Commercial Real Estate and Air Pollution

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Abstract

We analyze the causal effect of air pollution (acute fine particulate matter) exposure on the commercial real estate (CRE) market. We instrument for air pollution using changes in local wind direction to 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. Heterogeneous treatment analysis uncovers that the negative effect on market values is concentrated in the office sector, consistent with the notion that air pollution-induced decreases in CRE values are driven by a reduction in CRE assets' productive capacity. Additionally, we document that the negative impact on (net) income is concentrated in the apartment sector, which is consistent with a broad set of local dis-amenity mechanisms identified in previous residential real estate literature.

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1 Introduction

Recent empirical work finds that air pollution can reduce the productivity of workers in both physically and cognitively demanding occupations. Such reductions can result in declining output and impact labor markets at regional or even national scales in aggregate. At the neighborhood level, air pollution exposure represents a well documented negative externality (a local dis-amenity) affecting location choices of households that value access to clean air (Freeman et al., 2019). With productivity and local amenities intrinsically linked to real estate value and firm operation decision making, one might expect exposure to air pollution to be internalized into observable economic indicators associated with the valuation and operation of commercial real estate. A good deal of literature explores the effect of local air pollution dis-amenities on residential real estate and household sorting but we know little about how air pollution exposure impacts commercial real estate (CRE).[1] The goal of our paper is to explore this relationship.

The unit of interest in the present research is an individual commercial property. For office and industrial properties, each property represents a collection of workers who—when exposed to air pollution—may generate aggregate building-level declines in productivity and labour supply (via lower output and increases in absenteeism). We hypothesize that these declines can in turn influence building-level financial valuation and operations indicators that are connected to the internal economic activity of the building. As a result, property/firm owners may have an incentive to engage in mediating behaviour like improvements in air filtering and ventilation. For multifamily apartment and retail properties, residents and consumers may sort away from areas exposed to local pollution-related dis-amenities. These changes in demand may be capitalized into property rents and/or value.

[1]See Smith and Ju-Chin Huang (1995) for a meta-analysis of cross-sectional studies and Chay and Greenstone (2005), Bayer et al. (2009), Grainger (2012), Bento et al. (2015), Lang (2015), Zou et al. (2022), Amini et al. (2022), Christensen and Timmins (2022) and Sager and Singer (2022) for newer analysis.

Empirically estimating the potential causal effect of air pollution on commercial real estate market indicators can be challenging. This is due to well-known concerns in the residential literature regarding omitted variable bias and measurement. Namely, increasing levels of air pollution can be linked to increases in economic activity where such economic activity may be reflected in improvements in housing prices and rents. In the CRE context, the analog is building level economic indicators. This reverse causality can potentially upward bias a näive estimation of the effect of air pollution on various CRE indicators. Further, commonly used measures of air pollution in the United States rely on coarsely located monitors or distance to acute sources of air pollution like toxic waste plants (Currie et al., 2015).

We make progress on these two issues through the use of a wind direction instrument and granular $PM_{2.5}$ data that spans the whole of the United States for the 2000 to 2016 time period. Using instrument-derived exogenous variation in $PM_{2.5}$ across a broad geographic scale and over a long time period enables us to provide one of the first studies of the effects of air pollution on one of the largest asset classes – commercial real estate, and to explore treatment effect heterogeneity by property type. The identifying assumption in our instrumental variables (IV) approach is that, after comprehensively controlling for a vector of fixed effects and additional time-varying variables, changes in wind direction are unrelated to changes in the economic indicators of commercial real estate assets except through how changes in wind direction impact changes in local air pollution levels. A key innovation of our study is that our approach does not require knowing the location of topographic and infrastructure characteristics relative to a building that may influence local air pollution levels (e.g., locations of roads, rivers, and population centers, large pollution sources like airports, etc.). We augment the main IV approach with two additional instrument-based specifications—one method exploits a policy change in the mid-2000s, the other uses exogenous variation in air pollution exposure generated by wildfire smoke.

The results of our contemporaneous IV regressions indicate that a one standard deviation increase in $PM_{2.5}$ levels results in a 1.3% drop in CRE market values, and 2.7% decline in property (net) income on average. For every one standard deviation increase in $PM_{2.5}$ levels, capital expenditures increase by more than 11%. These results indicate that there is an air-pollution induced pricing discount due to the expected loss of income in the future which is partially mitigated by an increase in capital expenditures. After accounting for the potential increase in value generated from an increase in capital expenditures, we find that the estimated impact of instrumented fine particulate matter exposure on net asset value is somewhat larger than the effect on market value, suggesting that the negative effects of air pollution on real estate values are partially masked by rising capital expenditures. We additionally find suggestive evidence that increasing air pollution exposure continues to negatively impact market values and net asset values two years on.

Stratified results provide suggestive evidence of the heterogeneous effect air pollution exposure has on the different property types considered and highlights the property types driving the full sample results. We find that the negative effect of exposure to higher levels of air pollution on value is mostly concentrated in the office sector. Additionally, the results of the lagged analysis indicate a significant long-run effect on office real estate values that persists up to four years. This suggests that air pollution-induced declines in market value are driven by a reduction in a building's productive capacity. A large significant lagged effect on income for office and industrial versus a contemporaneous effect for apartment income hints towards the role of lease contract length in mediating changes in demand and sorting. However, caution is warranted regarding over-interpretation of stratified results given low sample sizes for some property types.

We conduct two additional robustness tests of our baseline results that aim to address potential endogeneity between air pollution exposure and CRE values. First, we use an alternative IV specification that exploits changes in the U.S Clean Air Act standards in 2005 and follows work done by Currie et al. (2020) and Sager and Singer (2022). Our results remain qualitatively similar. Second, following recent work by (Borgschulte et al., 2022) we sidestep the joint determination of air quality and economic activity by leveraging variation in air pollution induced by wildfire smoke. Our results remain qualitatively unchanged. Taken together, these sensitivity tests corroborate our main findings of a significant causal relation between air pollution and CRE market outcomes.

Additionally, our results predict considerable wealth loses in commercial property investments if $PM_{2.5}$ levels increase in the future. This is concerning on a societal level as pension, endowment, and foundation funds own a large share of commercial properties in the US.[2] To get a sense of the possible total loss in asset values in the future, we can combine statistics from the National Association of Real Estate Investment Trusts (Nareit) and the EPA with our findings. First, Nareit estimates that the 2021 total dollar value of commercial real estate in the U.S. was approximately $21 trillion.[3] Second, the EPA predicts that the average $PM_{2.5}$-levels will increase by $0.3\mu g/m^3$ by 2050, and by $0.7\mu g/m^3$ by 2100.[4] Multiplying the EPA predictions with our main estimate (-0.0061) and the total asset value from Nareit, a back-of-the-envelope calculation indicates an expected value loss of $40B and $70B by 2050 and 2100 respectively. However, these numbers are likely an underestimate of the true costs as investors also increase their capital expenditures after an increase in PM-levels in part to offset the asset value decreases. If we take the capital expenditures into account, the loss increases to $50B and $120B by 2050 and 2100 respectively.

The paper proceeds as follows: in Section 2 we discuss additional background information and relevant literature. Section 3 describes our empirical strategy, while Section 4 presents our data sources. In Section 5 we provide detailed information about our merged sample, and in Section 6 we discuss our main findings. In Section 7 we describe additional robustness

[2]Source: www.reit.com.
[3]Source: www.reit.com.
[4]Source: https://www.epa.gov/sites/default/files/2015-06/documents/cirahealth.pdf

checks. Finally, in Section 8 we conclude.

2 Background and Related Literature

2.1 Air Pollution in the Asset and Space Market

To understand how exposure to air pollution ($PM_{2.5}$) might impact CRE via channels of disamenity and productivity, both an asset market (owner/investor) and space market (user) perspective must be taken. We first consider the space market prospective. The users of CRE—residents, workers, and consumers—may be impacted by exposure through disamenity and/or productivity channels. It is probable that how this exposure subsequently influences changes in building-level economic indicators is related to lease structures which tend to vary across different property types.

For residents of multifamily housing, we would expect the same local disamenity effect and subsequent sorting of households over space observed in previous residential housing literature. The typical one-year lease term for multifamily units allows for declining demand to be readily observed in contemporaneous rent contracts as higher income households sort towards cleaner air neighborhoods. A local disamenity effect can similarly impact retail CRE. Foot traffic from the local residential population intrinsically links consumer demand for retail to the local housing market. This implies pollution induced household sorting may influence demand for space in the multifamily CRE sector and subsequently consumer demand for local retail. Declines in sales resulting from declining consumer demand may in turn induce retail tenant sorting and declines in rent. There is potential for both a long term and short term rent impact in the retail setting. While lease terms tend to be multiyear, many retail leases include revenue sharing whereby a portion of the monthly lease varies with monthly sales—fewer sales generates lower rent in the short term. Eventual tenant sorting may result in longer term rent impacts if sales continue to decline beyond the short term.

Productivity effects of air pollution exposure on retail workers has not been studied to our knowledge. However, retail work often requires both physical and cognitive labor thus we might expect productivity to decline with similar retail tenant sorting and subsequent rent declines.

For office and industrial workers, a productivity effect would likely dominate any amenity effect with exposure to air pollution negatively impacting both cognitive and physical work. Resulting declines in productivity could induce firm sorting and declines in rent for new rent contracts, but lease terms may prevent significant short term sorting and declines in rent. Office and industrial leases often span 3 to 10 years and are thus likely to be less sensitive to contemporaneous fluctuations in air pollution via productivity channels.

Within an asset market perspective, our interest lies in how owners/investors might respond to building-level air pollution exposure. Expectations of declines in *future* rents (as a result of the exposure effect in the space market) will likely decrease market values regardless of property type (and lease term length). This effect may be mediated by capital expenditures aimed at decreasing the effect of exposure on users. Such expenditures could include improvements in air filtration technology and building materials that minimize the flow of unfiltered outdoor air inside. A more clear picture of how air pollution exposure impacts market value can be seen when the potential positive effect of capital expenditures on values is accounted for. Thus, for all property types, when mediating activity takes place through increases in capital expenditures, we would expect a larger negative effect of exposure on market value net of the positive influence of the capital expenditures (i.e. net asset value). A priori it is not clear how air pollution exposure might affect net operating income via operating expenditures. Our expectation is that NOI will move with income (rents) for all property types. We summarize the above hypothesized short run effects in Table 1.

Table 1: Hypothesized effect of increasing $PM_{2.5}$ on building level economic indicators in the short run

Property Type	**Market Value**	**Rent**	**NOI**	**CapEx**	**Net Asset Value**
Multifamily	− but potentially mediated by CapEx	−	−	+ with CapEx pollution mediation	−
Retail	− but potentially mediated by CapEx	− for revenue sharing lease contracts, otherwise no effect in short run	− for revenue sharing lease contracts, otherwise no effect in short run	+ with CapEx pollution mediation	−
Industrial Office	− but potentially mediated by CapEx	no effect in short run	no effect in short run	+ with CapEx pollution mediation	−

2.2 Related Literature

There is a great deal of literature concerned with health-related outcomes associated with air pollution exposure; however, recent research additionally documents important non-health outcomes affecting both people and places.[5] Non-health outcomes include productivity and labor supply, cognitive performance, decision making, human capital effects of early exposure, and residential rents and prices. Below we briefly summarize relevant work but encourage readers to see Aguilar-Gomez et al. (2022) for a thorough summary of the non-health outcome literature.

