

THE IMPACT OF AIR POLLUTION  
ON THE HOUSING MARKET:  
THE CASE OF MADRID

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# THE IMPACT OF AIR POLLUTION ON THE HOUSING MARKET: THE CASE OF MADRID <sup>(\*)</sup>

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## Abstract

This paper estimates the causal impact of air pollution on housing prices in Madrid, a large European city with relatively high and persistent nitrogen dioxide (NO<sub>2</sub>) concentrations and a home ownership rate of around 70%. Using location-specific data on pollution levels and the universe of housing transactions, my estimation controls for house and neighborhood characteristics, year and neighborhood fixed effects, a bad weather index and a set of time-varying neighborhood characteristics. To address endogeneity concerns, I make use of quasi-experimental variation in nitrogen dioxide levels resulting from temperature inversions. The results suggest that a 10% increase in air pollution reduces housing prices by 0.65% (around €1,327 for the average house). This effect is robust to alternative measures of air pollution, different bad weather indices and the inclusion of seasonality dummies, and is highly non-linear, being larger for higher levels of pollution.

**Keywords:** air pollution, housing market, valuation of environmental effects.

**JEL classification:** Q53, R31, Q51.

## Resumen

En este documento se estima el efecto causal de la contaminación del aire sobre los precios de la vivienda en Madrid, una gran ciudad europea caracterizada por niveles relativamente elevados y persistentes de dióxido de nitrógeno ( $\text{NO}_2$ ) y tasas de propiedad cercanas al 70 %. A partir de datos georreferenciados sobre niveles de contaminación y el universo de las transacciones inmobiliarias, la estimación controla según las características de la vivienda y del vecindario, los efectos fijos de año y vecindario, un índice de condiciones meteorológicas adversas y un conjunto de características del vecindario que varían en el tiempo. Para abordar los problemas de endogeneidad, se aprovecha la variación cuasiexperimental en los niveles de  $\text{NO}_2$  generada por las inversiones térmicas. Los resultados sugieren que un aumento del 10 % en la contaminación del aire reduce los precios de la vivienda en un 0,65 % (aproximadamente 1.327 euros para la vivienda media). Este efecto es robusto ante las medidas alternativas de contaminación del aire, los distintos índices de condiciones meteorológicas adversas y la inclusión de variables de estacionalidad; asimismo, presenta una marcada no linealidad, siendo mayor para los niveles más elevados de contaminación.

**Palabras clave:** contaminación del aire, mercado de la vivienda, valoración de efectos medioambientales.

**Códigos JEL:** Q53, R31, Q51.

# 1 Introduction

Air pollution has important impacts for individuals' health, subsequently affecting economic outcomes such as increasing public health expenditure and lowering labor productivity.<sup>1</sup> As a result, national and international institutions have implemented more stringent regulations on air pollution in recent decades. Moreover, surveys in Europe and Spain show increased awareness about the harmfulness of air pollution, and concerns rise with local pollution levels (Commission, 2019; Dons et al., 2018; Forsberg et al., 1997). Evidence also shows that air pollution influences individuals' key choices such as where to live, making it reasonable to expect air pollution to affect housing prices.<sup>2</sup>

This paper estimates how air pollution is capitalized into housing prices in Madrid, a major European city with relatively high air pollution and high ownership rates (70%).<sup>3</sup> Thus, the paper does not evaluate environmental policies such as Madrid Central (for this, see Galdon-Sanchez et al., 2023). My empirical analysis combines housing price data from the Land Registry, which includes the exact location of each transaction, with air pollution data from the Madrid Council. In my estimation, I control for housing characteristics, year and neighborhood fixed effects, a bad weather index, and a set of time-varying neighborhood characteristics. Nevertheless, methodological challenges remain, for instance, improvements in public transport or individuals' preferences for living in denser areas to reduce commuting time could simultaneously influence both air pollution and housing prices. To address these concerns, I use an instrumental variable that exploits the variation in  $NO_2$  pollutants generated by thermal inversions, which trap pollutants close to the ground creating temporary increases in air pollution.<sup>4</sup> This

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<sup>1</sup>Guarnieri and Balmes (2014) and Chay and Greenstone (2003) show how air pollution increases the probability of asthma, Nyberg et al. (2000) focus on the effect on lung cancer and Deryugina et al. (2019) and Chay and Greenstone (2003) on mortality. Holub et al. (2020) and Hanna and Oliva (2015) find increases in labor productivity when air quality improves.

<sup>2</sup>Mikula and Pytliková (2021) find a 24% reduction in emigration after improvements in air pollution in the Czech Republic and Chen et al. (2022) find that a 10% increase in air pollution reduces local population through migration by 2.8% in China, using thermal inversion as an instrumental variable for air pollution.

<sup>3</sup>Although Madrid's air pollution may not rank among the most severe globally, it is a city with persistently high pollution levels compared to other European capitals (or compared to other large cities in the developed world). Indeed, Madrid registers the highest mortality burden attributable to nitrogen dioxide ( $NO_2$ ) among European cities (Khomenko et al., 2021). The homeownership rate in Madrid stands at approximately 70% in 2021 (National Statistic Institute, 2021), significantly surpassing that of other major European cities such as 47% in London (Census data, 2021), 33% in Paris (INSEE, 2021), and 15% in Berlin (Statistik Berlin Branderburg, 2022).

<sup>4</sup> $NO_2$  is used as a proxy for overall urban air pollution. In dense urban environments,  $NO_2$  is highly correlated with other combustion-related pollutants and is widely considered a marker of traffic-related

approach has been used by a number of recent papers to study the causal effect of pollution on infant mortality (Arceo et al., 2016), on mental health (Chen et al., 2018), on labor productivity (Fu et al., 2021), on migration (Chen et al., 2022) and on housing prices (Cai et al., 2024). My estimates suggest that a 10% increase in air pollution leads to a 0.65% decrease in housing prices, around €1,327 for the average house. These results are robust to alternative measures of air pollution and bad weather indices, and the inclusion of additional controls for seasonality of the housing market. Similar to Amini et al. (2022) and Chay and Greenstone (2005), I show that air pollution is highly non-linear, being larger for higher levels of pollution. Furthermore, housing prices in high-income and high-educated neighborhoods and in those with relatively more children, capitalize air pollution more, as in Cai et al. (2024) and Zheng et al. (2014). Finally, offering insights into the market mechanisms, I find that high levels of air pollution reduce the number of transactions in a neighborhood. This is consistent with findings in Lopez and Tzur-Ilan (2023), who show that landlords tend to withdraw properties from the market or delay posting new listings on days with high pollution levels.

