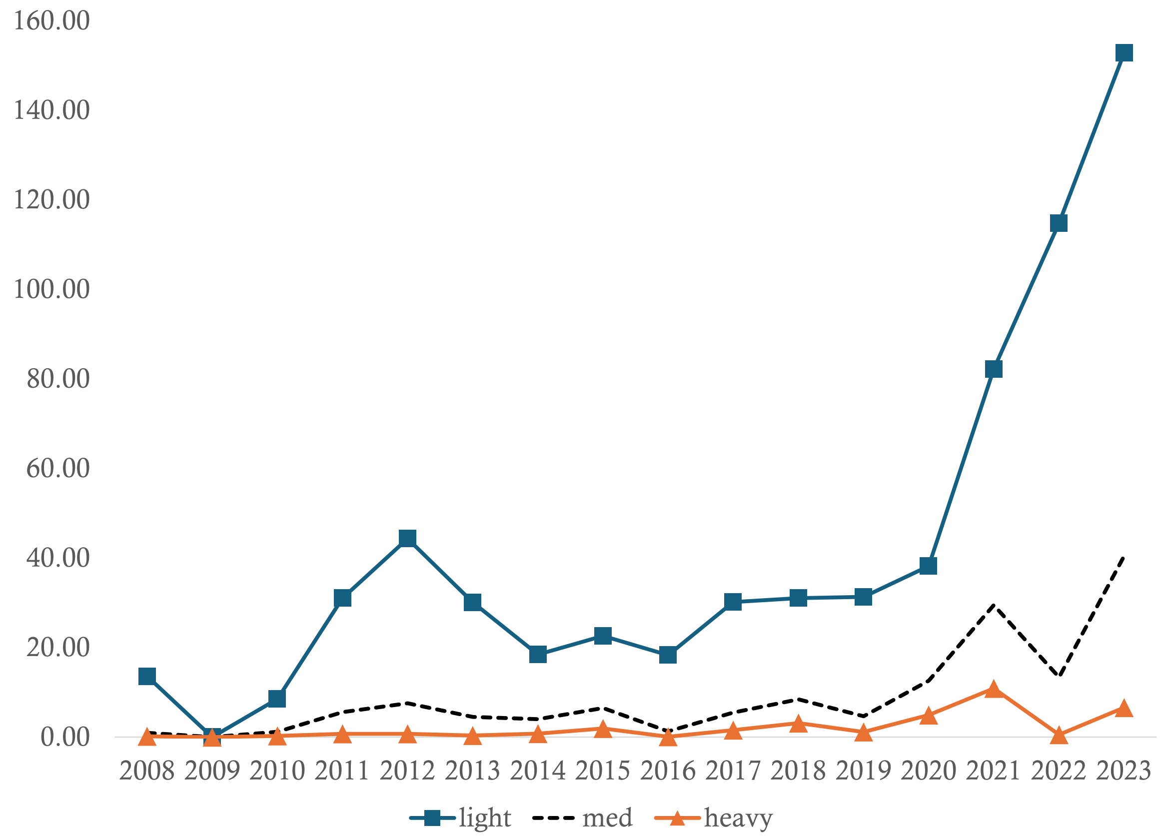
Table 5: Second stage of two-step procedure identifying the impact of (log) office employment on (log) effective rents

Model:	(1)	(2)	(3)	(4)
Days:	60	120	180	365
Variables				
log(Office employment)	2.229	1.818***	1.519***	1.726**
	(1.709)	(0.5274)	(0.4235)	(0.6933)
Max temperature (°C)	0.0000	0.0000	0.0012	-0.0032
	(0.0008)	(0.0010)	(0.0012)	(0.0046)
Min temperature (°C)	-0.0001	-0.0007	-0.0024*	-0.0009
	(0.0008)	(0.0010)	(0.0014)	(0.0061)
Precipitation (mm)	0.0002	0.0004	0.0019	-0.0017
	(0.0006)	(0.0009)	(0.0012)	(0.0033)
Wind speed (m/h)	0.0029	0.0001	-0.0026	-0.0037
	(0.0032)	(0.0024)	(0.0028)	(0.0085)
log(Square foot)	-0.0208***	-0.0210***	-0.0211***	-0.0214***
	(0.0018)	(0.0018)	(0.0018)	(0.0019)
Fixed-effects				
Lease type	Yes	Yes	Yes	Yes
Year × county	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Property level	Yes	Yes	Yes	Yes
Tenant industry	Yes	Yes	Yes	Yes
Fit statistics				
Observations	331,813	478,183	475,708	469,678
R^2	0.845	0.838	0.838	0.840
Dependent Variable:	log(effective rent)			

