Up in the air: How air pollution depresses housing prices in Paris

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Abstract

Air quality is a growing concern in large urban centres, yet the literature offers limited consensus on its impact on housing prices, particularly in France. This article provides new evidence that two pollutants, PM_{10} and NO_2, have a significant and negative effect on real estate prices in Paris and its inner suburbs. To establish causality, we employ wind patterns (speed and direction) as instrumental variable, isolating the causal impact of air pollution on housing prices.

JEL Classification: C26, Q51, Q53, R31.

Keywords: Air pollution, Housing prices, Hedonic regression method, Instrumental variable.

1 Introduction

The influence of air pollution on housing prices remains unclear in European cities despite evidence from studies conducted in Asia, particularly in China (Amini et al., 2022; Cai et al., 2024; Feng et al., 2024). In France, limited empirical research has yielded inconclusive results (Brécard et al., 2018; Saulnier, 2004). Furthermore, the causal relationship between air pollution and housing prices has not been firmly established.

This study addresses this gap by focusing on Paris and its inner suburbs between 2018 and 2023. The distinct demographic, economic, climatic, and geographic conditions differentiate Paris from cities like Beijing, where much of the previous research has been conducted. These contextual differences may lead to variations in how air quality impacts real estate markets. Paris's compact footprint concentrates roughly 20 000 inhabitants per km², about fourteen times the density of Beijing's built-up area. A statutory height cap of roughly 31 m keeps Paris's skyline uniformly low. Together with the city's flat, low-altitude basin and temperate oceanic climate, create markedly different pollution-dispersion and housing-market dynamics from those of the sprawling, high-rise, heavy-industrial megacities that dominate the existing literature.

Our analysis focuses on two key air pollutants: Particulate Matter (PM_{10}) and Nitrogen Dioxide (NO_2). To establish causality, we employ an instrumental variable approach, using wind patterns as an exogenous predictor of the spatial distribution of pollutants over time. Our findings indicate that variations in pollution levels significantly influence housing prices in the Greater Paris area.

In summary, this study fills a gap in the literature by applying a causal inference framework to a European context, offering insights for urban planners and policymakers by highlighting the economic costs associated with air pollution. Finally, the results reveal spatial inequalities in real estate induced by uneven pollution distribution that urban and environmental regulations could mitigate.

2 Data

Our analysis relies on three main datasets covering real estate transactions, air quality, and meteorological conditions in the Greater Paris area.

First, we use real estate transaction data from the *Demandes de valeurs foncieres (DVF) database*, provided by the French Ministry of Economy and Finance. This dataset includes sale prices, property characteristics, and geographic locations from 2018 to 2023. We compute the dependent variable as the average price per square meter per week at the municipal level.

Second, we obtain air pollution data from Airparif, covering daily concentrations of PM10 and NO2 across Paris and its inner suburbs from 2014 to 2018. We aggregate these data at the weekly municipal level to serve as our key explanatory variables. Because the pollution series ends in 2018 while the price series begins in 2018, observations in year t are matched to pollution measured in t–4; ; the full rationale for this four-year lag is provided in Supplemental Material (9.4). The spatial distribution of these variables can be found in the Supplementary Material section (9.5).

Third, we use meteorological data from the French weather monitoring system, which provides daily records on wind speed and direction in Paris. These variables, averaged weekly, serve as instruments for pollution dispersion.

Additionally, we incorporate socioeconomic controls, including median income and population from INSEE censuses, as well as school density from the French Ministry of Education.

3 Empirical Strategy

3.1 Empirical Specification

Following the framework developed by Freeman (1979), we estimate the following hedonic model to assess the existence of a significant relationship between pollution concentration and housing prices:

$$\ln \mathrm{HP}_{m,t} \quad = \quad \gamma \ln \mathrm{PC}_{m,t-4} + \Gamma \mathbf{X'}_{m,\mu} + \lambda_d + \lambda_y + \epsilon_{m,t} \quad (1)$$

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In this equation, $\mathrm{HP}_{m,t}$ stands for the weekly average square meter housing price in municipality m in week t. $\mathrm{PC}_{m,t-4}$ denotes the explanatory variable and is the mean of the concentration of PM_{10} or NO_2 in municipality m in week t. The vector of control variables, $\mathbf{X'}_{m,\mu}$, contains the logarithm of the median income, the logarithm of the population, and the logarithm of the number of schools in municipality m in month μ. Finally, λ_d and λ_y are region (akin to a french "*département*") and year fixed effects.