My paper contributes to recent literature on the causal effects of air pollution on housing prices, most of which use changes in environmental regulation to instrument for changes in air pollution. For instance, Bento et al. (2015) exploit Amendments to the Clean Air Act in the U.S., Tang (2021) examines London's congestion charge and Gruhl et al. (2022) study low-emission zones in Germany. Finally, Amini et al. (2022) examine the housing market in Tehran by exploiting an exogenous rise in air pollution triggered by sanctions on gasoline imports, which forced Iran to produce low-quality gasoline. All studies find that air pollution negatively affects housing prices. However, policy-induced changes in air quality may also lead to reductions in traffic and noise, as well as shifts in local economic conditions (i.e., income and employment) which are also likely to affect housing prices. My estimation using thermal inversion on the other hand enables me to isolate the pure effect of air pollution.<sup>5</sup> Furthermore, there are two reasons why relatively high ownership rates in Madrid (70%) make the context

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air pollution. Accordingly, my estimates capture the effect of short-run fluctuations in overall pollution exposure rather than a pollutant-specific dose-response relationship. This approach aligns with standard practice in the literature, including Lopez and Tzur-Ilan, 2023; Cai et al., 2024; Deryugina et al., 2019 and Chay and Greenstone, 2003, among others.

<sup>5</sup>Other studies have exploited alternative sources of exogenous variation, including long-range transported emissions (Nam et al., 2022; Zheng et al., 2014; Bayer et al., 2009), as well as wind patterns and emissions from coal-fired power plants (Freeman et al., 2019).

of my study particularly interesting: (i) Housing represents a substantial share of aggregate household wealth which will thus be directly affected by any pollution-induced changes in house prices. (ii) Evidence shows that effects of air pollution are generally more pronounced in owner-occupied housing markets than in rental markets (Amini et al., 2022; Gruhl et al., 2022; Bento et al., 2015).<sup>6</sup>

Madrid being a large city in a high-income country differentiates the current paper from Cai et al. (2024) who also use thermal inversion as an instrument to analyze the effect of air pollution on housing prices in Beijing. Furthermore, the authors only consider the contemporaneous effect of the quarterly average in  $PM_{2.5}$ <sup>7</sup> on housing prices while I follow Amini et al. (2022) and consider three, six, and nine months averages to account for the time-intensity of purchasing a house.<sup>8</sup> My findings show that buyers respond to persistent pollution: a 10% increase in  $NO_2$  over the last three, six, and nine months decreases housing prices by 0.65%, 0.99% and 1.25%, respectively.

The remainder of this paper is organized as follows: The next section presents the data, and in Section 3 I present the methodology. Section 4 discusses the results and provides robustness checks, and Section 5 concludes.

## 2 Data

Madrid, Spain's capital, has a population of around 3.2 million, representing 7% of Spain's total population. The city is divided into 131 neighborhoods, each with an average population of 24,400, grouped into 21 different districts.<sup>9</sup> Although, districts have certain autonomy regarding municipal affairs, I observe significant variation in key variables, such as household income, across neighborhoods within the same district. This is why I conduct my analysis at the neighborhood rather

<sup>6</sup>For instance, Lopez and Tzur-Ilan (2023) find that the size of the effect on house prices is more than three times the effect size observed with rent. They suggest that age-related factors-rather than expectations about the duration of exposure to air pollution-may help explain this difference. In Madrid homeowners are on average 14 years older (National Statistic Institute, 2017) compared to renters (average age 44) suggesting an additional reason for the differential effects for renters and buyers.

<sup>7</sup> $PM_{2.5}$  stands for particulate matter with 2.5 microns or less in diameter. It is one of the main components of Spain's national air pollution index.

<sup>8</sup>In fact, in 2017, 50% of the buyers took at least four months to buy a house in Spain and 34% between four and twelve months (Fotocasa, 2017).

<sup>9</sup>The term Madrid refers to an autonomous community, as well as a city. The difference relies in the administrative structure: the autonomous community consists on 179 municipalities, and the main one is the city of Madrid. Districts can process and solve applications for urban planning licenses or maintain park and garden facilities and services assigned to the district (Council of Madrid: Organic Regulation, 6/2021). Figure A.1 in the Appendix displays the distribution of neighborhoods and districts across Madrid

than the district level.<sup>10</sup>

My main dataset combines information on housing prices and characteristics from Land Registry data with data on air pollution and neighborhood characteristics from the Council of Madrid which I complement with additional information on weather and thermal inversion from the Copernicus website.

## 2.1 Housing prices and characteristics

Data on housing prices and characteristics (Registrars of Property of Spain, 2014-2020) encompass all property transactions in Madrid. Key property characteristics used in this analysis include sales price, transaction date, built square meters, location, property type (detached, semi-detached, flat with or without annexes), and whether the property is new or second-hand. Additional transaction details, such as ownership type (natural or legal person), price classification (open or regulated market), and the method of ownership acquisition (donation, inheritance, or transaction), are also considered. If there is missing data in one of these variables, I eliminate the transaction. I also drop transactions that have the same date or same cadastral reference but record different values for key variables of interest such as price or square meter given that I cannot tell which is the true value. This cleaning process removes approximately 10% of the observations. I supplement my data with year of construction from Moral-Carcedo (2024). Finally, following Amini et al. (2022), I trim the first and the last 0.5 percentile of price per square meter to avoid outliers. Note that all transactions are geocoded using cadastral references, which allows me to assign each transaction to a specific neighborhood. I deflate housing prices using the Consumer Price Index (CPI) (National Statistic Institute, 2014-2020), with a reference date of February 2020.

## 2.2 Air pollution data

Hourly air quality data (Council of Madrid, 2014-2020a) come from the monitoring network of the city of Madrid, which consists of 24 monitors that measure the concentration of  $NO_2$  (Figure A.1 in Appendix): 9 are traffic monitors close to a main road, 12 are urban monitors used to measure the general population's exposure to pollutants, and 3 are suburban monitors located on the outskirts of

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<sup>10</sup>Within the Salamanca district, the neighborhood Recoletos and Fuente del Berro have average household incomes of 80,000 and 42,000 respectively. The number of neighborhoods is not constant during the period of study. Three new neighborhoods were created: (i) Ensanche de Vallecas from district 18 (Villa de Vallecas), (ii) El Cañaveral, and (iii) Valderribas from district 19 (Vicalvaro) in 2017. Transactions are assigned to neighborhoods based on the relevant yearly classification. As a robustness check, I eliminate districts 18 and 19 to ensure that results do not change.