Clustered (Year × County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

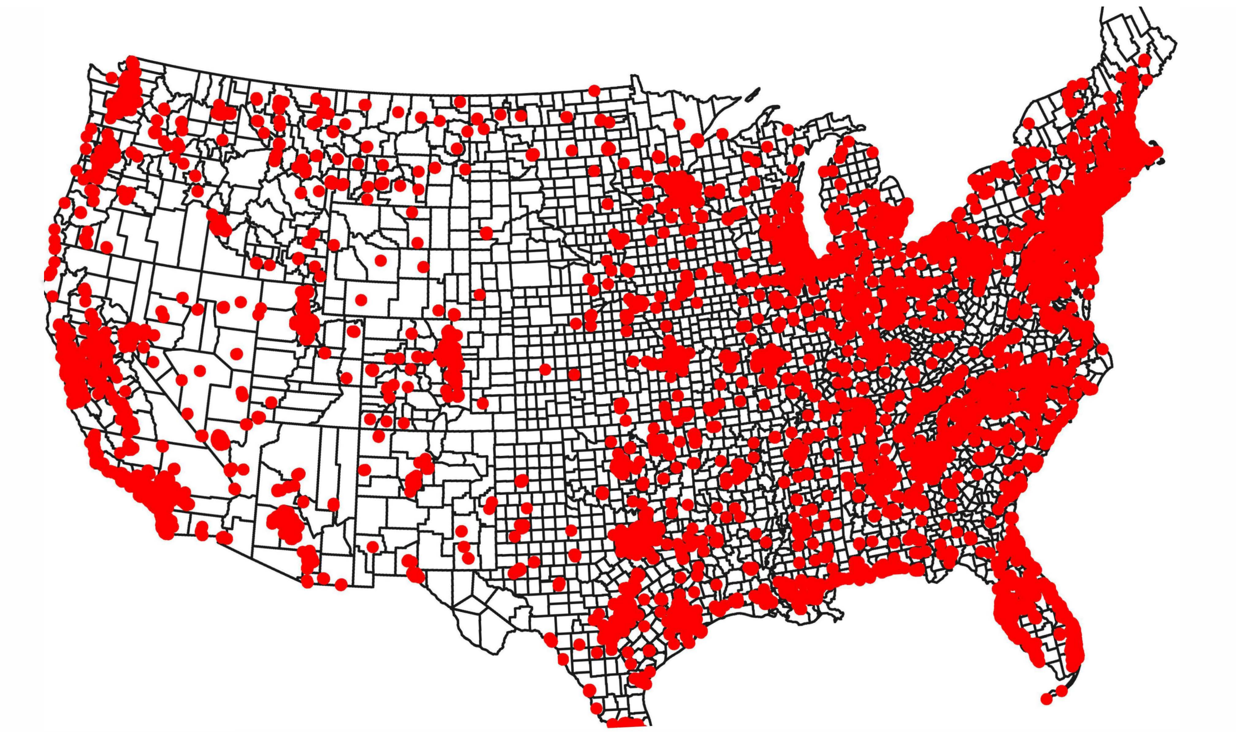
Figures

Figure 1: Smoke days over time.



Note: The average smoke days per county per year. The vertical axis gives the average smoke days, and the horizontal axis provides the years. (Based on EPA data.)

Figure 2: Location of leases

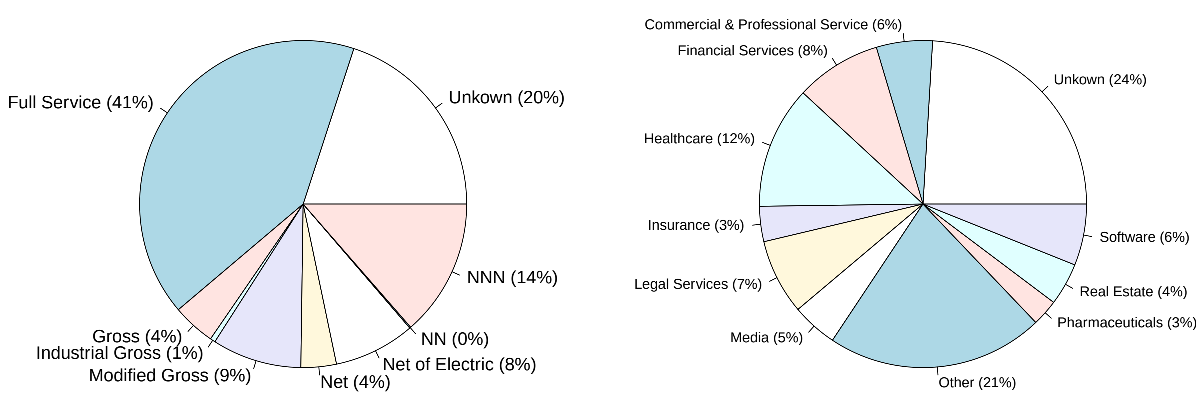


Note: Red dots represent each newly signed office lease in the data.

Figure 3: Lease type and tenant industry

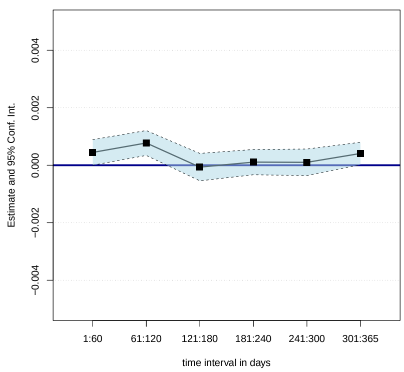
(a) Lease type

(b) Tenant industry

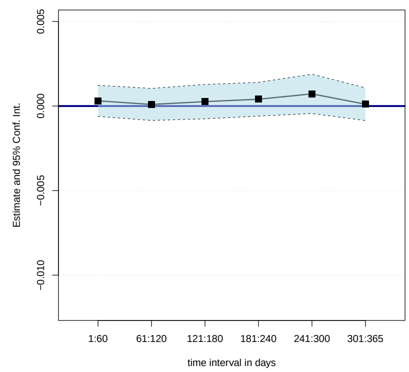


Note: We bundle each tenant industry category with less than 2.5% of the observations under "other."