For worker-focused outcomes, both physically or cognitively demanding occupations are impacted by exposure symptoms such as lethargy/fatigue, irritability/changes in mood, and lack of focus. Empirical findings confirm exposure does indeed impact productivity and labor supply. Physically demanding jobs such as outdoor agricultural work, indoor garment pro-

[5]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.

duction, and professional sports show decreases in productivity with exposure to pollutants such as ozone and $PM_{2.5}$ (Zivin and Neidell, 2012; Chang et al., 2016; He et al., 2019; Lichter et al., 2017; Guo and Fu, 2019; Mullins, 2018). Cognitively demanding occupations with monitored productivity show similar results. Major League Baseball umpire calls decline in accuracy with exposure to carbon monoxide and $PM_{2.5}$ (Archsmith et al., 2018). The number of daily calls for call center workers in China declines as the air pollution index increases (Chang et al., 2019) and case duration for trial judges in China increases with exposure to increased levels of $PM_{2.5}$. Huang and Du (2022) find evidence that greater exposure to air pollution can affect investor cognition and in turn reduce the price of land transactions. 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. Aragón et al. (2017); Hanna and Oliva (2015); Holub et al. (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.

Perhaps more related to the research question at hand—given our focus on building-level outcomes—is whether observations of pollution-induced individual level declines in productivity and labor supply aggregate up to produce larger scale declines. And further, whether short-run health effects might impact productivity in the medium- to long-run time frame. Particulate matter may remain in one's system for weeks or months and short-run exposure may in turn induce future acute health shocks—heart attack, stroke, asthma attacks. There is some evidence to support geographically and temporally aggregate impacts of exposure at both a regional and firm-level scale. Dechezleprêtre et al. (2019) show that regional economic activity in the European Union, as measured by real GDP, declines with increases in $PM_{2.5}$ within the same year. Nearly all of the effect is driven by reduced output per worker. Fu et al. (2021) find decreases in $PM_{2.5}$ increase the average firm's productivity based on a national sample of all firms in China's manufacturing sector. In the US context, there is somewhat contradictory evidence of the effect of air pollution exposure on GDP. Using variation in wildfire smoke exposure, Borgschulte et al. (2022) find that an additional day of county-level smoke exposure within a quarter, reduces quarterly per capita earnings by 0.10% which is equivalent to a 2% yearly average drop in US annual labor income. Avila Uribe (2023) finds a negative effect only for rural counties 0.37% per $\mu g/m^3$ of average exposure to $PM_{2.5}$ using similar wildfire smoke data. However, on an industry sector basis, both trade and educational services experience significant drops in GDP.

Given that an individual's exposure to outdoor PM typically occurs indoors (Lioy et al., 1988; Jenkins et al., 1992; Wallace, 1993; Klepeis et al., 2001), the green building literature offers additional insight into a related set of questions: do improvements in indoor air quality (IAQ) via building-level ventilation investments lead to improvements in worker health and productivity? And further, do these improvements impact firm income statements and/or property-level economic measures? There is a fair amount of evidence showing that improvements in IAQ are indeed linked to improvements in productivity and declines in absenteeism (Miller et al., 2009; Singh et al., 2010; MacNaughton et al., 2015; Allen et al., 2016; Palacios et al., 2020). In turn, related literature estimates positive net economic benefits—in various units including NPV per square foot, value per employee, overall net savings across the US office sector—based on observations of improvements in productivity and health (Kats, 2003; Fisk et al., 2012; MacNaughton et al., 2017). It should be noted that office workers and office buildings are the main focus of this literature and the findings of economic benefits tend to be based on back-of-the-envelope calculations extrapolating increases in productivity and declines in absenteeism to changes in line items on a firm's income statement.[6] While the literature does not document a direct relationship between productivity and health improvements with firm or building level economic indicators, it does observe rent and price premiums for *green* buildings implying a willingness to pay for amenities provided by these

[6]See Allen and Macomber (2022) Chapter 4 for an example of such an exercise.

buildings. The seminal paper by Eichholtz et al. (2010) estimates a 7% rent premium and a 16% price premium for green buildings. But whether this premium is actually associated with improvements in productivity via improved IAQ remains unclear. In a survey of 112 stakeholders (building owners, property and facilities managers, tenants, and mechanical system designers and consultants), a minority of respondents felt improvements in ventilation filtration would improve productivity (Hamilton et al., 2016). Further, the stakeholders' estimates of the cost of such improvements were more than double actual costs. Such results signal a lack of salience regarding the impact of IAQ on productivity and health.

Lastly, our work contributes to the large literature linking local pollution (local disamenities) to variation in residential house prices and rents. On the whole, extant research finds access to clean air is capitalized into house prices and rents (Chay and Greenstone, 2005; Bayer et al., 2009; Grainger, 2012; Bento et al., 2015; Lang, 2015; Zou et al., 2022; Amini et al., 2022; Sager and Singer, 2022; Lopez and Tzur-Ilan, 2023). There exists variation in the degree of capitalization, however, with rents often lagging prices (Lang, 2015) and the degree of pass-through to the renter estimated to be half of the effect on prices (Grainger, 2012). Further, heterogeneity exists with respect to income with declines in pollution driving house price appreciation for lower income households to levels nearly double the appreciation for higher income households (Bento et al., 2015).

3 Empirical Strategy

3.1 Ordinary Least Squares

The main objective of this study is to estimate the effect of air pollution exposure on commercial real estate productivity and values, net of any potentially confounding factors. In particular, we focus on exposure to fine particulate matter ($PM_{2.5}$). We model this relationship using the following log-linear OLS regression equation:

$$\ln Y_{ipct} = \beta PM_{it} + X_{it}'\gamma + \alpha_{pt} + \delta_{ct} + \eta_i + \epsilon_{ipct}, \tag{1}$$

where Y denotes a vector of dependent variables {Market values, Income, Net Operating Income, Capital Expenditures} for real estate asset i, belonging to property type p, located in Metropolitan Statistical Area (MSA) c, in year t. PM is our pollution measure—PM in grams per cubic meter—with coefficient estimate (of interest) β. Covariate matrix X contains time varying (climate) variables, such as wind speed, precipitation, and average temperature with corresponding vector of coefficients γ. To control for possible confounding effects influencing demand for certain property types that vary over time or MSA-level trends, we include property type $\times$ year fixed effects α_{pt}, as well as MSA $\times$ year fixed effects δ_{ct}. Inclusion of property fixed effects η_i, allows for the absorption of individual property-level time-invariant unobservable characteristics that might influence results. We hypothesize that $PM_{2.5}$ levels may have a differential impact on different property types via the amenity or productivity channels as well as lease contract length; hence, we consider specifications where we stratify Equation 1 by property type—apartment, retail, industrial, office. Given that our Eq. is in *levels*, the interpretation of the PM coefficient is as follows: A 1 microgram per meter air (μg/m^3) increase in $PM_{2.5}$ levels, will result in a log change of β in outcome variable Y.

Finally, we also allow for lagged effects. Given that real estate contracts can be long-term, the effect of a change in $PM_{2.5}$ levels might not be immediately observed in rents and values. We consider a one- and two-year lagged specification for the full sample as well as samples stratified by property type. The lagged specification is as follows:

$$\ln Y_{ipct} = \beta PM_{i,t-l} + X_{i,t-l}'\gamma + \alpha_{pt} + \delta_{ct} + \eta_i + \epsilon_{ipct} \tag{2}$$

where the lag length is given by l. All models are estimated by Ordinary Least Squares

(OLS) with standard errors clustered at the 4-digit ZIP code level.

3.2 Instrumental Variables Approach

As discussed in Section 1, OLS estimates of Equations (1) and (2) are prone to bias since exposure to $PM_{2.5}$ is not fully randomly assigned. A priori we expect the OLS estimates of β will be attenuated as higher levels of regional productivity are associated with higher levels of pollution. A key challenge for measuring the causal effect of air pollution on CRE values is finding geographically widespread fluctuations in air pollution that are not themselves driven by factors that directly impact economic activity. To address this issue, we follow Deryugina et al. (2019) and employ an IV strategy using annualized average daily wind direction ($WINDDIR$) at the MSA-level as an instrument for $PM_{2.5}$ and allow the effect of the wind instruments on $PM_{2.5}$ to vary over space. In this way, we are able to address a potential concern that transient changes in air pollution may induce short-run effects that reflect inter-temporal substitution, or reversion around a long-run mean, rather than true value-destroying CRE market effects.

A valid instrumental variables approach requires that the instruments (i) be sufficiently correlated with the endogenous variable of interest and (ii) not be correlated with any unobserved determinants of the outcome of interest. We instrument for changes in a grid-location's $PM_{2.5}$ concentration using changes in MSA-level wind direction interacted with a given ZIP code. This generates a ZIP code-specific wind direction coefficient. These coefficients capture the variation in the effect of MSA-level wind direction on local $PM_{2.5}$ by taking into account the building's ZIP code location relative to sources of pollution (heavy industry, airports, highway exits) and geographical features (mountain ranges, oceans and other bodies of water) that may impact the influence of MSA-level wind direction on local air pollution. The identifying assumption in our instrumental variables approach is that, after comprehensively controlling for a vector of fixed effects and additional time-varying variables, changes in wind direction are unrelated to changes in the economic indicators of commercial real estate assets except through how changes in wind direction impact changes in local air pollution levels.

The first stage specification is thus as follows:

$$PM_{ipct} = (ZIP_i' \times WINDDIR_{ct})\lambda_d + X_{it}'\omega + \nu_{pt} + \rho_{ct} + \phi_i + \varepsilon_{ipct}, \quad (3)$$

ZIP is an m by 1 dummy variable vector indicating the 4-digit ZIP code a given building i is located within.[7] $WINDDIR$ is an m by d matrix assigning d MSA-level wind directions to each ZIP code within a given MSA c where $d = 3$ (North, South, West, with East as the reference category). The use of more wind directions is of course possible, but we follow Deryugina et al. (2019) and limit to the four standard directions since increasing the number of instruments significantly increases computational complexity. The data on wind direction is measured 8 times a day on a 100km $\times$ 100km grid. We take the average wind direction (as a percentage) per year—to align it with the $PM_{2.5}$ frequency—per MSA. λ_d is a vector of d wind direction coefficients for a given ZIP code m. These coefficients are constant across buildings within the same ZIP code. ν_{pt} are property type $\times$ year fixed effects, ρ_{ct} are MSA $\times$ year fixed effects, and ϕ_i are property fixed effects.

While the Deryugina et al. (2019)-style instrument has been used to study the impact of acute exposure, several features of the wind-direction instrument combine to create a useful natural experiment for studying the cumulative effects of air pollution on CRE market outcomes. Theoretically, short-run health effects of air pollution may result in long-run productivity losses through either health channels or interactions with the labor market. Biomedical mechanisms exist through which short-run exposure may affect medium- and long-run health. The bulk of evidence to date indicates that acute exposure to a range of

[7] We use 4-digit ZIP codes, instead of the more common 5-digit ZIP codes due to the loss of observations and degrees of freedom otherwise. The loss of observations (because we need at least 2 observations to identify the effect) would mean we bias our data to larger ZIP codes. We found no such issues at the 4-digit ZIP code level. Also, the within 5-digit ZIP code variation became too small to infer any meaningful effects.

air-pollutants has been associated with quantifiable impairment of brain development and cognitive decline in the long run (Delgado-Saborit et al., 2021) suggesting that long-term implications on worker productivity can be substantial. There is mounting evidence in the epidemiology literature that long-term exposure to fine particulate matter $PM_{2.5}$ increases the risk of all cause mortality, and cardiovascular and respiratory morbidity (Clifford et al., 2016) and that it adversely impacts cognitive performance. Both long-term and short-term exposures have been shown to be associated with adverse cardiac and cerebro-vascular risks with the long-term effects being greater (Cleland et al., 2022). Temporary labor market disruptions can also have lasting impacts on earnings, productivity and welfare as shown in numerous studies of displaced workers and labor market entrants (see Borgschulte and Martorell (2018), among many others). This suggests that using a cumulative annual measure of acute exposure is suitable in our setting, in particular, since outcomes of interest (commercial real estate values) cannot be measured at higher frequencies.