the city.<sup>11</sup> From the hourly records, I compute the daily median for each monitor to minimize the impact of potential outliers. To assign air pollution levels to each neighborhood, I use the so-called “kriging” method, a spatial interpolation technique that estimates values for unsampled locations based on nearby sampled points, considering spatial correlation and variability (Anselin and Le Gallo, 2006).<sup>12</sup> After applying kriging interpolation, I obtain a continuous surface of pollutant concentrations across the area of study (1,200 spatial points), allowing me to assign pollution levels to specific neighborhoods based on their geographic location. For each neighborhood, I select the point closest to its centroid, and then I compute monthly mean pollution levels and finally calculate the mean over the preceding three months. During my study period, the low emission zone “Madrid Central” was introduced in the city centre.<sup>13</sup> This area covers less than 1% of the city’s surface and hosts around 4.2% of Madrid’s population. The analysis in this paper does not aim to evaluate the impact of this specific policy measure. Instead, robustness checks excluding the central district from late 2018 onward are used to verify that the estimated elasticities between air pollution and housing prices are not driven by this intervention.<sup>14</sup>

## 2.3 Thermal inversion and weather variables

Thermal inversion is a meteorological phenomenon, where the typical decrease in air temperature with increasing altitude is inverted, resulting in a layer of warm air forming above a layer of cooler air near the ground, see Figure A.6. This can cause pollutants and moisture to become trapped near the ground, leading to an increase in air pollution. Thermal inversions are more frequent in winter,

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<sup>11</sup>I select  $NO_2$  as a proxy of air pollution for two main reasons: i) it is one of the main pollutants in the national index and other pollutants in the index are measured at fewer monitors:  $PM_{10}$  and  $O_3$  at 13 monitors,  $PM_{2.5}$  at 8 monitors and  $SO_2$  at 4 monitors. ii) All monitors remain in the same place during the period of my analysis (Jan 2014-Feb 2020), and there is data available for all months. Moreover, there is a strong correlation among air pollutants; correlation between  $NO_2$  and  $PM_{10}$  0.37, between  $NO_2$  and  $O_3$  -0.71, between  $NO_2$  and  $PM_{2.5}$  0.54 and between  $NO_2$  and  $SO_2$  0.36. For further details about air pollution legislation of  $NO_2$  in Spain see Appendix B.

<sup>12</sup>As robustness checks, I show that results are similar if I select the daily mean or I select the closest monitor for each neighborhood or I select the inverse distance-weighted average of the three closest monitors for each neighborhood.

<sup>13</sup>The aim of this measure was the creation of a special area in the Central district (District 1) where only cars of residents or eco or zero-emission labeled cars could drive or park. In general terms, electric and plug-in hybrid cars that cover at least 40km are zero emission labeled. Cars which are plug-in hybrid or hybrid or powered by natural gas will be Eco-label. C label cars are those with EURO 4/IV, 5/V or 6/VI gasoline and EURO 6/VI diesel. B label cars are EURO 3/III gasoline and diesel Euro 4/IV or 5/V and those not included in these categories will be A label and are the most polluting vehicles.

<sup>14</sup>“Madrid Central” was announced on October 30<sup>th</sup>, 2018, and implemented on November 30<sup>th</sup>, 2018, it was not until March 15<sup>th</sup>, 2019 that fines were issued.

during strong anticyclonic conditions and calm winds that prevent air from rising, leading to persistent fog and frost. Also, dry soil surface and low elevation areas such as valleys and basins, are conditions that favor the development of inversions. Although thermal inversions are not determined by air pollution, in the long run, climate change can influence the frequency, intensity, and duration of thermal inversions. For instance, warmer winters reduce the strength of winter inversions, and increase the frequency of inversion events due to changes in circulation patterns. Data used for analyzing thermal inversion (Copernicus Climate Data Store, 2014-2020) hourly air temperature is provided in terms of 37 vertical layers, with a spatial resolution of approximately  $0.25^\circ \times 0.25^\circ$  (about every 25km x 25km). I compute thermal inversion as follows: (i) I apply kriging interpolation to generate a continuous surface of hourly layer temperatures, (ii) as a dummy variable equal to 1 when temperature at 875 hPa exceeds that at 900 hPa, and 0 otherwise. (iii) Finally, I compute the daily mean of the inversion indicator, subsequently calculate its monthly average and finally calculate a three-month moving average.<sup>15</sup> This approach is consistent with literature (Cai et al., 2024; Arceo et al., 2016), where near-surface inversions are measured using lower pressure levels (1000-975 hPa), corresponding approximately to 110 m and 320 m above sea level. However, Madrid is located on a plateau at around 660 m above sea level, and its highest district (Fuencarral-El Pardo) lies at about 743 m, with a maximum elevation reaching 842 m above sea level. This is why the 1000-975 hPa levels are below ground locally. Therefore, I use pressure layers corresponding approximately to 1000-1200 m above sea level, namely the 900-875 hPa levels.

I also use hourly weather data (Store, 2014-2020), including measures for wind, temperature, and rainfall, all available with a spatial resolution of approximately  $0.25^\circ \times 0.25^\circ$ .<sup>16</sup> Similar to my treatment of thermal inversion data, I first apply kriging interpolation to generate a continuous spatial surface for these weather variables. Then I assign corresponding values to each neighborhood, and after that I compute the daily mean of each weather variable. For rainfall and wind,

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<sup>15</sup>Results are similar if I use the strength of thermal inversion defined as the temperature difference between layer 875 and layer 900, and set it to zero whenever the difference is negative. Alternatively, I also obtain similar results constructing my instrument by comparing 925-900 hPa, which correspond to 760-1000 m above sea level.

<sup>16</sup>Temperature measures the air temperature two meters above the surface of land, sea, or inland waters. Wind refers to the horizontal speed of air moving northward at a height of ten meters above the Earth's surface. Total precipitation represents the accumulated amount of liquid and frozen water-such as rainfall and snow-that falls to the Earth's surface.

I define a dummy variable equal to 1 when the observation falls within the top 25th percent of its distribution and 0 otherwise. For temperature, the dummy equals 1 when the observation lies in either the top or bottom 10th percent of its distribution and 0 otherwise. The bad weather index is computed as the average of the three component indices. In this way the index captures whether a given day experienced unusually high rainfall or wind, or extreme temperatures relative to the empirical distribution.<sup>17</sup> For my analysis, I compute the lagged mean of the index over the last three months.

## 2.4 Neighborhood and traffic data

I use data on the number of shops, restaurants, educational institutions (schools, day care centers, language academies or driving schools), entertainment and recreational centers and other services at neighborhood and month level (Council of Madrid, 2014-2020b). I then compute the average number of services for each month and its mean over the last three months. I also compute population density for each neighborhood and month as well as over the last three months, combining information on total population from the census of Madrid (Council of Madrid, 2014-2020c) and information on the neighborhood surface (Council of Madrid, 2017).

In addition, I consider information on short-term rentals (Inside Airbnb, 2022) which can potentially have an important effect on housing prices, using data for September 2022 (the closest available data). I select the five districts with the highest concentration of Airbnb rentals per household (higher than 1.5% of total households), to control for potential different time trends in housing prices within this group of districts (see Table A.1 in the Appendix for the % of Airbnb rentals in each district relative to the number of households).<sup>18</sup> Moreover, for my heterogeneity analysis, I also use data from the Council of Madrid (2017) on average household income, education, number of children, and share of foreigners by neighborhood.