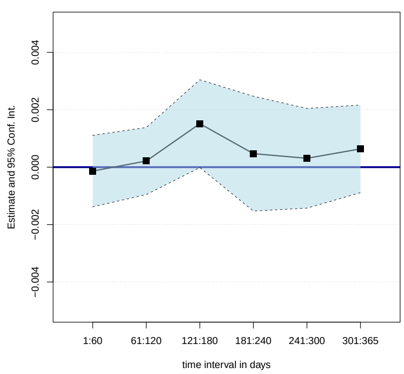
Figure 4: Inter-temporal impact of wildfire smoke on office rents and lease term length



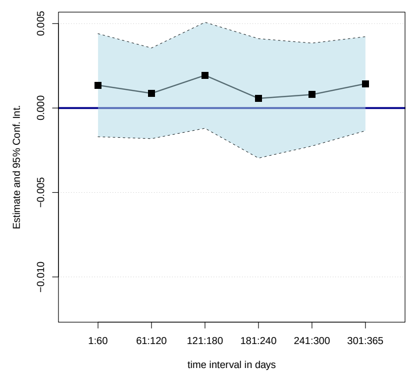
(a) Rent: light smoke



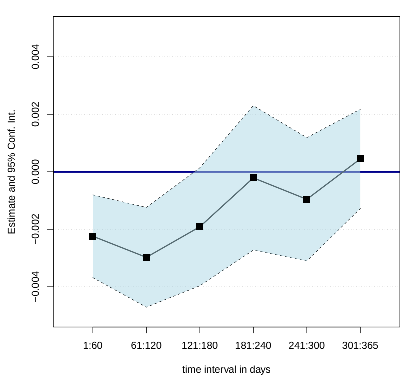
(b) Lease term: light smoke



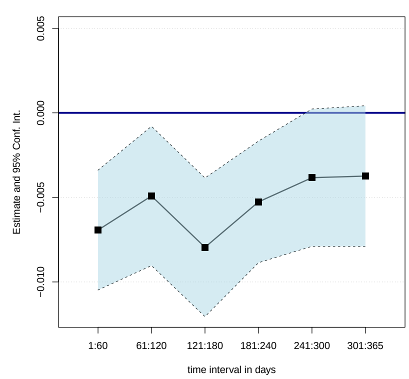
(c) Rent: medium smoke



(d) Lease term: medium smoke



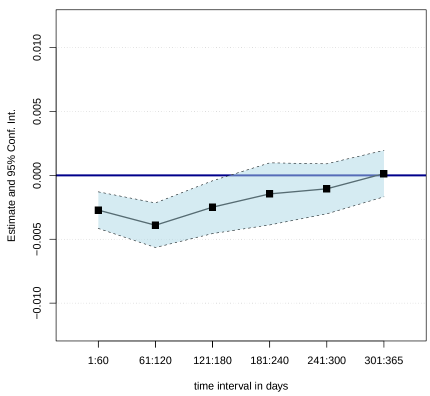
(e) Rent: heavy smoke



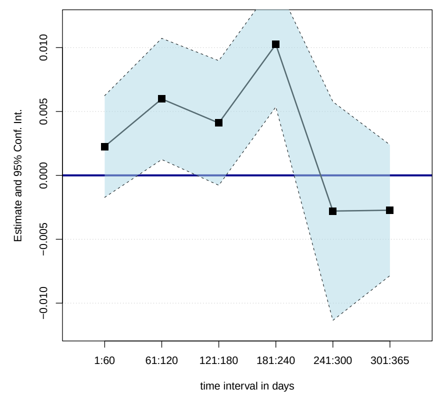
(f) Lease term: heavy smoke

Note: Estimates based on number smoke days in the preceding 1 to 60, 61 to 120, 121 to 180, 181 to 240, 241 to 300 and 301 to 365 days to signing the lease. 5%-significance level bounds provided.

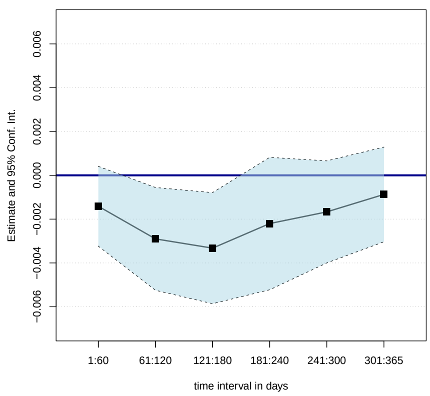
Figure 5: Heterogeneous effect of heavy smoke exposure on (log)rent with relative marginal effects in second column



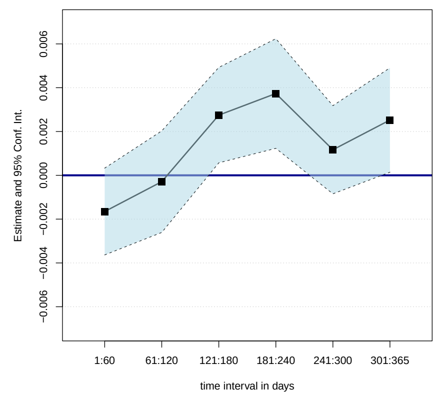
(a) Older buildings



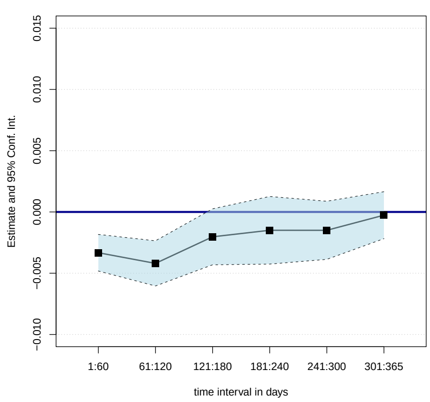
(b) ME of newer relative to older developments