4 Data

Our analysis combines several different data sources. We rely on the $PM_{2.5}$ data set constructed by Di et al. (2019) which provides detailed $PM_{2.5}$ data with national US coverage on an annual basis from 2000 to 2016. The authors construct annual $PM_{2.5}$ estimates on a 1km$\times$1km grid basis using satellite-derived aerosol optical depth, chemical transport model predictions, land-use data, meteorological data combined with machine learning algorithms.

Property data is provided by the National Council of Real Estate Fiduciaries (NCREIF). These data consist of quarterly financial and accounting information reported by member funds between 1980Q1 and 2020Q4. In addition to transaction prices and appraised market values, for each property we observe total income (rental plus other income), net operating income (NOI), quarterly capital expenditures (CapEx), and hedonic characteristics of the property.[8] We omit data before 2000 and after 2016 to align with the $PM_{2.5}$ data. While the NCREIF data is provided at quarterly level, the $PM_{2.5}$ data is observed on annual basis. To match the frequency, we either take a yearly averages (market values) or sum (income, net operating income, and CapEx) the variables. The locations of the sample properties are mapped in Figure 1. NCREIF members own properties all across the United States in both dense urban areas as well as in more suburban areas.

Climate data (mean temperature and precipitation) is retrieved from the PRISM climate group.[9] PRISM data is available daily for 481,631 16-sq-km (or 4×4 km) grid-locations covering the continental United States. We take yearly averages and match the PRISM grid cells to the properties in the NCREIF data.

Finally, the wind direction and 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 and consist of vector pairs, one for the east-west wind direction (u-component) and one for the north-south wind direction (v-component). We convert the average u- and v- components into wind direction and wind speed and average. Subsequently, we take the yearly average, as the raw data is measured 8 times a day. We define *wind direction* (north, south, east, west) as the direction the wind is blowing *towards* which is in line with how it is reported by the NARR.

[Place Figure 1 about here]

[8] Characteristics include property location, age, property type, leverage, ownership structure, owning fund, and type of fund.

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

5 Descriptives

Table 2 provides the descriptive statistics for our main variables of interest after merging all four datasets. The average property-level $PM_{2.5}$ exposure is 10.5 micrograms (one-millionth of a gram) per cubic meter air (μg/m^3). The average market value in the sample properties is approximately $54M. The total income produced by these properties is—on average—just over $5M a year, of which $4M is generated by rents and $1M by other means like parking and billboards. Subtracting operational costs (utility bills, standard maintenance, insurance, and property tax) for running the properties results in an average net operating income of $3M. Capital expenditures (CapEx) include the costs for renovating and expanding the properties as well as costs for hiring brokers to lease out the property. We find an average annual CapEx of close to $1M. For completeness we also combine market values and CapEx to create *net asset value* (NAV). Following Cvijanovic and Van de Minne (2021), we define NAV as:

$$
\begin{aligned}
NAV_{it=1} &= MV_{it=1} && \text{for } t = 1, \\
\Delta NAV_{it} &= \Delta MV_{it} - CapEx_{it}, && \text{for } t > 1, \qquad (4)
\end{aligned}
$$

where MV is Market Value of property i in year t. Thus, for every year, we subtract the price increase caused by capital expenditures (CapEx), leaving only a "pure" price change caused by market forces. The average NAV is about $4M less compared to the average market value. Note that investors can experience substantial intermediate negative net asset value during large scale investments/renovations/building expansions (i.e. CapEx) with the assumption of future payoffs.[10]

[10] An extreme case would be a development (which are not part of our data to be clear). The market value will be the price of the land, whereas the cost of development is counted towards CapEx. The average land value fraction in the US is 20% implying CapEx spending will be 4 times (80% of the value of the stabilized asset) the MV of land.

For the climate variables, the mean[11] yearly temperature is 16°C, average daily rainfall is 2.6mm, and wind speed is 4.6 miles an hour. The dominant wind direction in the United States is towards the South, with southerly winds occurring 33% of the time. Wind blowing towards the North is observed the least in the data—19% of the time.

Just under 30% of the assets in the merged sample are industrial properties with 90% of these properties being warehouses used for goods transportation purposes. Apartments and office have similar shares at 29% and 26% respectively. Retail has the lowest share at 16%. In total, the sample consists of approximately 47K observations tracking 10K unique properties, covering 1,228 4-digit ZIP codes within 215 MSAs (Table 3).

[Place Table 2 about here]

For identification purposes, variation (i.e. standard deviation) in $PM_{2.5}$ levels and wind direction is important for the first stage specification in Equation 3. In Table 3 we provide detailed statistics on *within* group variation of both $PM_{2.5}$ levels and wind direction. There may be concern that the variation in $PM_{2.5}$ declines substantially when making comparisons within year or within ZIP code. However, we retain 64% of the variation exhibited in the full dataset both on a within MSA and within 4-digit ZIP code basis. More specifically, the standard deviation of the full sample is 2.9 $\mu g/m^3$ (Table 3), the standard deviation within MSA is 1.613 $\mu g/m^3$, and within ZIP code it is 1.623 $\mu g/m^3$ (Table 3).

We do not have variation within MSA and year of wind direction, as the wind direction data is on a yearly-MSA level. However, we do observe some variation in wind direction over years within an MSA. For example, the standard deviation of wind blowing North is 0.098 (Table 2), whereas it is 0.024 within MSA (Table 3). We exploit precisely these differences in overall wind direction to identify the effect of $PM_{2.5}$ on our outcome variables.

[Place Table 3 about here]

[11] The daily mean temperature is given by the daily $\frac{max+min}{2}$.

6 Results

Table 4 presents the results of estimating Equation 1 using both the OLS (Panels A–C) and the IV approach (Panel D) on the full set of data. Separate regressions for dependent variables log(Market Value), log(Income), log(Net Operating Income), log(Capital Expenditures), and log(Net Asset Value) are provided in columns 1–6 respectively. A summary of the first stage estimates of Equation 3, as well as a detailed discussion of the associated tests we conduct to address the potential weak instruments bias, are provided in Appendix A1. Estimates of the climate variables can also be found in Appendix Table A2. In all cases, the interpretation of the $PM_{2.5}$ coefficient is a (log) change in the dependent variable (market value in Table 4, Panel A), given an increase of 1 $\mu g/m^3$ in $PM_{2.5}$ levels.

In Table 5 we provide IV results for various stratifications based on property type. We make comparisons between apartments versus all other CRE grouped (retail, industrial office) as well as separated. Caution is warranted when interpreting the stratified results as the sample sizes decline, most especially for the retail subsample. In the following subsections, we discuss the impact of air pollution on each dependent variable in turn.

6.1 Impact of $PM_{2.5}$ on Market Value

Beginning with the full sample in Table 4, the effect of $PM_{2.5}$ levels on property values is large when year fixed effects are omitted (Column 1, Panel A). This is likely due to the fact that overall $PM_{2.5}$ levels trended downwards in the United States since 2000, whereas property values trended upwards during that same time period. After including the year fixed effects in Panels B and C, the impact of $PM_{2.5}$ levels decreases dramatically with estimates remaining significant at the 1% level— -0.0215 (Panel A) to -0.0054 (Panel B) and -0.0058 (Panel C). It is likely these estimates are (upward) biased due to local endogeneity between economic activity and pollution levels. After instrumenting for local $PM_{2.5}$ levels

(Panel D), we indeed find that the impact of pollution on market values decreases compared the previous two OLS results. Obtaining a similar coefficient magnitudes when using the IV approach gives us confidence in our empirical approach. Based on the estimated coefficient in Panel D, we find that an increase of $1\mu\text{g}/m^3$ in $\text{PM}_{2.5}$ levels, deceases property values by approximately -0.61%. In other words, a one standard deviation increase in within-MSA $\text{PM}_{2.5}$ levels ($2.2\mu\text{g}/m^3$) generates a modest 1.3% ($\exp(-0.0061 \times 2.2) - 1$) drop in property values. These results suggest that properties exposed to increases in fine particulate matter tend to transact at a discount relative to those exposed to lower air pollution increases over time. Importantly, our results are not driven by time-invariant property-specific factors, such as size, or physical configuration, given the inclusion of property fixed effects.

The stratified results presented in Table 5 indicate that office properties may be driving the full sample result. The effect for apartments only is negative but insignificant and small in magnitude. The non-residential combined sample hints towards the relatively large and significant negative effect for office properties on their own. Here, a one standard deviation increase in within-MSA $\text{PM}_{2.5}$ levels generates a 3.4% ($\exp(-0.0156 \times 2.2) - 1$) decline in property values. The retail effect is also negative but insignificant whereas the industrial effect is positive and insignificant.

6.2 Impact of $\text{PM}_{2.5}$ on Total Income

In the OLS moels without year fixed effects, we find a large negative impact of $\text{PM}_{2.5}$ on total income (Table 4, Panel A, Columns 2). This is not surprising, as rents (the main driver of all our income variables, including NOI) have generally been on an upward trajectory between 2000–2016, whereas $\text{PM}_{2.5}$ has decreased over the same time period, resulting in a negative relationship. Again, it is therefore not surprising that the estimated coefficients are attenuated after including the year fixed effects in panels B and C. The statistical significance also decreases with the inclusion of the fixed effects structure.

After instrumenting for $PM_{2.5}$ levels (Panel D), the estimated coefficients increase in magnitude (i.e. in this case more negative) We find an coefficient of -0.0122, significant at the 1% level. In terms of the economic magnitude, a one standard deviation increase in $PM_{2.5}$ levels results in a 2.7% $(\exp(-0.0122 \times 2.2) - 1)$ drop in total income. Compared to the IV estimate reported for Market Value in Column 1, this indicates that in response to an increase in $PM_{2.5}$ levels, the observed decrease in total income is twice as large as the decline in property values (-1.3%) (Section 6.1).

Given that we measure property-level income using total gross income, this difference could arise due to two factors (or due to their combination). First, investors may believe the drop in income is only temporary, and that income will revert in the next period; thus, it is not fully capitalized in the price today. Second, investors may reduce their costs of operating the property which would partially offset the loss in income. In the following sections we extend our analysis to examine the effect on rental income, net operating income, and on capital expenditures in order to shed more light on these mechanisms.

The results by property type highlight a similar relationship with some caveats. For apartments and grouped non-residential commercial, the negative total income effect is significant at the 5% level. A one standard deviation increase in $PM_{2.5}$ levels results in a 1.31% and 3.14% decline in total income for apartments and non-residential commercial respectively. Coefficient magnitudes for both property types are larger in magnitude than the negative market value effect. This is especially true for the non-residential commercial sample as the total income effect is nearly double the magnitude of the market value effect. The total income effect remains negative when stratifying further into separate retail, industrial and office specifications but significance is lost. Across all property types, the effect size is largest for retail. The rate of rent adjustment is theoretically more frequent (monthly) for retail tenants with revenue sharing contracts. The larger magnitude of the retail effect as compared to the apartment effect is suggestive of this greater elasticity of adjustment where apartment rents typically adjust on a yearly basis. However, we cannot make a clear conclusion along these lines given lack of significance for the retail effect. This loss in significance for retail in particular is likely related to the small retail sample size providing us minimal power in the fixed effect IV setting.

6.3 Impact of $PM_{2.5}$ on Rental Income

Similar to the results in Section 6.2, the impact attenuates after fixed effects are added (Panels A through C, Column 3) but the coefficent increases in magnitude and significance in the IV setting. In general, we do not find large differences between the impact of $PM_{2.5}$ on total income and rental income.