Finally, for robustness, I control for neighborhood traffic given that is closely

<sup>17</sup>As robustness checks (section 4.2.1), I construct alternative indices using both smoother and stricter cutoff thresholds. The weather-component dummy is constructed excluding observations at the cutoff thresholds. Figure A.3 illustrates the monthly variability of the overall index and its components. For example, the temperature component is relatively high in August while the wind component is low; in May, this pattern is reversed.

<sup>18</sup>The five districts are: Central, Salamanca, Chamberí, Arganzuela and Retiro districts. I obtain similar results when I select either four or six districts with the highest concentration of Airbnb listings. Gil and Sequera (2022) show that Airbnb rentals in Madrid have increased significantly since 2015, and that they are concentrated in the Central district (District 1).

linked to air pollution, with more than 75% of  $NO_2$  emissions being caused by vehicles (Ministry of Ecological Transition, 2026). For this, I take data from the Council of Madrid (2014-2020d) on traffic monitors, and I use the percentage of time a traffic detector is active, during an hour, and I then compute the daily mean and after that the monthly mean. The specific location of each traffic monitor allows me to link it to the closest neighborhood based on the centroid coordinates of each neighborhood.<sup>19</sup>

## 2.5 Sample

Given that data on neighborhood characteristics is only available from 2014 onward my sample period starts in January of 2014. In order to avoid noise from Covid-19 lockdowns and restrictions, I use data until February 2020. Given that my approach focuses on individuals who may consider health-related factors when buying or selling a house, I restrict the sample to include dwellings whose prices are determined in the open market and purchased by natural persons. To minimize potential distortions, I exclude air pollution data from the three suburban monitors situated within large green areas such as El Pardo, Casa de Campo, and Barajas. I also exclude data from the monitor situated inside Retiro Park due to its controversial location in another large green area.<sup>20</sup> My final sample consists on 106,449 observations of housing transactions in Madrid between January 2014 and February 2020.

## 2.6 Descriptive statistics

Table 1 shows descriptive statistics for my main variables. The real house price per square meter is €2,722 (in €2020) and most houses are flats without annexes (no garage or storage). Most dwellings have been constructed before 1975 and have a mean size of around 75 m<sup>2</sup>. The lowest price per square meter is recorded in the San Fermín neighborhood (part of the Usera district), while the highest is recorded in Recoletos (located in the Salamanca district). Also, the largest share of big houses (> 100 m<sup>2</sup>) is found in the Hortaleza district whereas the largest share of small houses (< 55 m<sup>2</sup>) is found in the Central district. Figure

<sup>19</sup>For instance, an occupation of 50% means that over a period of 15 minutes, vehicles have been located over the detector for 7 minutes and 30 seconds. However, there are eight neighborhoods with no information on traffic which will have to be excluded from this robustness check.

<sup>20</sup>Between 2009 and 2010, 12 monitors were relocated, one of which was moved to Retiro Park, a large green space in the heart of Madrid. As a robustness check, I include data from these excluded monitors to assess their impact and to validate the main findings. Figure A.1 in the Appendix shows the location of the monitors.

A.4 in the Appendix represents average housing prices across neighborhoods in May between 2014 and 2019, showing that the highest average price increases occurred in the Central district.

Table 1: Descriptive statistics

| Variable                               | Mean     | Sd       | Min                  | Max       |
|----------------------------------------|----------|----------|----------------------|-----------|
| <b>1. House characteristics</b>        |          |          |                      |           |
| Real price/m <sup>2</sup> (in 2020 €)  | 2,722.63 | 1,573.48 | 96.40                | 10,316.83 |
| Built before 1960                      | 0.28     | 0.45     | 0                    | 1         |
| Built between 1960 - 1975              | 0.35     | 0.48     | 0                    | 1         |
| Built between 1975 - 2000              | 0.19     | 0.40     | 0                    | 1         |
| Built after 2000                       | 0.17     | 0.38     | 0                    | 1         |
| Flat without annexes                   | 0.84     | 0.37     | 0                    | 1         |
| Flat with annexes                      | 0.14     | 0.34     | 0                    | 1         |
| Semi-detached                          | 0.01     | 0.12     | 0                    | 1         |
| Detached                               | 0.01     | 0.09     | 0                    | 1         |
| Less than 55 m <sup>2</sup>            | 0.24     | 0.43     | 0                    | 1         |
| Between 55 and 75 m <sup>2</sup>       | 0.26     | 0.44     | 0                    | 1         |
| Between 75 and 100 m <sup>2</sup>      | 0.29     | 0.45     | 0                    | 1         |
| Greater than 100 m <sup>2</sup>        | 0.20     | 0.40     | 0                    | 1         |
| Second-hand                            | 0.83     | 0.37     | 0                    | 1         |
| <b>2. NO<sub>2</sub> concentration</b> |          |          |                      |           |
| Last 3 months                          | 38.40    | 10.06    | 17.34                | 70.07     |
| <b>3. Thermal inversions</b>           |          |          |                      |           |
| Last 3 months                          | 0.05     | 0.05     | 4.4*10 <sup>-6</sup> | 0.24      |
| <b>4. Neighborhood characteristics</b> |          |          |                      |           |
| Population density (Inh./Ha)           | 218.92   | 122.19   | 0.18                 | 462.78    |
| Number of establishments:              |          |          |                      |           |
| Health care                            | 39.99    | 19.80    | 1                    | 113.33    |
| Educational Centers                    | 42.07    | 21.20    | 1                    | 127.33    |
| Wholesale and Retail                   | 495.05   | 335.60   | 3                    | 1,705.33  |
| Accommodations                         | 190.10   | 127.01   | 5                    | 672.00    |
| Entertainment and Recreation           | 118.32   | 61.94    | 1                    | 294.67    |
| Other services                         | 27.48    | 15.10    | 1                    | 75.00     |
| <b>5. Weather variables</b>            |          |          |                      |           |
| Bad weather index                      | 0.22     | 0.05     | 0.07                 | 0.36      |
| Number of observations = 106,449       |          |          |                      |           |

Regarding air pollution, the mean of  $NO_2$  concentration is around 38  $\mu\text{g}/\text{m}^3$ , which is quite close to the annual limit of 40  $\mu\text{g}/\text{m}^3$  established by the European Union. Exceeding this limit triggers a legal obligation for public authorities to implement air-quality plans and corrective measures. Notably,  $NO_2$  concentrations vary across both time and space. For instance, their average value decreased from 33.39 in May of 2017 to 28.17 in May of 2019. Spatial variation is also evident: in May of 2016, average  $NO_2$  stood at 28 in the Valverde neighborhood, compared with 47.86 in Recoletos. Figure A.5 in the Appendix shows average

air pollution across neighborhoods in May between 2014 and 2019. The northern and eastern parts of the city exhibit generally lower pollution levels. With respect to thermal inversion a mean of 0.05 implies that the probability of a thermal inversion to occur over the last three months is 5%. Thermal inversions also exhibit substantial variation across both time and space. For example, in May of 2016 the thermal inversion value was 3.4% in the Peñagrande neighborhood and 1.17% in Palomas. Temporal variation is also evident: while mean thermal inversion in May of 2018 was 0.89%, it increased to 2.5% in May of 2019. Figure A.6 in the Appendix shows average thermal inversion values across neighborhoods in May between 2014 and 2019, with northern neighborhoods generally experiencing more inversions.