3.2 Endogeneity Concerns

The estimated effect of pollutant concentration on housing prices with the specification presented in Equation (1) may be biased for several reasons, including omitted explanatory variables and time-persistent reverse causality.

We adopt an instrumentation strategy to control for those potential endogeneity problems and infer causality. Environmental studies disentangled two channels through which wind impacts pollution concentration levels. On one hand, the literature shows that the more the wind blows, the more pollution will be pushed away from its source of emission (Yang et al., 2017; Zhang et al., 2018). On the other hand, it shows that the direction of the wind concentrates pollution in another location (Zabrocki et al., 2022).

Our instrument consists of the average wind speed over a week t (WS_t) weighted by a regional component. We distinguish four regions, denoted r ($r \in R$), including Paris, Seine-Saint-Denis, Hauts-de-Seine, and Val-de-Marne (cf Figures 2). To identify these regions, we use a dummy variable equal to one if a municipality m is located in a region r, denoted $\mathrm{D}_{r(m)}$, and zero otherwise. The instrument reads as follows:

$$\mathrm{WPatterns}_{r(m),t} \quad = \quad \mathrm{WS}_t \sum_{r \in R} \mathrm{D}_{r(m)} \mathrm{w}_{r,t} \tag{2}$$

First, we posit that pollution stays in Paris only when the average wind speed over a week t is lower than 18km/h. Therefore, when $r =$ Paris, the regional weight – denoted $\mathrm{w}_{r,t}$ – is given by the share of days over a week when the wind speed is lower than 18km/h.

Second, following the work of Zabrocki et al. (2022), we consider that the pollution is pushed outside Paris when the wind speed is larger than 18km/h. Here, we exploit the fact that the regions surrounding Paris align almost perfectly with the cardinal directions of a 360-degree compass rose (see Figures 2 and 3). Therefore, when $r \neq$ Paris, the regional weight is given by the share of days over a week when the wind is blowing from Paris to region r.

This instrumental variable, $\mathrm{WPatterns}_{r(m),t}$, serves as an exogenous predictor of pollution, capturing natural variations in the direction and speed of the wind driven by meteorological conditions.

4 Results

Table 1 presents our results estimated with a two-stage least squares estimator. The dependent variable is the average price per square meter in the municipality m during the week t. In columns (1), the independent variable is the weekly average of the concentration $PM_{10(m,t-4)}$ per municipality, influenced by the wind patterns. Column (2) takes as explanatory variables the weekly average of $NO_{2(m,t-4)}$ concentration, also at the municipality level. This table excludes the inner Paris for identification concerns that are developed in the Supplementary material (Table of Results).

We find a significant and negative effect of pollutant concentration on housing prices for both PM_{10} and NO_2. More precisely, column (1) indicates that an increase of 10% in the average concentration of PM_{10} decreases the average housing price per square meter by 1.28%. This result is significant at the 1% level. This is consistent with the findings of Zhang et al. (2022), who also noticed a negative significant relationship between PM_{10} concentration and housing prices in China. The results for NO_2, presented in column (2), highlight a stronger negative impact on property values compared to PM_{10}. A 10% increase in the levels of NO_2 leads to a 1.65% decrease in the average price per square meter. This result is also significant at the 1% level. Amini et al. (2022) published results that were lower in magnitude but highlighted the same evidence for Tehran in Iran. The difference in magnitude could be due to a difference in the methods used or in the geographical and economic contexts of the studies. However, we believe that combining an instrumentation strategy with a fixed effects model enables us to infer results that are closer in magnitude to the real impact of air quality on housing prices.

Finally, the first-stage coefficients exhibit the expected negative sign, confirming the expectation that wind patterns adequately predict the two air pollutants we analyse in this article, PM_{10} and NO_2.