In parallel, we additionally estimate the impact of air pollution on occupancy in the Appendix Table A4. Examining occupancy alongside rental income provides insight into which component of total income is being impacted by exposure to air pollution. If there is no impact on occupancy but rental income declines, we can conclude the decline in total income is driven by declining rent revenues and not a drop in occupancy.[12]

The effect of air pollution exposure on rental income for the full sample (Column 3, Table 4) is highly significant and slightly larger than the total income effect. Specifically, a one standard deviation increase in $PM_{2.5}$ leads to a 2.9% decline in rental income. We find no impact on vacancy levels for the full sample (see Appendix Table A4) and thus conclude that an increase in vacancies is not driving the decline in rental income and subsequently the decline in total income. Stratified results for rental income are qualitatively similar to the total income results. Occupancy remains insignificant for the stratified specifications (see Appendix Table A5 for the IV results).

[12]Note that there are 46 fewer observations for the occupancy model. This is a result of logging the left-hand side variable where 46 rental income observations are 0. The difference between total income and rental income is 20% on average in our data sample.

6.4 Impact of $PM_{2.5}$ on Net Operating Income

Following Geltner et al. (2014), we define net operating income as: net operating income = gross operating income - OpEx. For the full sample (Column 4, Table 4), OLS results appear to indicate that investors do not significantly cut operating expenses considerably after being exposed to higher levels of $PM_{2.5}$ given the relatively similar size in coefficients between NOI and the other income variables. We expect this estimate to be downward biased given that net operating income proxies for building-level productivity net of any expenses associated with running it (such as management fees, property taxes and insurance, utilities, etc.). After instrumenting for $PM_{2.5}$ levels, the coefficient increases in magnitude and significance (-0.0127 at the 5% level). This value is similar to the IV results for both total and rental income in Columns 2 and 3 respectively. The similarity suggests that (like with the OLS estimates before) operating expenses are not (considerably) impacted by air pollution. However, the full sample results obscure possible differences between apartments and non-residential property in Table 5. The magnitude increase in apartment NOI over both total income and rental income implies that operating expenditures are increasing with exposure to air pollution. This contrasts with the lower magnitude of NOI relative to total and rental income in Panel C. A further investigation into the changes in various components of OpEx shows (non-residential) commercial building owners spend less on utilities, maintenance, insurance, management fees, and tax after being exposed to increases in air pollution. This is likely a structural response as commercial leases are more likely to be gross leases (landlord pays) as compared to net leases (tenant pays) which are more common in apartment contracts.[13]

The combined results for apartment value and all three income variables—small insignificant impact on value, larger suggestive negative impact on income—contrast with the findings from the residential literature where rent effects are smaller and tend to lag price effects.

[13] Detailed OpEx analysis is available upon request.

This is not a surprising outcome given the difference in the users and investors in each market. In the residential market, both renters and owners are users of space with owners additionally taking the role of investors. Thus, owners are impacted two ways. First, through personal negative health outcomes associated with air pollution exposure—similar to renters. Second, through declining future rents via their investment position. Thus the value of a home declines as a result of declines in both consumption and investment utility. For apartments, renters are the sole users of space and are impacted by local air pollution disamenities. This local disamenity only impacts investors via expectations of future income (i.e. value). Thus, the null effect on value implies investors view the income drop as temporary with the positive capital expenditure coefficient suggesting a potential role for building investments to mediate contemporaneous drops in income.

6.5 Impact of $PM_{2.5}$ on Capital Expenditures

The baseline specification without fixed effects for the full sample identifies a negative relationship (-0.0537, Panel A, Column 5, Table 4) between $PM_{2.5}$ levels and capital expenditures. This hints at decreasing levels of investments in the properties after pollution increases and would imply investors are allowing properties to physically and functionally depreciate in the face of rising pollution levels. This is an unlikely scenario, however. Indeed, after including year fixed effects, the coefficient sign flips. Estimates in Panels B–D indicate that in response to increases in air pollution, owners invest in their properties to combat the negative impact. This could be done by—for example—introducing a new HVAC system to improve indoor air quality. However, we do not observe the type of capital investments being made. It is plausible that salience regarding the source of the decline in rents and value is limited and generic capital expenditures not necessarily targeting improvements in air quality are being made to combat these declines.

The estimated coefficient for the effect of $PM_{2.5}$ on capital expenditures is largest for the

IV approach (Panel D), although it is only significant at the 10% level. Here, a one standard deviation increase in $PM_{2.5}$ levels, results in $(\exp(0.0467 \times 2.2) - 1 \approx)$ 11% increase in capital expenditures in the same year. The effect size remains large and positive when stratifying by property type, although minimal significance is found.

Taken together, these results suggest that property values decline less compared to the property's income in response to increases in $PM_{2.5}$ levels, and that is in part due to increased capital expenditure activities aimed at increasing the rental cash flow in the future. Hence, we observe a contemporaneous decline in rents (gross income), which is anticipated to revert back to its pre-impact trajectory following investment in air-pollution remedying activities—as proxied by increases in capital expenditures. We caution here that we do not directly observe investment in air-pollution remedying activities but hypothesize likely scenarios that reflect the above estimates.

6.6 Impact of $PM_{2.5}$ on Net Asset Values

The impact of $PM_{2.5}$ on net asset values according to the IV estimate (Panel D, Column 6, Table 4) is -0.0083 with significance at the 5% level. This estimate is larger (and more significant) compared to the impact on market values of -0.0061 at a significance level of 10% (Panel D, Column 1) suggesting that in fact part of the market value decline associated with increased air pollution exposure is masked by contemporaneous increases in capital expenditures. Coupled with evidence presented above that net operating income declines significantly more, this indicates that increases in air pollution results in contemporaneous cap rate compression.

These results seem to be mostly driven by office properties. This is similar to our findings on market values (compare Column 6 to Column 1, in Panel E, Table 5).

[Place Table 4 about here]

[Place Table 5 about here]

6.7 Lagged Impact of $PM_{2.5}$ on Commercial Real Estate

Our analysis so far has focused on estimating contemporaneous effects of air pollution. Given that real estate contracts can be long-term, the effect of changes in $PM_{2.5}$ levels might not be immediately observed in rents and values. In this Section we address this potential concern by estimating Equation 2 using a 1 and 2-year lag. Table 6 summarizes the results of this estimation using the IV approach.

[Place Table 6 about here]

Beginning with all properties in Panel A of Table 6, we find only a marginally significant relationship between value (both market value and net asset value) and lagged $PM_{2.5}$. Similar to the previous results, these effects are negative and relatively small in magnitude. When stratifying by property type, we see that the lagged value effect for the full sample may be predominately driven by non-residential properties—office in particular. Here we observe a fairly large effect of two-period lagged $PM_{2.5}$ on both market value and net asset value of office properties. A one standard deviation increase in $PM_{2.5}$ two periods previous generates a 3.0% decrease in market value and 3.2% decrease in net asset value for office properties. While not presented here for brevity purposes, these delayed effects persist for three- and four-period $PM_{2.5}$ lags as well.

Apartments display no significant lagged effects (Panels B); this contrasts with the more immediate effect on apartment income as seen in the total income, rental income, and NOI results in Table 5. No significant lagged effects are found for retail as well (Panel D).

The insignificant coefficients for the income specifications (Columns 2-4) for the grouped commercial specification (Panel C) mask the relatively large and significant negative effects for both office and industrial properties (Panels E and F). Previous results for industrial properties indicated no significant contemporaneous impact of increases in $PM_{2.5}$ on any form of income. However, we find a negative one-period lagged effect for industrial properties for all three forms of income. Here a one standard deviation increase in $PM_{2.5}$ decreases total income, rental income, and NOI by 3.6%, 4.7%, and 5.9% respectively. We additionally find large lagged $PM_{2.5}$ effects on CapEx for industrial properties: 26% and 25% for the one-period and two-period lag respectively. Three observations can be made based on these lagged income and CapEx results for industrial properties. First, the relatively large effect sizes for the income specifications contrast with the small and insignificant effects for the value specifications indicating pollution exposure—past and present—is not capitalized into values and only operates through income. The second observation provides some insight into this dynamic: the large positive increase in CapEx combined with insignificant value effects and insignificant but positive income effects with respect to the two-period lag of $PM_{2.5}$ suggests investments in CapEx after a period of high pollution exposure may be mitigating subsequent loses in income and value. Lastly, the difference in magnitudes for total income versus NOI hints at a small positive correlation between operating expenses and lagged $PM_{2.5}$ for industrial properties.

Similar to industrial properties, office properties display a marginally significant one-period lagged $PM_{2.5}$ effect on rental income that is not present in the contemporaneous specification. Here a one standard deviation increase in $PM_{2.5}$ one year ago generates a 5.2% decrease in current year rental income.

Taking these lagged results together, there is evidence of a delayed effect of air pollution exposure on building-level economic indicators. This is particularly true for industrial and office properties whose long lease terms may prevent more immediate impacts from being observed. Again, we cautiously interpret the stratified results given smaller sample sizes.

7 Robustness

We consider two additional empirical strategies that aim to address potential endogeneity between air pollution exposure and CRE values. First, we use an alternative IV specification that exploits changes in the U.S Clean Air Act standards in 2005 and follows work done by Currie et al. (2020) and Sager and Singer (2022). Second, following recent work by (Borgschulte et al., 2022) we sidestep the joint determination of air quality and economic activity by leveraging variation in air pollution induced by wildfire smoke.

7.1 Changes in U.S. Clean Air Act Standards

Our first strategy is policy driven and exploits changes to the U.S Clean Air Act standards in 2005. The U.S Clean Air Act identified locations of high $PM_{2.5}$ concentrations—deemed "nonattainment areas". This designation allowed the EPA to enforce air quality improvement plans, withhold federal funding, and deny permits for infrastructure projects.[14] We operationalize this IV strategy through a combined propensity score matching and Difference in Difference specification. One limitation for comparison purposes to our main IV approach is the timeframe. This strategy requires 2001-2003 and 2006-2008 windows of observation. This is due to the fact that the nonattainment categorization was based on a measurement period of 2001-2003 with the act coming into effect in 2006. After 2008, areas were reassessed and thus could move from nonattainment to attainment. Direct comparison to our main IV specification is not possible given the differing timeframes and samples; however, the use of a multiyear average exposure in the DiD framework does provide a window into longer run effects. Additional details on the policy and the propensity score matching-DiD specification

[14] Bishop et al. (2018) use the individual-level variation from the EPA's nonattainment designations as an instrument to identify how cumulative $PM_{2.5}$ exposure from 2004-2013 affects the probability of receiving a new diagnosis of dementia during this period among Medicare beneficiaries age 65 and above who did not have dementia in 2004, and find that a 1 μg/m3 increase in average $PM_{2.5}$ concentrations increases the probability of receiving a new dementia diagnosis by the end of the decade by an average of 2.15 percentage points.

are provided in the Appendix.

We match properties in attainment areas with properties in nonattainment areas based on their annual average $PM_{2.5}$ levels in 2001 – 2003 only. Thus, average pre-$PM_{2.5}$ levels are comparable between control and treated group. After matching, we run a first stage specification that predicts $PM_{2.5}$ based on nonattainment status. Fitted values are then used in the second stage which is similar to our main IV specification. Results are provided in Table 7.

[Place Table 7 about here]

Beginning with the first stage, we find that the nonattainment designation reduced $PM_{2.5}$ concentration levels by 0.757 μg/m^3. This is nearly double the magnitude of what was found in Sager and Singer (2022) where they find that the legislation reduced $PM_{2.5}$ concentration levels by 0.4 μg/m^3. The difference could simply be a locational one. Sager and Singer (2022) consider the entire US, whereas our sample of CRE tends to be concentrated in large cities and predominately in more urban areas.

The second stage findings remain qualitatively similar to the main IV specification. More specifically, signs for the effect of pollution exposure on income and value dependent variables remain negative with the effect on CapEx remaining positive although insignificant. Effects size is larger in this setting. It is difficult to directly compare these results with the main IV results given the very different empirical frameworks, time dimension, and sample size. The DiD framework averages $PM_{2.5}$ over multiple years for both the pre and post measures. Thus, we cannot similarly identify a contemporaneous or lagged effect as we do in the main specification and the small sample size renders the estimation sensitive to the control group.