Regarding other neighborhood characteristics, average population is 31,257 with a density of 218.92 (Inh./Ha), ranging from 0.18 in El Pardo neighborhood to 462.78 in Gaztambide. Most common establishments are wholesale and retail stores, followed by accommodation and entertainment and recreational establishments, with the Central district having the highest concentration of the latter. Finally, the bad weather index has a mean of 0.22, with values above this threshold reflecting weather conditions worse than average. Note that the index displays variation across both years and neighborhoods. For instance, its annual value was 0.203 in 2017, increasing to 0.254 in 2018. Spatial variation is also evident: in November of 2017, the mean index was 0.077 in the San Andrés neighborhood, compared with 0.092 in El Pardo.

### 3 Methodology

To analyze the effect of air pollution on housing prices in Madrid, I rely on a hedonic model:

$$\begin{aligned} \ln P_{i,g,d,t} = & \gamma_0 + \gamma_1 \frac{1}{3} \sum_{s=t-2}^t \ln NO2_{g,d,s} + \gamma_2 X_{i,g,d,t} + \gamma_3 \frac{1}{3} \sum_{s=t-2}^t N_{g,d,s} + \\ & + \gamma_4 \frac{1}{3} \sum_{s=t-2}^t W_{g,d,s} + \alpha_g + \alpha_y + \alpha(y_t * I_{A>1.5\%}) + \omega_{i,g,d,t}, \end{aligned} \quad (1)$$

where the dependent variable ( $\ln P_{i,g,d,t}$ ) is the logarithm of housing price per square meter, indices  $i$ ,  $g$ ,  $d$  and  $t$  refer to transaction, neighborhood, district and month, respectively.  $\frac{1}{3} \sum_{s=t-2}^t \ln NO2_{g,d,s}$  denotes the logarithm of the mean of air pollution over the last three months.  $X_{i,g,d,t}$  are housing characteristics such as property type (new or second-hand), property size, and year of construction,

$\frac{1}{3} \sum_{s=t-2}^t N_{g,d,s}$  is the three-months mean of neighborhood characteristics (number of establishments, population density) and  $\frac{1}{3} \sum_{s=t-2}^t W_{g,d,s}$  is the bad weather index combining temperature, rainfall and wind.  $\alpha_g$  and  $\alpha_y$  are neighborhood and year fixed effects to capture time-invariant determinants of housing prices in a neighborhood and to control for time-varying factors which affect housing prices across Madrid respectively. To address concerns of increasing housing prices due to the proliferation of short-term rentals like Airbnb, I also control for a linear time trend interacted with a high-Airbnb-intensity district indicator ( $y_t * I_{A>1.5\%}$ ). Finally,  $\omega_{i,g,d,t}$  is the idiosyncratic error term clustered at the neighborhood level.

I expect my coefficient of interest  $\beta_1$ , which reflects the relationship between air pollution and housing prices within a neighborhood to be negative and significant. While equation (1) attempts to address endogeneity concerns controlling for neighborhood-fixed effects, business activities, population density and year-fixed effects, it is challenging to account for all variables that may influence housing prices and air pollution. For instance, improvements in public transport such as extended bus schedules or new bus stops along a neighborhood route, could potentially increase housing prices and reduce air pollution at the same time. Conversely, areas with high daytime population density due to work-related activities have higher air pollution levels, while, to minimize commuting time, individuals may nevertheless prefer to live there, leading to higher housing prices as well.

To address these concern,<sup>21</sup> I use a two-stage least squares (2SLS) framework, exploiting quasi-experimental variations in  $NO_2$  levels attributed to thermal inversion. I denote by  $\frac{1}{3} \sum_{s=t-2}^t \ln Z_{g,d,s}$ , the logarithm of the mean of thermal inversion in neighborhood  $g$ , district  $d$  and month  $t$  over the last three months. The first stage IV equation is:

$$\begin{aligned} \frac{1}{3} \sum_{s=t-2}^t \ln NO2_{g,d,s} = & \gamma_0 + \gamma_1 \frac{1}{3} \sum_{s=t-2}^t \ln Z_{g,d,s} + \gamma_2 X_{i,g,d,t} + \gamma_3 \frac{1}{3} \sum_{s=t-2}^t N_{g,d,s} + \\ & + \gamma_4 \frac{1}{3} \sum_{s=t-2}^t W_{g,d,s} + \alpha_g + \alpha_y + \alpha(y_t * I_{A>1.5\%}) + \omega_{i,g,d,t}, \end{aligned} \quad (2)$$

where all variables except  $\frac{1}{3} \sum_{s=t-2}^t \ln Z_{g,d,s}$  correspond to those in equation

<sup>21</sup>Smith and Huang (1995) document that hedonic willingness-to-pay estimates are highly sensitive to specification and omitted variables, motivating a subsequent literature that uses panel data, dynamic models, and improved data practices to strengthen identification and reduce bias (Bishop and Timmins, 2018; Bishop and Murphy, 2019; Bishop et al., 2020).

(1). The second stage equation estimates housing prices using predicted pollution  $\ln NO2_{g,d,t}^*$  from equation (2),

$$\begin{aligned} \ln P_{i,g,d,t} = & \gamma_0 + \gamma_1 \frac{1}{3} \sum_{s=t-2}^t \ln NO2_{g,d,s}^* + \gamma_2 X_{i,g,d,t} + \gamma_3 \frac{1}{3} \sum_{s=t-2}^t N_{g,d,s} + \\ & + \gamma_4 \frac{1}{3} \sum_{s=t-2}^t W_{g,d,s} + \alpha_g + \alpha_y + \alpha(y_t * I_{A>1.5\%}) + \omega_{i,g,d,t}. \end{aligned} \quad (3)$$

For this approach to generate an unbiased estimate for  $\gamma_1$  two key assumptions have to hold: (i) thermal inversion has to have no direct effect on housing prices other than via increased ambient concentrations of air pollution, and (ii) thermal inversion needs to be correlated with air pollution.