Table 1: Two-Stage Least Squares Regression Results on the Impact of Air Pollutant Concentrations (PM_{10}, NO_2) on Housing Prices in the Greater Paris Area

Estimation Results	(1)	(2)
$\ln PM_{10(m,t-4)}$	-0.128***	
	(0.043)	
$\ln NO_{2(m,t-4)}$		-0.165***
		(0.039)
ln Population	0.177***	0.183***
	(0.033)	(0.033)
ln Median income	0.785***	0.784***
	(0.105)	(0.109)
ln Nr. of Schools	0.031	0.032
	(0.021)	(0.022)
First-Stage Results		
$\ln \mathrm{WPatterns}_{r(m),t}$	-0.149***	-0.116***
	(0.009)	(0.007)
Obs.	4,748	4,748
First-Stage F Stat.	75.63	58.37
Fixed effects	region, year	region, year

Notes: Regression results are based on a two-stage least squares regression model with fixed effects at the region and year level. Robust standard errors are reported in parentheses. The dependent variable is the (log) mean housing price in municipality m at week t, and the independent variables are the pollution concentration levels in PM_{10} (Column 1) and NO_2 (Column 2). ***, ** and * respectively denote significance at the 1%, 5% and 10% level.

5 Conclusion

Our results confirm that higher concentrations of PM_{10} and NO_2 are associated with lower properties values in the Parisian suburbs, highlighting the economic cost of air pollution. By leveraging exogenous wind variations as an instrumental variable, this study provides causal evidence of this relationship in a French context. Further discussions on the limits of this work can be found in the Supplemental Material section.

6 Disclosure of interest

We would like to report that there are no competing interests to declare.

7 Funding Declaration

We would like to report that no funding was received to carry out this research.

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9 Supplementary Material

9.1 Data description

- Real estate database: The dataset contains information about the date and price of each transaction, the address of the property, and the area of the property in square meters. We use sale prices to build our dependent variable, which is expressed as the average price per square meter per week for each municipality of the sample between 2018 and 2023.
- Air pollution database: This dataset provides information on the concentrations of PM10 and NO2 per day across the different arrondissements of Paris and municipalities of the inner suburbs between January 2014 and April 2018. We express the average concentration of each pollutant per week and per municipality between 2014 and 2018. These indices then serve as our explanatory variables.
- Daily weather database: These data come from a wind monitoring database in Paris's 14th arrondissement. We compute the average wind direction and wind speed per day between 2014 and 2018 to instrument pollutant concentration. Our instrumentation strategy thus aims to capture the impact of wind patterns on pollution concentration levels across space and over time.

9.2 Table of Results

OLS Results

To gauge the magnitude and direction of potential endogeneity, Online Appendix Table 2 reports ordinary-least-squares result. The OLS coefficients are positive (0.037 for PM_{10}; 0.082 for NO_2), whereas the IV estimates are negative and substantially larger in absolute value (–0.128 and –0.165, respectively). This stark divergence indicates considerable upward bias in the naïve regression, consistent with spatial sorting whereby amenity-rich and therefore more expensive locations also experience higher traffic-related pollution. By exploiting exogenous variation in wind patterns, our IV strategy removes this bias and reveals a sizeable negative causal effect of air pollution on housing prices.

Table 2: Ordinary Least Squares Regression Results on the Impact of Air Pollutant Concentrations (PM_{10}, NO_2) on Housing Prices in the Greater Paris Area

Estimation Results	(1)	(2)
$\ln PM_{10(m,t-4)}$	0.037***	
	(0.017)	
$\ln NO_{2(m,t-4)}$		0.082***
		(0.021)
ln Population	0.174***	0.171***
	(0.011)	(0.008)
ln Median income	0.780***	0.779***
	(0.033)	(0.033)
ln Nr. of Schools	0.030***	0.030***
	(0.008)	(0.008)
Obs.	4,748	4,748
Fixed effects	region, year	region, year
R^2	0.301	0.303

Notes: Regression results are based on an ordinary least squares regression model with fixed effects at the region and year level. Robust standard errors are reported in parentheses. The dependent variable is the (log) mean housing price in municipality m at week t. Columns (1) presents the results for PM_{10} concentration, whereas column (2) shows the results for NO_2 concentration. ***, ** and * respectively denote significance at the 1%, 5% and 10% level.