7.2 Wildfire Smoke

Next we consider an alternative IV strategy that also allows for the examination of cumulative effects of transitory air pollution shocks on CRE markets. This strategy is motivated by Borgschulte et al. (2022) who use transient wildfire smoke as an instrument for potentially endogenous local pollution exposure. Wildfires account for around 20 percent of the fine particulate matter emitted in the United States (EPA, 2020). Wind can carry wildfire smoke for thousands of miles, generating plausibly exogenous air pollution events that are geographically dispersed, widespread, and unrelated to economic factors such as regulations (Langmann et al., 2009). Recent years have seen an increase in frequency, intensity, and geographic scope of wildfires making wildfire smoke a significant source of pollution nationwide.

Our analysis exploits variation in wildfire smoke exposure at the county level to estimate the impact of transient air pollution events on CRE market outcomes. Several features of wildfire smoke make it suitable for studying the effects of air pollution on CRE market outcomes in our setting. Wildfire smoke events occur regularly throughout the United States. During our study period, U.S. counties included in our sample were fully covered by wildfire smoke for an average of 24 days per year, and nearly every county experienced some exposure. Transient wildfire smoke plumes create sharp air pollution shocks that drastically reduce air quality well below the typical daily variation in U.S. air quality. At the daily level, an additional day of wildfire smoke increases concentrations of ground-level fine particulate matter ($PM_{2.5}$) by an average of $0.0081\mu g/m^3$. The relationship between smoke exposure and $PM_{2.5}$ can also be detected at the annual level, which is the time frequency of our CRE NCREIF data. The above smoke days and PM average figures imply that if a county was covered by smoke for an entire year, the increase in $PM_{2.5}$ levels would amount to 365*0.0081 $= 3.0\mu g/m^3$. Based on the average $PM_{2.5}$ level of $10.5\mu g/m^3$ in our sample (Table 2), this smoke induced increase corresponds to an increase in $PM_{2.5}$ by 30%.

We use three main sources of data in this analysis. High-resolution daily remote sensing data from satellites show the locations of wildfire smoke plumes in the United States. These data are available from NOAA.[15] [16] Air quality data are collected from ground-level pollution monitors.

The first stage specification is as follows:

$$PM_{ipct} = SmokeDays_{ict}\lambda_d + X'_{it}\omega + \nu_{pt} + \rho_{ct} + \phi_i + \varepsilon_{ipct}, \tag{5}$$

We instrument for $PM_{2.5}$ using the number of smoke days in any given year t for the county c the property i is located in. Note that in the satellite generated wildfire smoke plume data there are three "levels" of smoke: light / medium / heavy. Whenever *any* level of smoke covers a county at any point in time, we consider the *entire* county as *treated* for that day. Covariate matrix X contains time varying (climate) variables such as wind direction, average temperature and precipitation with corresponding vector of coefficients ω. As before, ν_{pt} are property type $\times$ year fixed effects, ρ_{ct} are MSA $\times$ year fixed effects, and ϕ_i are property fixed effects.[17]

The identifying assumption in this IV approach is that conditional on the fixed effects, the presence of wildfire smoke only influences CRE market outcomes through its impact on air pollution. Thus, our identification relies on the assumption that an area's year-over-year variation in smoke exposure is driven largely by quasi-random factors (including the location and magnitude of fire events and shifting wind patterns) which are unlikely to be correlated with unobservable determinants of CRE market outcomes.

Results of this estimation are shown in Table 8. Beginning with the first stage, we

[15] We use wildfire smoke exposure data developed by Miller et al. and adapt it to fit the unit of analysis for the CRE market data.

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

[17] In unreported regressions, we re-estimate this specification by using state $\times$ year fixed instead of MSA $\times$ year fixed effects, as in Borgschulte et al. (2022). Our results remain unchanged.

find that at the daily level, an additional day of wildfire smoke increases concentrations of ground-level fine particulate matter ($PM_{2.5}$) by an average of $0.0081\mu g/m^3$. The second stage findings remain qualitatively similar to the main IV specification and the DiD alternative IV specification. Similar to the DiD strategy, signs for the effect of pollution exposure on income and value dependent variables remain negative with the effect on CapEx remaining positive. We do, however, lose significance on total income, NOI and CapEx. Of note is the size of the coefficients for the various specifications. These coefficients are larger than the coefficients from the main IV strategy. We again caution direct comparison to the main IV results given the nature of discete-(like) instruments. Existing literature (Newey and Stouli, 2021; Reiss, 2016) suggests that the qualitative pattern of estimates of treatment effects in case of instruments with discrete-(like) functional forms mimics that of continuous instruments; however, estimates may not be numerically comparable.[18]

Taken together, the results of these two alternative IV approaches confirm our main IV findings of a significant causal effect of air pollution (acute fine particulate matter) exposure on the commercial real estate (CRE) market outcomes. The consistency in the qualitative nature of our findings across all IV approaches gives us confidence that our estimates do not suffer from reverse causality or omitted variable bias.

8 Conclusion

Understanding how air pollution affects commercial real estate (CRE) values is important given the sizeable exposure of institutional investors (pension funds, mutual funds, private equity funds, among many others) to this large asset class. However, endogeneity and measurement error make it challenging to identify the causal effects of air pollution. This problem is further exacerbated by the fact that CRE assets are heterogeneous.

[18]Recent literature (Brinch et al., 2017) offers further insights on the potential gap between ATE and ATT on one side, and LATEs on the other, in case of discrete-style instruments.

We make progress on these two issues through the use of a wind direction instrument and granular $PM_{2.5}$ data that spans the whole of the United States for the 2000 to 2016 time period. Using instrument-derived exogenous variation in $PM_{2.5}$ across a broad geographic scale and over a long time period enables us to conduct one of the first studies of the effects of air pollution on one of the largest asset classes – commercial real estate, and to explore treatment effect heterogeneity by property type.

The results of our contemporaneous IV regressions indicate that a one standard deviation increase in $PM_{2.5}$ levels results in a 1.3% drop in CRE market values and a 2.7% decline in property (net) income on average. For every one standard deviation increase in $PM_{2.5}$ levels, capital expenditures increase by more than 11%.

These results imply that there is an air-pollution induced pricing discount due to the expected loss of income in the future, which is partially mitigated in the longer run due to an increase in capital expenditures. To further explore this channel, we run our model on *net asset value* (NAV). This allows for the capture of *pure* price change net of capital expenditures. Estimates on the impact of instrumented fine particulate matter exposure on net asset values are slightly larger than the market value impact— 1.35% drop in market value versus a 1.84% drop in net asset value given a one standard deviation increase in $PM_{2.5}$. This suggests that the negative effects of air pollution on real estate values are partially masked by rising capital expenditures.

The results of the heterogeneous treatment effects analysis indicate that the negative effect of air pollution on market values is most pronounced in the office sector in terms of both contemporaneous and lagged increases in air pollution exposure. This is suggestive of the role of reduced worker productivity in future income expectations and thus the value of the property to investors. Heterogeneity in the effect of air pollution on income by property type and timing implies lease contract length may be playing a mediating role. In particular, in the fully stratified specifications, it is only the apartment sector and that experiences a contemporaneous decline in income as a response to increasing air pollution exposure. Whereas a large significant lagged effect on income is found for both industrial and office where lease contract lengths range from 3 to 10 years compared to the common one year lease for apartments. We again reiterate that these stratified results warrant further investigation via additional CRE data given our somewhat small sample sizes. We especially highlight the need for more investigation into retail properties in particular given that our results hint towards a short term negative income effect potentially related to the presence of revenue sharing lease contracts for these property types.

All together, we find evidence of a significant negative effect of air pollution exposure on CRE values, which can partially be mitigated through capital investments. This first exploration into these relationships has a number of limitations we hope future work will address. First, we cannot separately identify if or how the hypothesized channels of productivity and local amenities influence our results. The literature on air pollution exposure and productivity as well as the effect of exposure on residential prices is fairly clear. We logically extend these findings to our work here but cannot, for example, observe causal declines in productivity subsequently causing declines in income and value (building productivity) within our data. Second, our framework is not ideal for capturing very long run effects. Our instrument is not useful when looking over multiple years as wind direction "averages" out over longer periods of time. However, the alternative IV strategy that makes use of changes to the Clean Air Act does allow for the identification of a longer run average effect and finds slightly larger but qualitatively similar results. With the limitations in mind, we hope this study will spur future research that will endeavour to further disentangle the short-run and long-run implications of air pollution exposure on building-level productivity and its effect on local economic growth prospects of the affected communities.

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Tables and Figures

Table 2: Descriptive Statistics

Statistic	Mean (1)	St. Dev. (2)	Min (3)	Max (4)
$PM_{2.5}$ ($\mu g/m^3$)	10.467	2.853	0.008	28.712
Market value ($)	54,173,509	105,557,701	292,459	2,797,666,667
Total income ($)	5,065,462	8,746,733	21,591	194,674,617
Rental income ($)	4,057,338	6,362,960	0	139,813,076
Net operating income ($)	3,064,798	5,364,132	55	105,299,093
Capital expenditures ($)	972,487	3,807,176	1	280,466,557
Net asset value ($)	50,894,403	99,650,380	-149,455,272	2,697,248,504
Age (years)	20.818	16.189	1	175
Temperature (mean C°)	15.675	4.573	4.230	26.029
Precipitation (mm)	2.596	1.252	0.062	6.468
Wind speed (m/h)	4.612	0.803	2.802	8.377
Wind direction north (%)	0.187	0.098	0.046	0.896
Wind direction south (%)	0.333	0.177	0.005	0.696
Wind direction west (%)	0.265	0.138	0.008	0.649
Wind direction east (%)	0.215	0.048	0.025	0.419
Property type (dummies)				
Apartment	0.287			
Retail	0.160			
Industrial	0.290			
Office	0.263			
Observations	46,696			
Unique properties	9,957			

Table 3: Variation in Wind Direction

Within standard deviations (SD)	$PM_{2.5}$ ($\mu g/m^3$) (1)	North (2)	South (3)	East (4)	West (5)
SD within year	2.526	0.097	0.177	0.134	0.047
SD within MSA	1.613	0.024	0.027	0.029	0.022
SD within MSA and year	0.683	-	-	-	-
SD within 4-digit ZIP code	1.623	0.022	0.026	0.027	0.022
Unique categories					
# of unique years	17				
# of unique MSAs	215				
# of unique 4-digit ZIP codes	1,228				

Note: *SD* = standard deviation. *MSA* = metropolitan statistical area. The wind direction gives the direction the wind is blowing towards. The simple standard deviations over the entire sample can be found in Table 2.

Figure 1: NCREIF properties in sample with county Census boundaries. Alaska and Hawaii dropped for visual ease.