## 4 Results

Table 2 reports OLS estimates (in column 1), IV estimates (column 2) and results from the first stage (column 3). All regressions control for house and neighborhood characteristics, bad weather index, year and neighborhood fixed effects and a set of time-varying neighborhood characteristics. Results from column (1) suggest that there is a negative and significant relationship between housing prices and  $NO_2$  concentration. An increase of 1% in air pollution is associated with a decline in housing prices by 0.054%. Results in column (2) reveal that the causal effect of  $NO_2$  on housing prices is -0.065%, suggesting that a 1% increase in air pollution will decrease housing prices by 0.065%. This represents a stronger negative effect, meaning that omitted variables seem to mitigate the impact of air pollution on housing prices. For instance, individuals' preferences for living in denser areas to reduce commuting time could simultaneously influence both positively air pollution and housing prices. Note that the magnitude of my estimate is consistent with findings in existing literature for other cities. For Tehran, Amini et al. (2022) estimate that a 1% increase in  $NO_2$  over the last three months leads to a decrease in housing prices of 0.061% and for Beijing, Cai et al. (2024) find an average quarterly reduction of 1  $\mu\text{g}/\text{m}^3$  in  $\text{PM}_{2.5}$  to reduce housing prices by 0.0852%.<sup>22</sup> Note that as F-statistics exceed 10 ( $F=3,446$ ) in the first stage and the correlation between air pollution and thermal inversion is 0.21, thermal inversion is a strong instrument. Moreover, I also evaluate the explained variation of air pollution and thermal inversion by comparing the  $R^2$  values from equation

<sup>22</sup>This value is slightly lower than the 0.17% implied by my log-linear specification (see in Table A.5).

(2) as controls are added sequentially. The  $R^2$  is 0.196 when air pollution is the dependent variable and all controls are included and it increases to 0.752 when thermal inversions are included, see Table A.2 in the Appendix. In Section 4.2.4, I carry out a Placebo test to further evaluate the strength and validity of my instrument.

Table 2: Effect of air pollution on housing prices

| Dep. Var:                       | (1)                      | (2)                     | (3)                          |
|---------------------------------|--------------------------|-------------------------|------------------------------|
| Estimator                       | ln(Price/ $m^2$ )<br>OLS | ln(Price/ $m^2$ )<br>IV | ln(Pollution)<br>First-stage |
| ln(Pollution) last 3 months     | -0.053***<br>(0.008)     | -0.065***<br>(0.009)    |                              |
| ln(Thermal inv.) last 3 months  |                          |                         | 0.21***<br>(0.003)           |
| Observations                    | 106,449                  | 106,449                 | 106,449                      |
| R-squared                       | 0.581                    | 0.581                   | 0.752                        |
| First-stage F statistic         |                          | 3,446                   |                              |
| House characteristics           | ✓                        | ✓                       | ✓                            |
| Neighborhood                    | ✓                        | ✓                       | ✓                            |
| Bad Weather Index               | ✓                        | ✓                       | ✓                            |
| Year                            | ✓                        | ✓                       | ✓                            |
| Airbnb(Districts) $\times$ Year | ✓                        | ✓                       | ✓                            |

The dependent variable in columns (1) and (2) is the natural logarithm of the housing price per square meter. In column (3) it is the natural logarithm of NO<sub>2</sub> over the last three months. Column (1) is estimated by OLS and column (2) by second-stage IV where column (3) represents results from the first-stage IV. All columns include house characteristics (year of construction, built square meters, property type and whether it is new/second hand) and neighborhood characteristic (population density, number of establishments such as health care and education), a bad weather index based on temperature, wind and precipitation, year and neighborhood fixed effects and a linear time trend interacted with a high-Airbnb-intensity district indicator (threshold: 1.5%). Robust standard errors in parentheses are clustered by neighborhood. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10%, respectively. Sources: Author' calculations using Land Registry records (Registrars of Property of Spain, 2014-2020), year of construction from Moral-Carcedo (2024), air pollution (Council of Madrid, 2014-2020a), neighborhood data (Council of Madrid, 2014-2020b) (Council of Madrid, 2014-2020c) (Inside Airbnb, 2022), thermal inversion (Copernicus Climate Data Store, 2014-2020) and weather variables (Store, 2014-2020).

Tables A.3 and A.4 in the Appendix present the full set of coefficients for OLS and IV regressions, respectively, including all control variables sequentially. Both estimation methods show similar results regarding all other coefficients. Once I control for neighborhood characteristics and neighborhood fixed effects (column 3), I obtain sensible results highlighting the importance of these controls in the regression. Column (4) includes a bad weather index, column (5) time fixed

effects, and column (6) controls for potentially different time trends for neighborhoods with a high share of Airbnb rentals, which is my preferred specification. In both estimations, the older the building or the larger the property, the lower the housing price per square meter. Finally, the number of wholesale and retail, accommodation, and entertainment establishments does not appear to have a significant effect on housing prices, and the coefficient on the bad weather index becomes negative and significant once year fixed effects are included.

## 4.1 Increasing Time Horizon and non-linear effects

Buying a house takes time, which makes it less likely to observe contemporaneous effects of changes in air pollution on housing prices. To test for this notion, I compute the mean of air pollution levels over the last six and nine months, also increasing the time horizon for neighborhood characteristics, bad weather index, and thermal inversion, respectively. Results in Table 3 suggest that individuals are likely to consider a longer-term air quality reading when buying a house. An increase of 1% in  $NO_2$  concentration over the last three, six, or nine months decreases housing prices by 0.065%, 0.099% and 0.125% respectively. Consistent with Amini et al. (2022)'s findings for Tehran, my results imply that in areas where pollution is persistent, buyers will offer less money for the purchase of a house. To put these numbers in perspective, between 2019 and 2023, air pollution in Madrid decreased by 23.1%. This would imply an increase in housing prices of 1.5%, 2.3% and 2.9% when taking into account air pollution measured over the last three, six and nine months, respectively. With an average house price of €204,197 this results in price increases of €3,063, €4,697 and €5,922.

It is reasonable to assume that the impact of air pollution on housing prices may not follow a linear pattern. In fact, as air pollution levels rise, individual awareness has been found to increase, leading to a decline in housing prices (Gruhl et al., 2022, Amini et al., 2022; Chay and Greenstone, 2005) or an increase in work absenteeism (Holub et al., 2020). I explore such non-linearities by dividing my sample into two groups with air pollution levels below and above the mean of the whole distribution. Table 4 show stronger and statistically significant effects on housing prices in areas with high pollution (columns 2). In contrast, areas with lower pollution levels (columns 1) show no significant price changes. These results align with findings in Le Boennec and Salladarré (2017), who report no significant effects of air pollution on housing prices in a city like Nantes with relatively low pollution levels.