9.3 Sample Restriction

Columns (1) and (2) of Table 3 reveal no significant relationship between air quality and housing prices in Paris and its suburbs during the study period. This could be explained by a very rigid housing market in Paris. Rigidity, which can be characterized by the attractiveness and the housing regulation of inner Paris, makes isolating the impact of pollutant concentration on housing prices complex. This phenomenon has been shown in Manhattan by Glaeser et al. (2005). Thus, we replicate our analysis in columns (3) and (4) for a subsample that excludes the inner Paris, which is Table 1 presented in the main text.

Table 3: Two-Stage Least Squares Regression Results on the Impact of Air Pollutant Concentrations (PM_{10}, NO_2) on Housing Prices in the Greater Paris Area

	Whole Sample		Paris Excluded	
Estimation Results	(1)	(2)	(3)	(4)
$\ln PM_{10(m,t-4)}$	-0.179		-0.128***	
	(0.161)		(0.043)	
$\ln NO_{2(m,t-4)}$		-0.258		-0.165***
		(0.292)		(0.039)
ln Population	0.092	0.099	0.177***	0.183***
	(0.068)	(0.062)	(0.033)	(0.033)
ln Median income	0.777	0.784	0.785***	0.784***
	(0.091)	(0.099)	(0.105)	(0.109)
ln Nr. of Schools	0.004	0.004	0.031	0.032
	(0.028)	(0.030)	(0.021)	(0.022)
First-Stage Results				
$\ln WPatterns_{r(m),t}$	-0.061***	-0.042***	-0.149***	-0.116***
	(0.007)	(0.006)	(0.009)	(0.007)
Obs.	6,694	6,694	4,748	4,748
First-Stage F Stat.	75.44	82.91	75.63	58.37
Fixed effects	region, year	region, year	region, year	region, year

Notes: Regression results are based on a two-stage least squares regression model with fixed effects at the region and year level. Robust standard errors are reported in parentheses. The dependent variable is the (log) mean housing price in municipality m at week t. Columns (1) and (2) are based on the whole sample of municipalities in the Greater Paris area, whereas columns (3) and (4) are based on municipalities located in the three surrounding regions (Seine-Saint-Denis, Hauts-de-Seine and Val-de-Marne). ***, ** and * respectively denote significance at the 1%, 5% and 10% level.

9.4 Discussion

Our analysis opens the following points for discussion. First, we assume that air pollution in the Greater Paris area is mainly emitted in inner Paris. However, looking at the spatial distribution of PM_{10} and NO_2 (Figures 2 and 3) reveals high levels of concentration in the surrounding regions, which may result from local emissions rather than pollution carried by the wind.

Second, we introduced a four-year time lag on explanatory variables with respect to real estate prices (Data on real estate are available from 2018, while data on pollutants are available from 2014 to 2018). Doing so, we postulate that the real estate market does not adjust immediately to air pollution variations, which aligns with Kakoui et al. (2023). While we are confident that this lag is salient as the real estate market does not adjust straight away to air quality variations, the duration of this lag could be further explored.

Third, recent studies have used spatial correlation models to eliminate the correlation between geographically closed units. These models, such as the Spatial Durbin Model, intend to consider spatial correlation of prices. Future research could implement such a model for the Greater Paris area as done by Miluch and Kopczewska (2024).

Lastly, future work that spans a longer period could incorporate higher-frequency data on median age, healthcare accessibility, and housing stock to explore long-run socioeconomic channels beyond the scope of the present short-term analysis.

9.5 Maps

The map below (Figure 1) shows the spatial distribution of the average price per square meter in each municipality over the study period. The darker the colour, the higher the housing prices. Besides noticing higher prices within Paris, we also see that the Hauts-de-Seine which is located in the west of Paris, exhibits, on average, higher real estate prices than the two other regions located in the east of Paris.