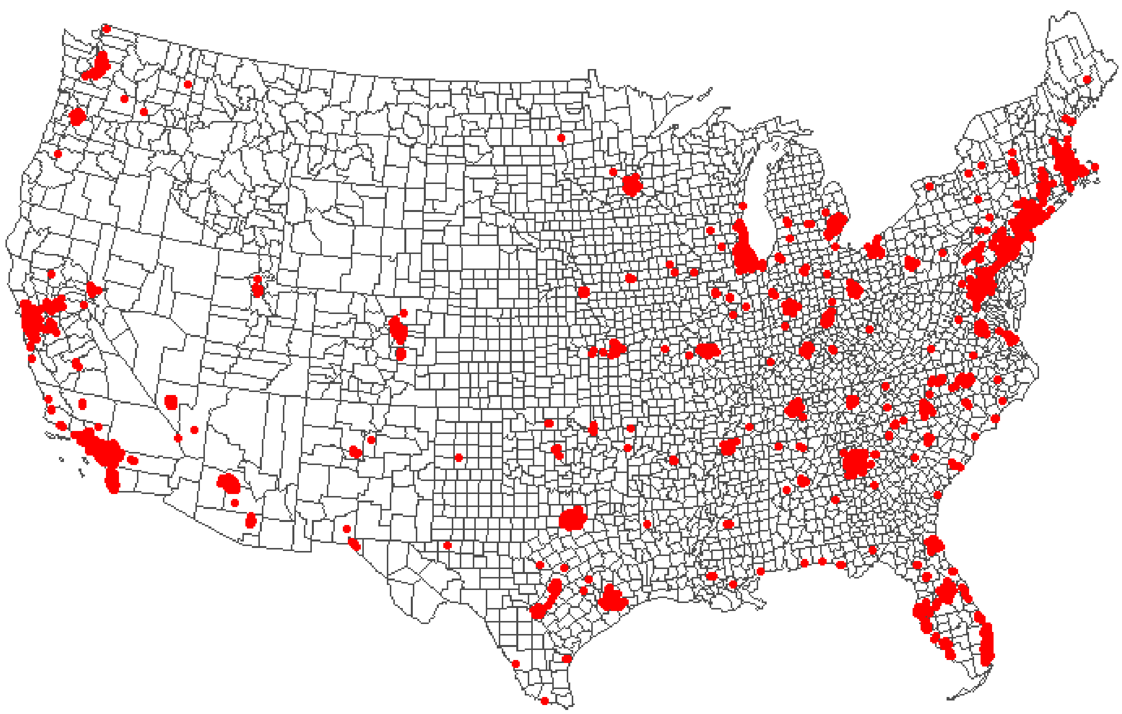


Table 4: Full Sample OLS & IV Results

Dependent var. (in ln):	Market value (1)	Total Income (2)	Rental Income (3)	NOI (4)	CapEx (5)	Net Asset Value (6)
Panel A: OLS						
$PM_{2.5}$ (μg/m^3)	-0.0215***	-0.0130***	-0.0099***	-0.0042*	-0.0537***	0.0006
	(0.0021)	(0.0014)	(0.0016)	(0.0022)	(0.0055)	(0.0029)
R^2	0.977	0.977	0.975	0.925	0.621	0.970
Property FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations			46,696			
Panel B: OLS						
$PM_{2.5}$ (μg/m^3)	-0.0054***	-0.0027*	-0.0036*	-0.0020	0.0168**	-0.0070**
	(0.0014)	(0.0015)	(0.0016)	(0.0024)	(0.0028)	(0.0027)
R^2	0.985	0.979	0.977	0.930	0.630	0.978
Property FE	Yes	Yes	Yes	Yes	Yes	Yes
Prop. type × year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations			46,696			
Panel C: OLS						
$PM_{2.5}$ (μg/m^3)	-0.0058***	-0.0030*	-0.0039*	-0.0016	0.0199**	-0.0065***
	(0.0019)	(0.0016)	(0.0017)	(0.0028)	(0.0085)	(0.0024)
R^2	0.988	0.981	0.980	0.934	0.652	0.983
Property FE	Yes	Yes	Yes	Yes	Yes	Yes
Prop. type × year FE	Yes	Yes	Yes	Yes	Yes	Yes
MSA × year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations			46,696			
Panel D: IV						
$PM_{2.5}$ (μg/m^3)	-0.0061*	-0.0122***	-0.0134***	-0.0127**	0.0467*	-0.0083**
	(0.0036)	(0.0038)	(0.0038)	(0.0065)	(0.0253)	(0.0041)
R^2	0.988	0.981	0.980	0.934	0.652	0.983
Property FE	Yes	Yes	Yes	Yes	Yes	Yes
Prop. type × year FE	Yes	Yes	Yes	Yes	Yes	Yes
MSA × year FE	Yes	Yes	Yes	Yes	Yes	Yes
First State F-stat			19.1			
Observations			46,696			

Clustered (4-digit zip code) standard-errors used to determine signif.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: All specifications contain the climate controls of temperature (C°), precipitation (mm), and wind speed (m/h). The instruments for the IV specification are interactions between the main four wind directions (N/S/W/E) and 4-digit zip code. For rental income we have slightly less observations, namely 46,650.

Table 5: Property Type IV Results

Dependent var. (in ln):	Market value (1)	Total Income (2)	Rental Income (3)	NOI (4)	CapEx (5)	Net Asset Value (6)
Panel A: Apartments						
$PM_{2.5}$ ($\mu g/m^3$)	-0.0046	-0.0060**	-0.0056*	-0.0152**	0.0423	-0.0014
	(0.0035)	(0.0028)	(0.0029)	(0.0062)	(0.0313)	(0.0036)
R^2	0.987	0.988	0.988	0.966	0.679	0.984
Observations			13,420			
Panel B: Commercial						
$PM_{2.5}$ ($\mu g/m^3$)	-0.0077*	-0.0145**	-0.0158**	-0.0089	0.0575*	-0.0085*
	(0.0081)	(0.0048)	(0.0051)	(0.0086)	(0.0288)	(0.0049)
R^2	0.988	0.980	0.977	0.930	0.656	0.982
Observations			33,276			
Panel C: Commercial - Retail						
$PM_{2.5}$ ($\mu g/m^3$)	-0.0047	-0.0104	-0.0065	-0.0089	0.0346	-0.0071
	(0.0081)	(0.0069)	(0.0068)	(0.0095)	(0.0647)	(0.0084)
R^2	0.990	0.989	0.989	0.973	0.709	0.988
Observations			7,474			
Panel D: Commercial - Industrial						
$PM_{2.5}$ ($\mu g/m^3$)	0.0042	-0.0013	-0.0004	0.0042	0.0273	0.0068
	(0.0058)	(0.0076)	(0.0082)	(0.0142)	(0.0540)	(0.0061)
R^2	0.985	0.962	0.957	0.885	0.536	0.980
Observations			13,531			
Panel E: Commercial - Office						
$PM_{2.5}$ ($\mu g/m^3$)	-0.0156**	-0.0009	-0.0013	0.0112	0.0139	-0.0191***
	(0.0061)	(0.0069)	(0.0066)	(0.0129)	(0.0318)	(0.0070)
R^2	0.988	0.977	0.974	0.920	0.675	0.980
Observations			12,271			

Clustered (4-digit zip code) standard-errors used to determine signif.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: All specifications contain the climate controls of temperature (C°), precipitation (mm), and wind speed (m/h). Market value is defined as either appraised (average over a year) or transaction price (if sold). Income is the total amount of revenue the property generated over the year (rent and other income). NOI (Net Operating Income) is the total income, minus operating expenses (OpEx). OpEx include: utilities, taxes, management fees, and regular maintenance. CapEx (Capital Expenditures) are discretionary costs, which include: renovations, property additions, and fees for brokers. All models are estimated via our instrumental variable approach. The instruments are interactions between the main four wind directions (N/S/W/E) and 4-digit zip code.

Table 6: One- and Two-Period IV Lag Results

Dependent var. (in ln):	Market value (1)	Total Income (2)	Rental Income (3)	NOI (4)	CapEx (5)	Net Asset Value (6)
Panel A: All properties						
$PM_{2.5}$ ($\mu g/m^3$)						
Lag: 1	-0.0050	-0.0014	-0.0030	0.0030	0.0288	**-0.0069***
Lag: 2	**-0.0049***	0.0013	0.0001	-0.0004	0.0233	**-0.0054***
Panel B: Apartments						
$PM_{2.5}$ ($\mu g/m^3$)						
Lag: 1	-0.0004	-0.0020	-0.0022	-0.0053	0.0090	-0.0010
Lag: 2	-0.0025	-0.0017	-0.0018	0.0025	-0.0045	-0.0037
Panel C: Commercial						
$PM_{2.5}$ ($\mu g/m^3$)						
Lag: 1	**-0.0073***	-0.0039	-0.0041	0.0016	0.0267	**-0.0091****
Lag: 2	**-0.0070****	0.0008	0.0010	-0.0025	0.0114	**-0.0065***
Panel D: Commercial - Retail						
$PM_{2.5}$ ($\mu g/m^3$)						
Lag: 1	0.0035	0.0066	0.0082	0.0146	0.0313	0.0009
Lag: 2	0.0067	0.0052	0.0070	0.0046	-0.0323	0.0058
Panel E: Commercial - Industrial						
$PM_{2.5}$ ($\mu g/m^3$)						
Lag: 1	-0.0053	**-0.0165***	**-0.0221****	**-0.0276***	**0.1048****	-0.0008
Lag: 2	-0.001	0.0029	0.0066	0.0049	**0.1027*****	0.0021
Panel F: Commercial - Office						
$PM_{2.5}$ ($\mu g/m^3$)						
Lag: 1	-0.0015	0.0069	**-0.0243***	0.0137	-0.0043	-0.0089
Lag: 2	**-0.0138****	-0.0038	-0.0051	-0.0115	0.0145	**-0.0149****

Clustered (4-digit zip code) standard-errors used to determine signif.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: All specifications contain the climate controls of temperature (C°), precipitation (mm), and wind speed (m/h) and property type×year and MSA×year fixed effects. Market value is defined as either appraised (average over a year) or transaction price (if sold). Income is the total amount of revenue the property generated over the year (rent and other income). NOI (Net Operating Income) is the total income, minus operating expenses (OpEx). OpEx include: utilities, taxes, management fees, and regular maintenance. CapEx (Capital Expenditures) are discretionary costs, which include: renovations, property additions, and fees for brokers. All models are estimated via our instrumental variable approach. The instruments are interactions between the main four wind directions (N/S/W/E) and 4-digit zip code.

Table 7: Robustness: Changes in U.S. Clean Air Standards: PSM

Dependent var. (in ln):	Market Value	Total Income	Rental Income	NOI	CapEx	Net Asset Value
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
$PM_{2.5}$ (μg/m^3)	-0.0503*	-0.0243*	-0.0252**	-0.0129*	0.1132	-0.0849*
	(0.0050)	(0.0022)	(0.0016)	(0.0017)	(0.0446)	(0.0114)
Fixed-effects						
Property FE	Yes	Yes	Yes	Yes	Yes	Yes
Prop. type × year FE	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	576	576	576	576	576	576
R^2	0.988	0.983	0.980	0.955	0.699	0.977
First Stage						
Nonattainment			-0.757**			
F-test			13.900			

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

Note: time period: 2001 – 2003 and 2006 – 2008. All specifications contain the climate controls of temperature (C°), precipitation (mm), and wind speed (m/h) and property specific and property type×year fixed effects. Market value is defined as either appraised (average over a year) or transaction price (if sold). Income is the total amount of revenue the property generated over the year (rent and other income). NOI (Net Operating Income) is the total income, minus operating expenses (OpEx). OpEx include: utilities, taxes, management fees, and regular maintenance. CapEx (Capital Expenditures) are discretionary costs, which include: renovations, property additions, and fees for brokers. All models are estimated using an instrumental variable approach, and all explained variables are log transformed. The instrument is properties that got designated to be in nonattainment (NA) in 2006. Properties in attainment areas are matched 1-on-1 with properties in nonattainement areas using a logit model (Table A6) using pre-$PM_{2.5}$ concentration levels only.