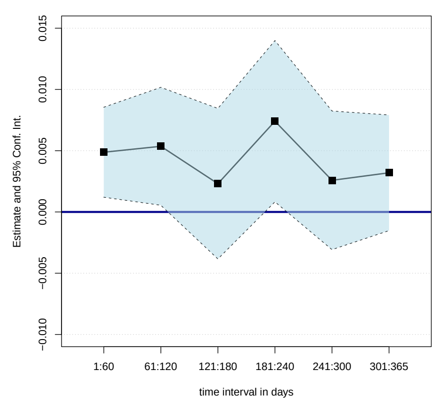
(c) Class B/C



(d) ME of class A relative to class B/C

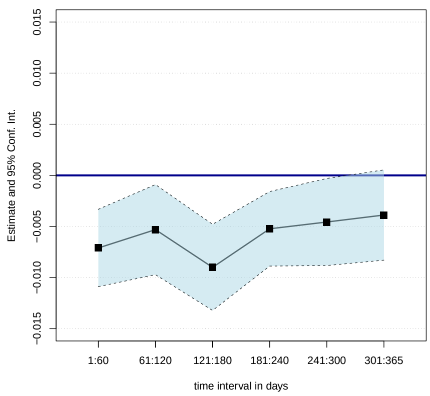


(e) Counties below historic smoke levels

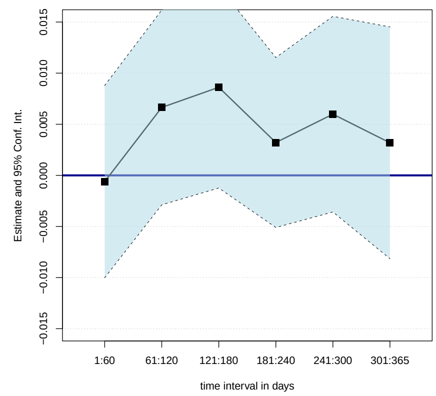


(f) ME for above relative to below historic smoke levels

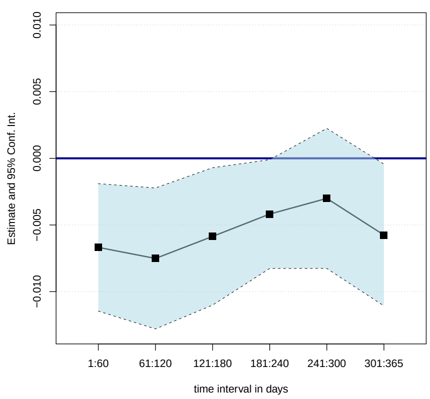
Figure 6: Heterogeneous effect of heavy smoke exposure on lease term length with relative marginal effects in second column



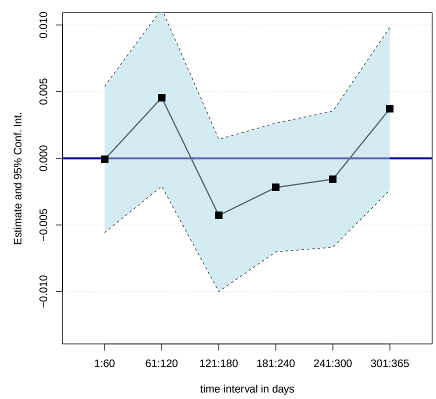
(a) Older buildings



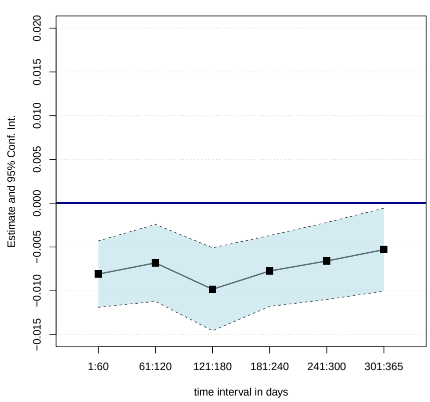
(b) ME of newer relative to older developments