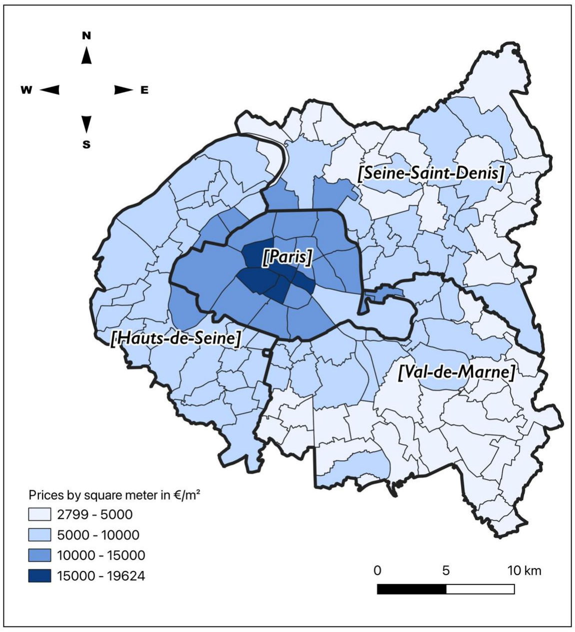

Figure 1: Average price per square meter in municipalities of the Greater Paris area

The two maps below (Figures 2, 3) represent the average concentration of PM_{10} and NO_2 per municipality during the study period. Pollutant concentrations follow a wind corridor, with the highest concentration following a west-to-northeast vector. The fact that the wind mostly blows the PM_{10} and the NO_2 particles towards the northeast of Paris has been shown by Zabrocki et al. (2022).

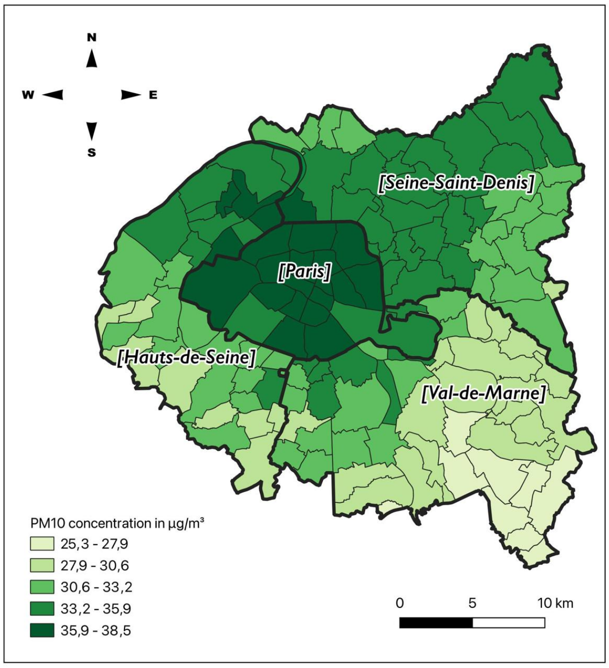

Figure 2: Spatial distribution of PM_{10} levels in municipalities of the Greater Paris area

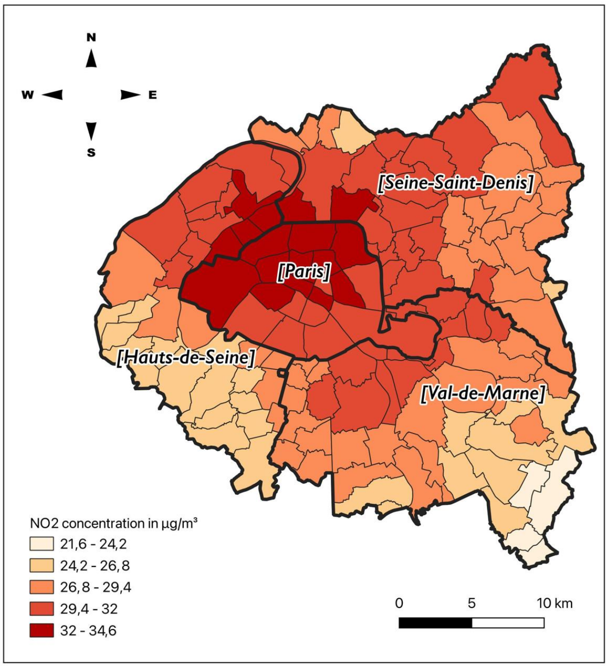

Figure 3: Spatial distribution of NO_2 levels in municipalities of the Greater Paris area