Table 8: Robustness: Wildfire Smoke

Dependent var. (in ln):	Market Value (1)	Total Income (2)	Rental Income (3)	NOI (4)	CapEx (5)	Net Asset Value (6)
Variables						
$PM_{2.5}$ ($\mu g/m^3$)	-0.1199*	-0.1204	-0.1274*	-0.1606	0.5549	-0.1094*
	(0.0785)	(0.0815)	(0.0746)	(0.1280)	(0.4983)	(0.0648)
Fixed-effects						
Property FE	Yes	Yes	Yes	Yes	Yes	Yes
MSA × year FE	Yes	Yes	Yes	Yes	Yes	Yes
Prop. type × year FE	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	37,763	37,763	37,745	37,763	37,763	37,730
R^2	0.986	0.979	0.978	0.929	0.612	0.983
First Stage						
Smoke days			0.0081**			
F-test			23.400			

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

Note: All specifications contain the climate controls of temperature (C°), precipitation (mm), and wind speed (m/h) and property specific and property type×year fixed effects. Market value is defined as either appraised (average over a year) or transaction price (if sold). Income is the total amount of revenue the property generated over the year (rent and other income). NOI (Net Operating Income) is the total income, minus operating expenses (OpEx). OpEx include: utilities, taxes, management fees, and regular maintenance. CapEx (Capital Expenditures) are discretionary costs, which include: renovations, property additions, and fees for brokers. All models are estimated using an instrumental variable approach, and all explained variables are log transformed. The instrument is the number of smoke days during a specific year.

Appendix

A1 First Stage Summary of Main Results

The use of ZIP code-specific wind direction instruments generates over 3,000 instrumental variables in the first stage. Further, first stage results are generated for each property type stratification as well as for the full sample and property type stratified samples with the lags. As a result, for brevity we refrain from reporting a full set of estimated first stage coefficients and report a summary in Table A1 for the main specification. The left hand side variable in our first stage regression are $PM_{2.5}$ levels per year per building, as shown in Eq. (3).

[Place Figure A1 about here]

Given the reference wind direction of East, the instrument coefficients can be interpreted as follows: how much higher/lower would the levels of $PM_{2.5}$ be, if the wind had blown—for a full year—in the given direction, compared to the baseline of the wind blowing to the East for a full year? On average, the estimated coefficients are not large since they are essentially "averaged out" over the entire country. A possible exception being wind direction toward the West which increases $PM_{2.5}$ levels by 14 μg/m^3 over a full year as compared to the East wind.

Still, this number is low compared to the standard deviation of the coefficients, implying there is substantial variation in the coefficient within the United States. More importantly however, when looking at the summary statistics within the MSA, we find that the standard deviation decreases, but still remains large (the mean is zero by definition). This gives us confidence in the instruments used in this study. Weak instrument bias is not a concern in our setting. As illustrated by Table 3, wind direction is a strong predictor of air pollution levels, and this is confirmed by the large first-stage F-statistics provided in results Tables 4 to 6.

[Place Figure A1 about here]

[Place Figure A2 about here]

To get a sense of what the estimates look like within an MSA we provide two examples. Figure A1 gives the choropleth plot for Chicago, and Figure A2 for Los Angeles.

For Chicago we find that wind blowing towards the West lowers $PM_{2.5}$ the most for downtown Chicago (blue color), which is caused by Lake Michigan located directly to the East. However, this does increase pollution levels in the western suburbs given the likely flow of central urban pollution.

In Los Angeles, wind blowing to the East and the North results in the lowest levels of pollution. This is likely related to the location of the ocean shoreline—directly to the West and the South. Wind blowing to the West results in the most pollution for Los Angeles on average. Also note that the range of pollution is larger for Los Angeles compared to Chicago.[19] For example, downtown Los Angeles will experience over 50 $\mu g/m^3$ more in $PM_{2.5}$ if the wind direction is going to the West instead of going to the East. In downtown Chicago the biggest difference is approximately 30 $\mu g/m^3$ of $PM_{2.5}$.

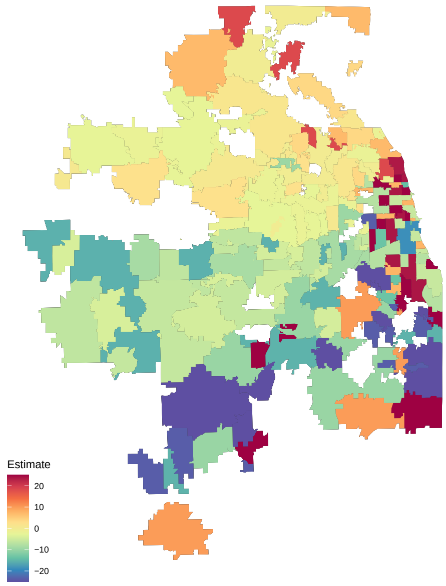
[19] See legend in Figures A1 – A2.

Table A1: Summary of First Stage Coefficients

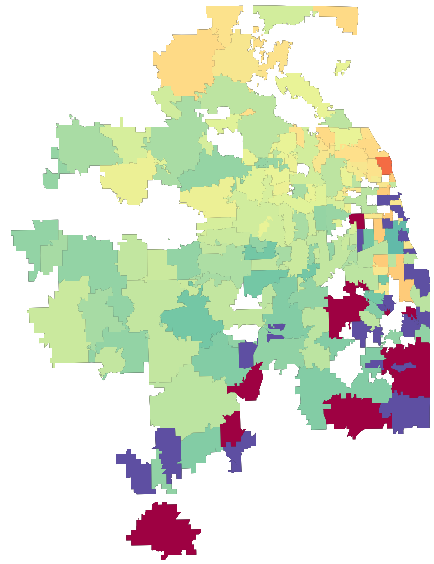
Wind going towards:	Mean	St. Dev.
North	0.568	122.659
- within MSA	0.000	37.385
South	-1.128	87.345
- within MSA	0.000	35.055
West	13.881	74.294
- within MSA	0.000	30.630

Note: Left hand side variable is local $PM_{2.5}$ level. The first stage is described in Eq. (3). The instruments are interactions between the main four wind directions (N/S/W/E) and 4-digit zip code. As a result we have 100s of coefficients. Wind blowing towards the East is the reference category, and is therefore left out to circumvent multicollinearity issues.

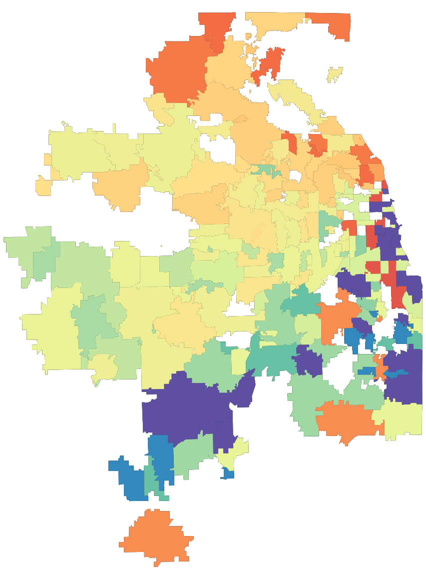
Figure A1: First Stage Coefficients: Chicago



(a) North



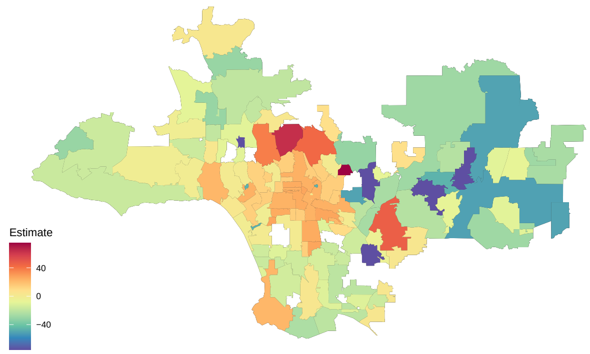
(b) South



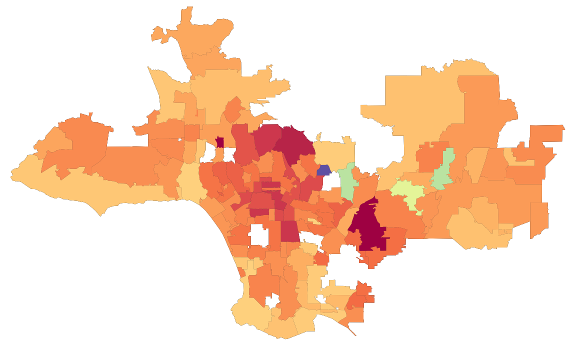
(c) West

Note: Each choropleth plots the values of the first stage coefficient of wind direction interacted with zip code. The direction indicated beneath each subfigure references the direction the wind is moving towards not coming from.

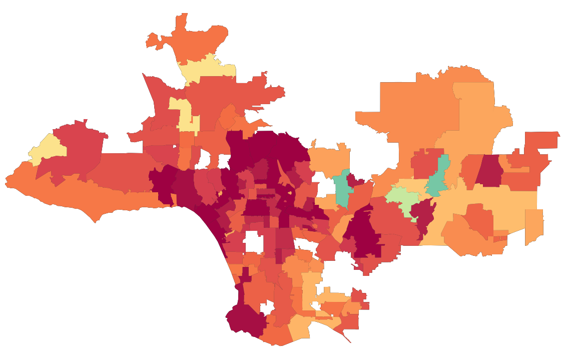
Figure A2: First Stage Coefficients: Los Angeles



(a) North



(b) South



(c) West

Note: Each choropleth plots the values of the first stage coefficient of wind direction interacted with zip code. The direction indicated beneath each subfigure references the direction the wind is moving towards not coming from.

A2 Additional Results

[Place Table A2 about here]

[Place Table A4 about here]

[Place Table A5 about here]

Table A2: Estimates of Climate Covariates (Table 4).

Dependent var. (in ln):	Market value (1)	Total Income (2)	Rental Income (3)	NOI (4)	CapEx (5)	Net Asset Value (6)
Panel A: OLS						
Precipitation (mm)	-0.0099**	-0.0011	-0.0014	-0.0050	-0.0206	-0.0085**
Temperature (°C)	0.0409***	0.0075***	0.0078***	0.0134***	0.0603***	0.0378***
Wind speed (m/h)	-0.0302**	-0.0082	-0.0067	-0.0105	-0.1162**	-0.0080
Property FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: OLS						
Precipitation (mm)	-0.0040*	-0.0025	-0.0034*	-0.0052	-0.0102	-0.0036
Temperature (°C)	0.0102***	0.0012	0.0023	0.0049	0.0070	0.0138***
Wind speed (m/h)	0.0288***	0.0082	0.0089	0.0089	-0.0127	0.0303***
Property FE	Yes	Yes	Yes	Yes	Yes	Yes
Prop. type × year FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel C: OLS						
Precipitation (mm)	-0.0027	-0.0059	-0.0065	-0.0133	0.0562	-0.0036
Temperature (°C)	0.0086	-0.0219*	-0.0234*	-0.0394	0.0307	0.0140
Wind speed (m/h)	0.0163	0.0099	0.0320	0.0100	-0.2625	-0.0003
Property FE	Yes	Yes	Yes	Yes	Yes	Yes
Prop. type × year FE	Yes	Yes	Yes	Yes	Yes	Yes
MSA × year FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel D: IV						
Precipitation (mm)	-0.0027	-0.0059	-0.0065	-0.0133	0.0562	-0.0036
Temperature (°C)	0.0086	-0.0229*	-0.0245*	-0.0407*	0.0337	0.0138
Wind speed (m/h)	0.0163	0.0095	0.0316	-0.0116	-0.2615	-0.0004
Property FE	Yes	Yes	Yes	Yes	Yes	Yes
Prop. type × year FE	Yes	Yes	Yes	Yes	Yes	Yes
MSA × year FE	Yes	Yes	Yes	Yes	Yes	Yes

Clustered (4-digit zip code) standard-errors used to determine signif.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The instruments for the IV specification are interactions between the main four wind directions (N/S/W/E) and 4-digit zip code.

Table A3: Estimates of Climate Covariates per Property Type (Table 5).