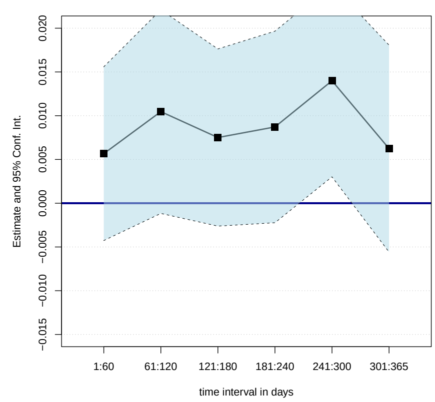
(c) Class B/C



(d) ME of class A relative to class B/C



(e) Counties below historic smoke levels



(f) ME for above relative to below historic smoke levels

Appendix

A1 Air pollution from wildfire smoke

Wildfire smoke is a strong determinant of air pollution (O'Dell, Ford, Fischer and Pierce, 2019). In previous work, we exploited the exogenous features of wildfire smoke to identify the effect of air pollution ($PM_{2.5}$) on various economic indicators of commercial real estate (Cvijanovic et al., 2024). The work presented in the main text turns the focus towards wildfire smoke within a reduced form setting. We add to these findings by estimating how much of the wildfire smoke effect on rents and lease terms is running through increased levels of $PM_{2.5}$. Our "back-of-the-envelope" calculation is straightforward: we compare the reduced form impact of smoke on rent and lease term length to the effect of $PM_{2.5}$ on our dependent variables using smoke as an instrument. In other words, we observe the effect of an increase in smoke days on $PM_{2.5}$ in the first stage, and the resulting effect of that increase in $PM_{2.5}$ on the dependent variables.

Here we rely on the cumulative bins of time specification introduced in the main text for simplicity purposes. More specifically, in the first stage, we regress $PM_{2.5}$ exposure on the number of heavy smoke days in the past τ days. We use cumulative windows of 60, 120, 180, 365 days within separate specifications. The second stage regresses rent or lease term length on the predicted level of $PM_{2.5}$ along with a set of controls common with the first stage. The first and second stage specifications are as follows:

$$PM^{\tau}_{ntpmi} = \alpha_0 + \beta \mathbf{heavy}_{np\tau} + \gamma T_{p\tau} + \mu L_n + \rho_{tp} + \omega_m + \theta_i + \varepsilon_{ntpmi} \tag{A1}$$

$$\ln Y_{ntpmi} = \alpha'_0 + \lambda \widehat{PM}^{\tau}_{ntpmi} + \gamma' T_{n\tau} + \mu' L_n + \rho'_{tp} + \omega'_m + \theta'_i + \varepsilon'_{ntpmi} \tag{A2}$$

where $\mathbf{heavy}_{i\tau}$ is the number of heavy smoke days within the past τ days. PM^{τ}_{ntpmi} is the average level of $PM_{2.5}$ measured in $\mu g/m^3$ over the past τ days for a given lease n in property i in year t in county p in month m. Y_{ntpmi} is either rent per square foot or lease term length for a given lease n in property i in year t in county p in month m. $PM_{2.5}$ data is provided by the Environmental Protection Agency (EPA) (Environmental Protection Agency, 2024). We aggregate daily discrete monitor readings up to the county level to construct average readings for the 60, 120, 180, 365 day windows. The set of controls in each regression includes a matrix T of climate variables (average maximum day temperature, average minimum night temperature, average precipitation (mm), and average wind speed in the τ days before the lease contract was signed), tenant and lease characteristics (L) including dummy variables for who pays for the OpEx (Gross, Hybrid, Net, NN, and NNN) and dummy variables for tenant industry, county times years fixed effects ρ, and within-year month-fixed effects ω. We include error term ϵ, and constant α_0.

The reduced form effect from the main text (Table 2) indicates that an additional 10 days of heavy smoke decreases rents in the range of 1.3 to 1.8% for the various windows of time considered. Unsurprisingly, the first stage coefficients on heavy smoke (Table A4) display significant and positive effects of the increase in heavy smoke on $PM_{2.5}$ levels. Taking the first column as an example (a window of 60 days), a 10 day increase in heavy smoke, increases average $PM_{2.5}$ levels by $6.437 \mu g/m^3$. From the second stage (Table A2), this increase in $PM_{2.5}$ generates a 1.6% decrease in rent. Repeating this exercise for all windows of time, we find that the reduced form effect of smoke on rent is nearly identical to the instrumented $PM_{2.5}$ effect. The same exercise for the lease term length results found in Table A3 again yields nearly identical results to the reduced form specification.

This simple exercise highlights air pollution, $PM_{2.5}$ in particular, as the channel through which wildfire smoke is affecting rents and lease term length. However, we cannot rule out that additional pollutants highly correlated with $PM_{2.5}$ present in wildfire smoke may also be driving this result.

Tables

Table A1: Coefficients for control variables from main specification of smoke on (log) rents and lease term.