Table 3: The effect of air pollution on housing prices over different time horizons

| Dep. Var: $\ln(\text{Price}/m^2)$ | (1)                  | (2)                  | (3)                 |
|-----------------------------------|----------------------|----------------------|---------------------|
| Pollution:                        | Last 3 months        | Last 6 months        | Last 9 months       |
| $\ln(\text{Pollution})$           | -0.065***<br>(0.009) | -0.099***<br>(0.023) | -0.125**<br>(0.055) |
| Observations                      | 106,449              | 103,222              | 100,427             |
| R-squared                         | 0.581                | 0.580                | 0.579               |
| First-stage F statistic           | 3,446                | 3,341                | 2,738               |
| House characteristics             | ✓                    | ✓                    | ✓                   |
| Neighborhood                      | ✓                    | ✓                    | ✓                   |
| Bad Weather Index                 | ✓                    | ✓                    | ✓                   |
| Year                              | ✓                    | ✓                    | ✓                   |
| Airbnb(Districts) $\times$ Year   | ✓                    | ✓                    | ✓                   |

The dependent variable in all columns is the natural logarithm of housing prices per square meter. All specifications are estimated using instrumental variables. Columns (1)–(3) use average air pollution over the last three, six, and nine months, respectively. All columns include house characteristics (year of construction, built square meters, property type and whether it is new/second hand) and neighborhood characteristic (population density, number of establishments such as health care and education), a bad weather index based on temperature, wind and precipitation, year and neighborhood fixed effects and a linear time trend interacted with a high-Airbnb-intensity district indicator (threshold: 1.5%). Robust standard errors in parentheses are clustered by neighborhood. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10%, respectively. Sources: Author’ calculations using Land Registry records (Registrars of Property of Spain, 2014-2020), year of construction from Moral-Carcedo (2024), air pollution (Council of Madrid, 2014-2020a), neighborhood data (Council of Madrid, 2014-2020b) (Council of Madrid, 2014-2020c) (Inside Airbnb, 2022), thermal inversion (Copernicus Climate Data Store, 2014-2020) and weather variables (Store, 2014-2020).

## 4.2 Robustness checks

I check the robustness of my results, addressing measurement issues, exclusion of observation, and inclusion of additional controls. I also carry out a Placebo test.

### 4.2.1 Measurement issues

To ensure that my results do not depend on how I measure air pollution: (i) I use the daily mean instead of the daily median to then aggregate air pollution measures; (ii) I use a Log-Lin specification<sup>23</sup>; (iii) I use an inverse distance weighted average of the three nearest monitors as in Amini et al. (2022) instead of kriging interpolation, and (iv) I rely exclusively on the closest monitor instead of kriging interpolation. Results in Table A.5 in the Appendix show that these

<sup>23</sup>In the Log-Lin specification, the estimation show that an increase of 1 unit in  $NO_2$  decreases housing prices by 0.17%. Evaluated at the mean pollution level (38.4), this implies an elasticity of approximately  $0.17\% \times 38.4 = 0.065$ , which is consistent with the log–log results.

Table 4: Non-linearity of effects of air pollution on housing prices

| Dep. Var: $\ln(\text{Price}/m^2)$     | (1)                   | (2)                   |
|---------------------------------------|-----------------------|-----------------------|
|                                       | $< \text{mean}(NO_2)$ | $> \text{mean}(NO_2)$ |
| $\ln(\text{Pollution})$ last 3 months | -0.058<br>(0.045)     | -0.107**<br>(0.050)   |
| Observations                          | 60,372                | 46,077                |
| R-squared                             | 0.574                 | 0.591                 |
| First-stage F statistic               | 474                   | 2,996                 |
| House characteristics                 | ✓                     | ✓                     |
| Neighborhood                          | ✓                     | ✓                     |
| Bad Weather Index                     | ✓                     | ✓                     |
| Year                                  | ✓                     | ✓                     |
| Airbnb(Districts) $\times$ Year       | ✓                     | ✓                     |

The dependent variable in all columns is the natural logarithm of housing prices per square meter. All specifications are estimated using instrumental variables. The sample is split at the mean pollution level: column (1) reports estimates for observations with below-mean pollution levels, while column (2) reports estimates for above-mean pollution levels. All columns include house characteristics (year of construction, built square meters, property type and whether it is new/second hand) and neighborhood characteristic (population density, number of establishments such as health care and education), a bad weather index based on temperature, wind and precipitation, year and neighborhood fixed effects and a linear time trend interacted with a high-Airbnb-intensity district indicator (threshold: 1.5%). Robust standard errors in parentheses are clustered by neighborhood. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10%, respectively. Sources: Author' calculations using Land Registry records (Registrars of Property of Spain, 2014-2020), year of construction from Moral-Carcedo (2024), air pollution (Council of Madrid, 2014-2020a), neighborhood data (Council of Madrid, 2014-2020b) (Council of Madrid, 2014-2020c) (Inside Airbnb, 2022), thermal inversion (Copernicus Climate Data Store, 2014-2020) and weather variables (Store, 2014-2020).

alternative specifications lead to somewhat larger point estimates implying that my preferred specification might be on the conservative side, expect for the log-lin specification that my results are virtually identical.

I also make sure that my results are not driven by the selected threshold of my bad weather index (top 25th percentile for rainfall and wind and top/bottom 10th percentile for temperature). To do so I construct alternative indices using both smoother and stricter cutoff thresholds: top 50th percentile for rainfall and wind and top/bottom 25th percentile for temperature (column (1), Table A.6); and, alternatively, top 10th percentile for rainfall and wind and top/bottom 5th percentile for temperature (column (2), Table A.6). Results are very similar to my baseline specification, suggesting that my results are not driven by how my bad weather index is specified.

### 4.2.2 Exclusion of observations

As mentioned before, my main analysis excludes air pollution data from the "Retiro monitor" located inside a park and from the three suburban monitors located at the outskirts of the city. To make sure that results do not depend on this, columns (1) and (2) of Table A.7 show that the inclusion of readings from these monitors does not change my results much; if any they become stronger. I also address concerns that my results could be driven by "Madrid central" announced in October 2018. Results in column (3) of Table A.7 where I exclude the central district from the analysis from October 2018 onwards, are in line with my benchmark estimates. Finally, to address the concern of a different price trends in newly created neighborhoods, I eliminate observations from districts 18 (Villa de Vallecas) and 19 (Vicálvaro). Again, results in column (4) of Table A.7 are hardly affected.