Dependent var. (in ln):	Market value (1)	Total Income (2)	Rental Income (3)	NOI (4)	CapEx (5)	Net Asset Value (6)
Panel A: Apartment						
Precipitation (mm)	0.0002	0.0010	0.0007	0.0015	-0.0607	-0.0057
Temperature (°C)	-0.0121	-0.0024	-0.0006	-0.0064	-0.3205***	-0.0113
Wind speed (m/h)	-0.0573	-0.0121	-0.0152	-0.0740	-0.3309	-0.1012**
Panel B: Commercial						
Precipitation (mm)	-0.0028	-0.0070	-0.0077	-0.0160	0.0589	-0.0024
Temperature (°C)	0.0155	-0.0234	-0.0255	-0.0415	0.1229	0.0202
Wind speed (m/h)	0.0600	0.0339	0.0610	0.0262	-0.1282	0.0664
Panel C: Commercial - Retail						
Precipitation (mm)	0.0054	-0.0057	-0.0160	-0.0187	-0.0031	0.0177
Temperature (°C)	-0.0151	-0.0215	-0.0280	-0.0234	0.2645	-0.0183
Wind speed (m/h)	0.0145	0.0658	0.1039	0.2069	0.5845	0.0496
Panel D: Commercial - Industrial						
Precipitation (mm)	-0.0089	-0.0206	-0.0122	-0.0344	0.2508**	-0.0056
Temperature (°C)	0.0548***	0.0145	0.0251	0.0220	0.0510	0.0552*
Wind speed (m/h)	0.0274	-0.0586	-0.0226	-0.0453	-0.8516	-0.0595
Panel E: Commercial - Office						
Precipitation (mm)	0.0032	0.0038	-0.0010	-0.0189	-0.1411	-0.0121
Temperature (°C)	0.0152	-0.0536	-0.0623*	-0.0944	0.2256	0.0222
Wind speed (m/h)	0.1157*	-0.0132	0.0536	-0.0106	-0.2409	0.1852**
Property FE	Yes	Yes	Yes	Yes	Yes	Yes
Prop. type × year FE[1]	Yes	Yes	Yes	Yes	Yes	Yes
MSA × year FE	Yes	Yes	Yes	Yes	Yes	Yes

Clustered (4-digit zip code) standard-errors used to determine signif.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The instruments for the IV specification are interactions between the main four wind directions (N/S/W/E) and 4-digit zip code.
[1] Only for panel B.

Table A4: Impact of $PM_{2.5}$ ($\mu g/m^3$) on Occupancy.

	OLS (1)	OLS (2)	OLS (3)	IV (4)
Variables				
$PM_{2.5}$ ($\mu g/m^3$)	0.0023***	-0.0000	-0.0009	-0.0029
	(0.0006)	(0.0007)	(0.0010)	(0.0022)
Fixed-effects				
Property FE	Yes	Yes	Yes	Yes
Prop. type × year FE		Yes	Yes	Yes
MSA × year FE			Yes	Yes
Fit statistics				
Observations	46,696	46,696	46,696	46,696
First Stage F-stat	-	-	-	19.1
R^2	0.975	0.977	0.980	0.980

Clustered (4 digit zip code) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: All specifications contain the climate controls of temperature (C°), precipitation (mm), and wind speed (m/h) and property type×year and MSA×year fixed effects. Market value is defined as either appraised (average over a year) or transaction price (if sold). Occupancy is the percentage of space that is leased to tenant and is logged. The instruments for the IV approach (column IV) are interactions between the main four wind directions (N/S/W/E) and 4-digit zip code.

Table A5: Impact of $PM_{2.5}$ ($\mu g/m^3$) on Occupancy Rate per Property Type, using the IV Approach Only.

	apartment (1)	commercial (2)	retail (3)	industrial (4)	office (5)
Variables					
$PM_{2.5}$ ($\mu g/m^3$)	-0.0022	-0.0012	0.0038	0.0048	-0.0045
	(0.0019)	(0.0026)	(0.0033)	(0.0052)	(0.0038)
R^2	0.768	0.562	0.795	0.509	0.605
Observations	13,420	33,276	7,474	13,531	12,271
First Stage F-stat	15.1	12.8	10.8	20.7	12.2
Property FE	Yes	Yes	Yes	Yes	Yes
Prop. type × year FE		Yes			
MSA × year FE	Yes	Yes	Yes	Yes	Yes

Clustered (4-digit zip code) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: All specifications contain the climate controls of temperature (C°), precipitation (mm), and wind speed (m/h) and property type×year and MSA×year fixed effects. Market value is defined as either appraised (average over a year) or transaction price (if sold). Occupancy is the percentage of space that is leased to tenant and is logged. All models use the IV approach, where the instruments are interactions between the main four wind directions (N/S/W/E) and 4-digit zip code.

A3 Alternative IV Approach

To compliment our main IV approach, we employ an alternative IV specification that exploits changes in the U.S. Clean Air Act standards in 2005. The act came into effect the following year and identified locations of high $PM_{2.5}$ concentrations—deemed "nonattainment areas". This designation allowed the EPA to enforce air quality improvement plans, withhold federal funding, and deny permits for infrastructure projects. Areas were designated to be in nonattainment if the *average* yearly $PM_{2.5}$ concentration levels were above $15\mu g/m^3$ during a three year measurement period between 2001 and 2003.[20] The nonattainment areas largely coincide with Metropolitan Statistical Areas or Commuting Zones, with some adjustments made to reflect the fact that pollution can spill over to neighboring areas.[21]

As a first pass, one may be inclined to simply instrument $PM_{2.5}$ with a dummy variable for nonattainment under the assumption that nonattainment areas experience an exogenous shock to $PM_{2.5}$. In other words, isolate the variation in $PM_{2.5}$ caused by the policy to causally identify the relationship between changes in $PM_{2.5}$ and building level economic indicators. However, extant literature shows that when identifying the effect of the policy on $PM_{2.5}$ in a difference-in-difference setting (DiD), the parallel trends assumption is violated. More specifically, heavily polluted areas see larger reductions in $PM_{2.5}$-levels even without being designated as nonattainment (Currie et al., 2020; Sager and Singer, 2022). As a result, DiD can overestimate the impact of nonattainment on $PM_{2.5}$ concentration levels without further caution.

To circumvent this issue, we follow Sager and Singer (2022) and employ a matched DiD methodology for the first stage of our IV regression. The matching approach centers on two observations. First, some properties in the data were exposed to high yearly $PM_{2.5}$

[20] Technically, there were two thresholds. If the three year average of the 98^{th} percentile daily $PM_{2.5}$ concentrations was above $65\mu g/m^3$, the area was also designated as being in nonattainmnet, whichever came first. However, as Sager and Singer (2022) shows, the yearly average threshold was the leading indicator; thus, similarly to Sager and Singer (2022), we focus on this threshold throughout the paper.

[21] The shapefiles are readily available from the EPA green book.

concentration levels, sometimes even in excess of $15\mu g/m^3$ during 2001 and 2003, but were contained in MSAs/CZs that were not designated as nonattainment. Second, some properties in the nonattainment areas did not experience high levels of $\text{PM}_{2.5}$ even though the larger MSA/CZ they were contained in did on average. In other words, on the *property level*, there is overlap in the average $\text{PM}_{2.5}$ concentration levels in 2001 – 2003, even though only some are designated as being in nonattainment (based on the larger area average). We exploit this feature in our matching exercise where every property in a nonattainment area is matched to a property in an attainment area on the basis of the 2001 – 2003 average $\text{PM}_{2.5}$ concentration levels. Nonattainment areas where the average $\text{PM}_{2.5}$ concentration levels in 2001 – 2003 (designated pre-$\text{PM}_{2.5}$ levels going forward) was higher than the highest pre-$\text{PM}_{2.5}$ levels found for properties in the attainment areas. This results in a control and treatment group with relatively similar pre-$\text{PM}_{2.5}$ levels. Details of the matching exercise follow in the next section.

After completing the filtering and matching, we run the following regressions (2SLS);

$$\ln Y_{ipt} = \beta PM_{it} + X'_{it}\gamma + \alpha_{pt} + \eta_i + \epsilon_{ipt}, \tag{A1}$$

where PM are the fitted values of property unique $\text{PM}_{2.5}$ concentration levels from a first stage which is provided by;

$$PM_{ipt} = \lambda NA_{it} + X'_{it}\omega + \nu_{pt} + \phi_i + \varepsilon_{ipt}, \tag{A2}$$

where NA is a (1/0) dummy for properties located in nonattainment areas *after* the designation took place. In both Equations A1 and A2 we include the full set of controls used in main specification. The matching exercise generates a sample where half of the observations are treated and half are not, but both halves have comparable pre-$\text{PM}_{2.5}$-levels. Note that we omit the MSA-by-year fixed effects in both equations, as they are highly collinear with the nonattainment designation. In our main method (Section 3.2) the impact of nonattainment designation is therefore absorbed by the MSA-by-year fixed effects.

Finally, it is important to describe the data structure for this setup. First, we only consider data between 2001 – 2003, and data between 2006 – 2008. The main reason to look at such a short window only is that regulations changed over time, weakening the instrument. For example, a rule change in 2006 resulted in a few additional counties being designated in nonattainment in 2012. In addition, the first states to appeal the nonattainment status was in 2011. Even more stringent regulations came into effect in April of 2015 (reducing the average pre-$\text{PM}_{2.5}$ levels to $12\mu g/m^3$). We do not consider 2009 and 2010 due to the large impact of the Great Financial Crisis had on CRE in this period.

A4 Propensity Score Matching Details

We perform propensity score matching (PSM) in order to match properties in attainment and nonattainment (NA). We use a logit model with nonattainment (1/0) on the left-hand side:

$$NA_i = \alpha + \tau \text{pre-PM}_i + \epsilon_i \tag{A3}$$

where pre-PM are average annual $\text{PM}_{2.5}$ levels in 2001 and 2003 for property i. The matching is done at the individual property level; hence, the time subscript t is dropped. Note that nonattainment status does not vary over the time period considered. The results are provided in Table A6. Reassuringly, we see that higher pre-$\text{PM}_{2.5}$ levels are (significantly) associated with properties being in nonattainment areas.

[Place Table A6 about here]

Next, we use the coefficients to match properties in our control group (i.e. properties in attainement areas) with properties in the treated group (i.e. properties in nonattainment areas). In Table A7, we provide the averages of our variables of interest before and after matching.

[Place Table A7 about here]

Comparing the full sample we find that pre-$PM_{2.5}$ levels are lower on average for properties in attainment areas compared to those in nonattainment areas, in line with the results in Table A6. After the matching we find that the sample is balanced, which is a result of matching 1-on-1 without replacement. Matched properties have very similar pre-pre-$PM_{2.5}$ concentration levels compared to those in nonattainment areas. More specifically the pre-$PM_{2.5}$ levels is 13.2 (13.3) μg$/m^3$ for properties in our control (treated) group.

Table A6: Results from Propensity Score Matching

Dependent var.:	nonattainment (1)
Pre-$PM_{2.5}$ levels	0.173***
	(0.060)
Constant	-3.481***
	(0.799)
Observations	222
Log Likelihood	-111.434
Akaike Inf. Crit.	226.867

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

Note: Pre-$PM_{2.5}$ levels are average yearly $PM_{2.5}$ between 2001 – 2003. Dependent variable is nonattainment status (0/1), model estimated via logit.

Table A7: Mean of Match Variables Before and After Employing Propensity Score Matching

Sample	Status	Pre-$PM_{2.5}$ levels (1)	Observations (2)
Full sample	nonattainment	13.345	288
Full sample	attainment	11.944	1,044
After PSM	attainment	13.345	288

Note: Pre-$PM_{2.5}$ levels are average yearly $PM_{2.5}$ between 2001 – 2003. PSM is propensity score matching, based on Table A6. After matching, the number of observations is equal, as we match one-to-one without replacement. We match attainment and nonattainement properties only based on Pre-$PM_{2.5}$ levels.