Dependent Variables: Model:	log(rent) (1)	log(term) (2)
Variables		
Max temperature (°C) Days: 1 to 60	-0.0002	-0.0033***
	(0.0004)	(0.0010)
Max temperature (°C) Days: 61 to 120	0.0000	-0.0007
	(0.0004)	(0.0010)
Max temperature (°C) Days: 121 to 180	0.0002	-0.0005
	(0.0004)	(0.0010)
Max temperature (°C) Days: 181 to 240	-0.0003	-0.0031***
	(0.0004)	(0.0010)
Max temperature (°C) Days: 241 to 300	0.0000	-0.0033***
	(0.0004)	(0.0011)
Max temperature (°C) Days: 301 to 365	-0.0010**	-0.0011
	(0.0004)	(0.0011)
Min temperature (°C) Days: 1 to 60	-0.0002	0.0035***
	(0.0005)	(0.0011)
Min temperature (°C) Days: 61 to 120	-0.0009*	-0.0004
	(0.0005)	(0.0011)
Min temperature (°C) Days: 121 to 180	-0.0006	0.0007
	(0.0005)	(0.0012)
Min temperature (°C) Days: 181 to 240	0.0002	0.0023**
	(0.0005)	(0.0012)
Min temperature (°C) Days: 241 to 300	-0.0006	0.0028**
	(0.0005)	(0.0012)
Min temperature (°C) Days: 301 to 365	0.0007	-0.0004
	(0.0005)	(0.0011)
Precipitation (mm) Days: 1 to 60	-0.0001	-0.0003
	(0.0003)	(0.0007)
Precipitation (mm) Days: 61 to 120	-0.0003	0.0008
	(0.0003)	(0.0006)
Precipitation (mm) Days: 121 to 180	0.0005	0.0011
	(0.0004)	(0.0008)
Precipitation (mm) Days: 181 to 240	-0.0004	-0.0008
	(0.0003)	(0.0007)
Precipitation (mm) Days: 241 to 300	-0.0001	0.0000
	(0.0004)	(0.0007)
Precipitation (mm) Days: 301 to 365	-0.0005	0.0000
	(0.0003)	(0.0008)
Wind speed (m/h) Days: 1 to 60	-0.0008	-0.0022
	(0.0008)	(0.0021)
Wind speed (m/h) Days: 61 to 120	-0.0004	0.0001
	(0.0009)	(0.0020)
Wind speed (m/h) Days: 121 to 180	-0.0015**	-0.0000
	(0.0007)	(0.0019)
Wind speed (m/h) Days: 181 to 240	-0.0006	-0.0013
	(0.0008)	(0.0020)
Wind speed (m/h) Days: 241 to 300	-0.0011	-0.0025
	(0.0008)	(0.0018)
Wind speed (m/h) Days: 301 to 365	0.0005	-0.0008
	(0.0009)	(0.0018)
log(Square foot)	-0.0216***	0.2037***
	(0.0019)	(0.0022)
Fixed-effects		
Lease type	Yes	Yes
Year × County	Yes	Yes
Month	Yes	Yes
Building-level	Yes	Yes
Tenant industry	Yes	Yes
Fit statistics		
Observations	459,305	460,593
R^2	0.841	0.554

Clustered (Year × County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A2: Impact of $PM_{2.5}$-levels on (log) effective rents, instrumented by heavy smoke days. Corresponding first stage-results can be found in Table A4.

	(1)	(2)	(3)	(4)
Days:	60	120	180	365
Variables				
$PM_{2.5}$ (μg / m^3)	-0.0025***	-0.0051***	-0.0066***	-0.0109**
	(0.0009)	(0.0017)	(0.0022)	(0.0046)
Max temperature (°C)	-0.0012*	-0.0014	0.0002	0.0081
	(0.0007)	(0.0010)	(0.0014)	(0.0052)
Min temperature (°C)	0.0007	0.0009	-0.0007	-0.0145**
	(0.0007)	(0.0011)	(0.0015)	(0.0065)
Precipitation (mm)	-0.0010**	-0.0015*	-0.0001	-0.0026
	(0.0005)	(0.0008)	(0.0012)	(0.0035)
Wind speed (m/h)	-0.0011	-0.0027	-0.0032	-0.0063
	(0.0016)	(0.0028)	(0.0034)	(0.0099)
log(Square foot)	-0.0206***	-0.0207***	-0.0208***	-0.0211***
	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Fixed-effects				
lease type	Yes	Yes	Yes	Yes
Year × county	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Property level	Yes	Yes	Yes	Yes
Tenant industry	Yes	Yes	Yes	Yes
Fit statistics				
Observations	449,288	448,717	446,867	442,408
R^2	0.838	0.838	0.838	0.839
Dependent Variable:	log(effective rent)			

Clustered (Year × County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A3: Impact of $PM_{2.5}$-levels on (log) lease terms in months, instrumented by heavy smoke days. Corresponding first stage-results can be found in Table A4.

	(1)	(2)	(3)	(4)
Days:	60	120	180	365
Variables				
$PM_{2.5}$ (μg / m^3)	-0.0057**	-0.0094**	-0.0159***	-0.0331***
	(0.0022)	(0.0037)	(0.0044)	(0.0090)
Max temperature (°C)	-0.0025	-0.0014	0.0003	-0.0006
	(0.0016)	(0.0023)	(0.0029)	(0.0106)
Min temperature (°C)	0.0029	0.0021	0.0017	-0.0133
	(0.0018)	(0.0026)	(0.0032)	(0.0117)
Precipitation (mm)	-0.0021*	-0.0003	0.0023	0.0047
	(0.0012)	(0.0016)	(0.0023)	(0.0065)
Wind speed (m/h)	-0.0027	-0.0019	-0.0000	-0.0214
	(0.0030)	(0.0042)	(0.0054)	(0.0198)
log(Square foot)	0.2043***	0.2042***	0.2040***	0.2041***
	(0.0021)	(0.0021)	(0.0021)	(0.0021)
Fixed-effects				
lease type	Yes	Yes	Yes	Yes
Year × county	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Property level	Yes	Yes	Yes	Yes
Tenant industry	Yes	Yes	Yes	Yes
Fit statistics				
Observations	450,438	449,863	447,999	443,532
R^2	0.547	0.546	0.546	0.548
Dependent Variable:	log(lease term)			

Clustered (Year × County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A4: First stage results of using heavy smoke as an instrument for $PM_{2.5}$ (μg / m^3).

	(1)	(2)	(3)	(4)
Days:	60	120	180	365
Variables				
Heavy smoke	0.6347***	0.3397***	0.2346***	0.1302***
	(0.0534)	(0.0338)	(0.0205)	(0.0088)
Max temperature (°C)	-0.2141***	-0.2956***	-0.2628***	0.5068***
	(0.0458)	(0.0589)	(0.0668)	(0.0688)
Min temperature (°C)	0.2781***	0.3566***	0.3289***	-0.5224***
	(0.0533)	(0.0672)	(0.0731)	(0.0775)
Precipitation (mm)	-0.2107***	-0.1845***	-0.1565***	0.0465
	(0.0398)	(0.0534)	(0.0587)	(0.0407)
Wind speed (m/h)	-0.3456***	-0.4054***	-0.3870***	-0.4470***
	(0.0823)	(0.1087)	(0.1204)	(0.1247)
log(Square foot)	-0.0032	-0.0025	-0.0016	0.0008
	(0.0039)	(0.0030)	(0.0024)	(0.0011)
Fixed-effects				
Lease type	Yes	Yes	Yes	Yes
Year × county	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Property level	Yes	Yes	Yes	Yes
Tenant industry	Yes	Yes	Yes	Yes
Fit statistics				
F-test	37,231	36,271	39,684	69,045
Wald	140.99	101.26	130.29	219.83
Dependent Variable:	$PM_{2.5}$-levels			

Clustered (Year × County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A5: Impact of (log) unemployment rate (%) on (log) effective rents, instrumented by heavy smoke days. Corresponding first stage results are in Table A6. Unemployment is measured on a monthly-by-county level.

Model:	(1)	(2)	(3)	(4)
Days:	60	120	180	365
Variables				
log(Unemployment)	-0.4420	-0.2386***	-0.0919***	-0.0857***
	(0.2846)	(0.0764)	(0.0228)	(0.0319)
Max temperature (°C)	-0.0019	-0.0022	0.0000	0.0024
	(0.0017)	(0.0015)	(0.0012)	(0.0039)
Min temperature (°C)	0.0009	0.0017	-0.0009	-0.0068
	(0.0018)	(0.0017)	(0.0013)	(0.0051)
Precipitation (mm)	0.0003	-0.0013	0.0005	-0.0034
	(0.0009)	(0.0010)	(0.0012)	(0.0031)
Wind speed (m/h)	0.0020	-0.0002	-0.0018	-0.0013
	(0.0033)	(0.0029)	(0.0027)	(0.0078)
log(Square foot)	-0.0206***	-0.0208***	-0.0209***	-0.0211***
	(0.0018)	(0.0018)	(0.0018)	(0.0019)
Fixed-effects				
Lease type	Yes	Yes	Yes	Yes
Year × county	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Property level	Yes	Yes	Yes	Yes
Tenant industry	Yes	Yes	Yes	Yes
Fit statistics				
Observations	486,497	484,578	481,916	475,465
R^2	0.828	0.835	0.837	0.838
Dependent Variable:	log(effective rent)			

Clustered (Year × County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A6: First stage results of using heavy smoke as an instrument for (log) unemployment rate (%). Unemployment is measured on a monthly-by-county level.

	(1)	(2)	(3)	(4)
Days:	60	120	180	365
Variables				
Heavy smoke (days)	0.0034	0.0074**	0.0170***	0.0158***
	(0.0027)	(0.0031)	(0.0032)	(0.0034)
Max temperature (°C)	-0.0030	-0.0097	-0.0203**	0.0054
	(0.0038)	(0.0067)	(0.0091)	(0.0169)
Min temperature (°C)	0.0020	0.0102	0.0191*	0.0312*
	(0.0040)	(0.0074)	(0.0100)	(0.0185)
Precipitation (mm)	0.0017	-0.0029	-0.0054	-0.0123
	(0.0018)	(0.0033)	(0.0051)	(0.0124)
Wind speed (m/h)	0.0045	0.0015	-0.0091	0.0058
	(0.0062)	(0.0103)	(0.0127)	(0.0324)
log(Square foot)	0.0000	-0.0004	-0.0004	-0.0001
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Fixed-effects				
Lease type	Yes	Yes	Yes	Yes
Year × county	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Property level	Yes	Yes	Yes	Yes
Tenant industry	Yes	Yes	Yes	Yes
Fit statistics				
F-test	192	1,769	14,157	15,008
Wald	1.64	5.60	28.77	21.80
Dependent Variable:	log(unemployment rate (%))			

Clustered (Year × County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A7: Second stage results of using heavy smoke as an instrument for (log) unemployment rate (%) by building age.

Dependent Variable:	log(rent)	
Model:	age $<$ 10	age $\geq$ 10
Variables		
log(employment_off)	1.681	1.579***
	(1.306)	(0.4347)
tmax	0.0029	8.38×10^{-5}
	(0.0019)	(0.0014)
tmin	-0.0034	-0.0014
	(0.0022)	(0.0015)
ppt	0.0013	0.0019
	(0.0021)	(0.0013)
WindSpd	0.0004	-0.0027
	(0.0041)	(0.0031)
log(sqft)	-0.0158***	-0.0226***
	(0.0025)	(0.0019)
Fixed-effects		
leasetype	Yes	Yes
YrCounty	Yes	Yes
MONTH	Yes	Yes
prop.id	Yes	Yes
TenantIndusty	Yes	Yes
Fit statistics		
Observations	125,828	297,332
R^2	0.80752	0.84092

Clustered (YrCounty) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

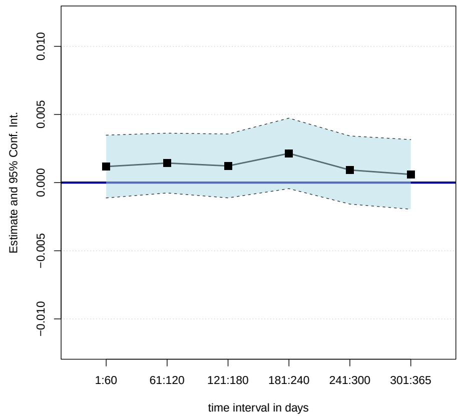
Table A8: Second stage results of using heavy smoke as an instrument for (log) unemployment rate (%) by building age.

Dependent Variable:	log(office employment)	
Model:	age < 10	age ≥ 10
Variables		
heavy	-0.0009***	-0.0011***
	(0.0002)	(0.0002)
tmax	2.38×10^{-6}	0.0004
	(0.0005)	(0.0006)
tmin	0.0002	-0.0003
	(0.0005)	(0.0006)
ppt	-0.0008**	-0.0006*
	(0.0004)	(0.0003)
WindSpd	0.0008	0.0010
	(0.0011)	(0.0010)
log(sqft)	-3.48×10^{-5}	1.45×10^{-5}
	(4.55×10^{-5})	(2.99×10^{-5})
Fixed-effects		
leasetype	Yes	Yes
YrCounty	Yes	Yes
MONTH	Yes	Yes
prop.id	Yes	Yes
TenantIndusty	Yes	Yes
Fit statistics		
F-test (1st stage)	1,126.5	7,216.4
Wald (1st stage)	19.464	34.674

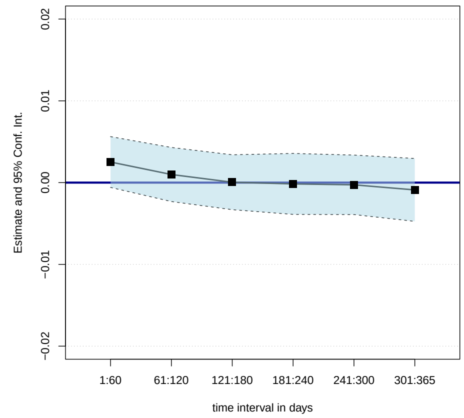
Clustered (YrCounty) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Figures

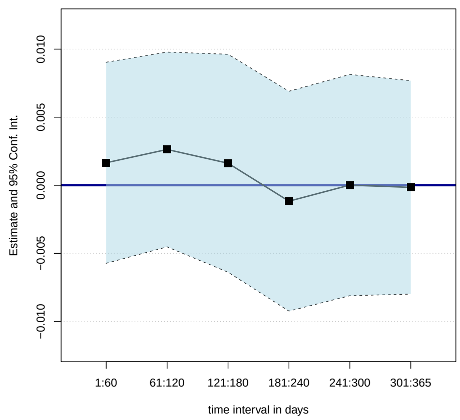
Figure A1: Impact of Smoke days on Retail, with 95% CI



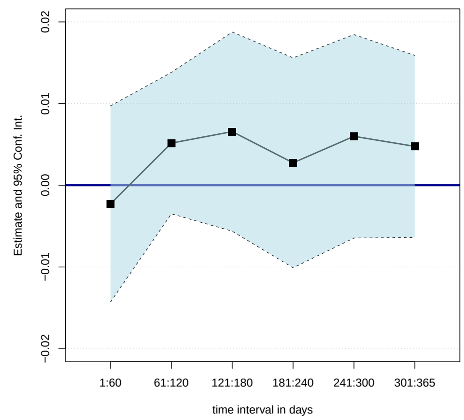
(a) Rent: light smoke



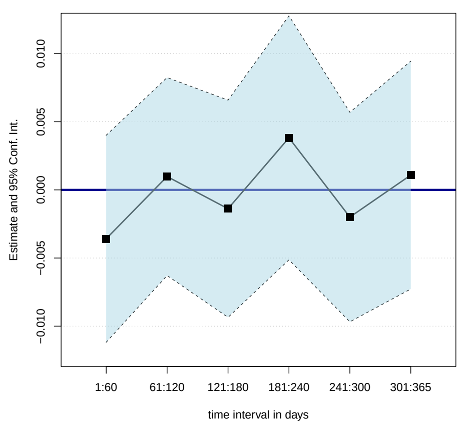
(b) Lease term: Light smoke



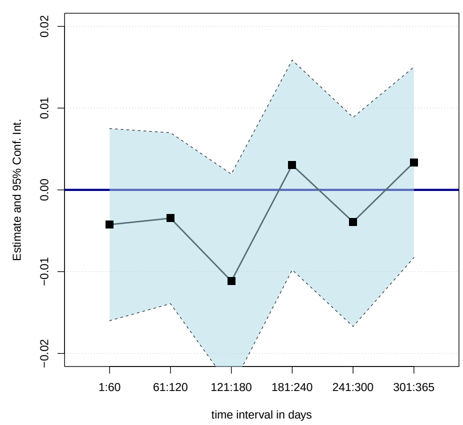
(c) Rent: medium smoke



(d) Lease term: medium smoke



(e) Rent: Heavy smoke



(f) Lease term: Heavy smoke