### 4.2.3 Additional controls

To show that my results are not driven by seasonal variation in prices and transactions trends between "hot" and "cold" seasons as Ngai and Tenreyro (2014) observe for the United Kingdom and the United States, I include a dummy equal to 1 when a house is sold in spring or summer and 0 otherwise. Results are very similar to those obtained in my baseline regression, see column (1) of Table A.8 in the Appendix. In column (2), I control for the possibility that some houses are sold at the end of the year for tax-related reasons, given that in Spain capital gains taxes are assessed on a calendar-year basis. To do so, I include a dummy variable for December transactions. Note that results become stronger, suggesting that the December dummy captures a distinct housing price trend. Finally, in column (3) I add traffic as an additional control. However, coefficients are indistinguishable from those of my baseline model, suggesting that once air pollution is controlled for, traffic does not have any additional effect on housing prices.<sup>24</sup> One possible explanation for this maybe surprising result is that my traffic data is not disaggregated enough as it is constructed at the neighborhood rather than the street level.

I also add an additional control for houses built before and after 2000. During my study period 82% of houses sold were built before 2000. In Table A.9, I divide my sample into two groups: older houses (built before 2000, column (1)) and

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<sup>24</sup>I also test alternative traffic indicators-including traffic intensity (vehicles per hour), and track load (an index ranging from 0, indicating free flow, to 100, indicating collapse, based on occupancy and intensity). I obtain similar results.

newer houses (built after 2000, column (2)). Results show that in both panels the relationship between air pollution and housing prices is very similar to my benchmark results. However, coefficients are larger for newer houses, suggesting that buyers of recently built homes might be more sensitive to air pollution.

#### 4.2.4 Placebo test

Finally, I carry out a placebo test to make sure that my estimations are not merely pick up spurious correlations. To this end, I randomize average three-month thermal inversion values for each neighborhood-year observation. I apply this randomization procedure 500 times. For instance, for the neighborhood of Recoletos, the thermal inversion value initially recorded in February may be re-assigned to November within that same year.<sup>25</sup> The resulting distribution of regression estimates and confidence intervals are reported in Table A.10. The confidence intervals include zeros, which strengthens the validity of the instrument under the randomized thermal inversion design. Moreover, only two cases (less than 0.5% of all placebo estimates) yield a negative and statistically significant coefficient at the 10% level.

### 4.3 Heterogeneity analysis

To provide a better sense of the mechanisms at play, I check how the effect of air pollution on housing prices might vary across different types of neighborhoods. Studies show that more educated (Mikula and Pytliková, 2021) and high-income individuals (Cai et al., 2024) exhibit a stronger response to air pollution.

Panel 1 of Table 5 presents results for heterogeneity by income with neighborhoods split into bottom and top 25%. My coefficient of interest is 94% larger for high-income neighborhoods, suggesting that these neighborhoods capitalize air pollution more strongly than low-income neighborhoods. I find very similar results when differentiating neighborhoods by level of education (see Panel 2, Table 5).<sup>26</sup> Results show that neighborhoods with higher levels of education capitalize air pollution at a rate 121% higher than less-educated neighborhoods (based on the difference between -0.043 and -0.95). Panel 3 highlights another dimension. In particular, in neighborhoods with relatively more children individuals tend

<sup>25</sup>As my instrument (thermal inversion) is constructed as a three-month moving average, the randomization is applied to this three-month average rather than to monthly values. Reassigned values may hence incorporate information from previous calendar years even though randomization is performed at the neighborhood-year level. The procedure yields  $12!$  (479,001,600) possible permutations per year.

<sup>26</sup>I compute the share of highly educated as the percentage of individuals with a tertiary or an advanced vocational degree.

to factor air pollution into their decisions to buy and sell houses. This aligns with the idea that families with young children prioritize environmental aspects, given the vulnerability of children to health issues related to pollution (Chay and Greenstone, 2003).

Table 5: Heterogeneity of the effect of air pollution on housing prices

| Dep. Var: $\ln(\text{Price}/m^2)$     | (1)                  | (2)                  |
|---------------------------------------|----------------------|----------------------|
|                                       | Bottom 25%           | Top 25%              |
| <i>1. Income:</i>                     |                      |                      |
| $\ln(\text{Pollution})$ last 3 months | -0.047***<br>(0.013) | -0.091***<br>(0.015) |
| Observations                          | 30,935               | 20,511               |
| R-squared                             | 0.481                | 0.309                |
| First-stage F statistic               | 840                  | 726                  |
| <i>2. Education:</i>                  |                      |                      |
| $\ln(\text{Pollution})$ last 3 months | -0.043***<br>(0.014) | -0.095***<br>(0.015) |
| Observations                          | 27,417               | 20,208               |
| R-squared                             | 0.361                | 0.294                |
| First-stage F statistic               | 1,565                | 778                  |
| <i>3. Children 0-14:</i>              |                      |                      |
| $\ln(\text{Pollution})$ last 3 months | -0.066***<br>(0.019) | -0.071***<br>(0.019) |
| Observations                          | 31,923               | 19,002               |
| R-squared                             | 0.451                | 0.645                |
| First-stage F statistic               | 968                  | 1,142                |

The dependent variable in all columns is the natural logarithm of housing prices per square meter. All specifications are estimated using instrumental variables. Each panel reports results for a different sample split. Panel 1 divides neighborhoods by income, panel 2 by the share of highly educated residents and panel 3 by the number of children aged 0-14. Column (1) reports estimates for observations in the bottom quartile, while column (2) reports estimates for those in the top quartile. All columns include house characteristics (year of construction, built square meters, property type and whether it is new/second hand) and neighborhood characteristic (population density, number of establishments such as health care and education, a bad weather index based on temperature, wind and precipitation, year and neighborhood fixed effects and an interaction term between year and a linear time trend interacted with a high-Airbnb-intensity district indicator (threshold: 1.5%). Robust standard errors in parentheses are clustered by neighborhood. \*\*\*, \*\* and \* indicate statistic significance at the 1%, 5%, and 10%, respectively. Sources: Author' calculations using Land Registry records (Registrars of Property of Spain, 2014-2020), year of construction from Moral-Carcedo (2024), air pollution (Council of Madrid, 2014-2020a), neighborhood data (Council of Madrid, 2014-2020b) (Council of Madrid, 2014-2020c) (Inside Airbnb, 2022) (Council of Madrid, 2017), thermal inversion (Copernicus Climate Data Store, 2014-2020) and weather variables (Store, 2014-2020).

I also analyze the heterogeneity of effects along variations in house quality and the share of foreigners in a neighborhood. Table A.11 in the Appendix shows air pollution is capitalized among buyers of high-quality houses (top 25% by price per square meter), but not among buyers of low-quality houses (bottom 25%). Moreover, Panel 2 shows that neighborhoods with a high share of foreigners from outside the EU and OECD do not seem to capitalize air pollution when purchasing a house. These results are consistent with the fact that these foreigners typically having lower levels of education and income compared to Spaniards.

#### 4.4 Transaction frictions

For air pollution to affect house prices, I would need to observe changes in demand or supply of houses. In particular, a decline in prices driven by reduced demand would be associated with fewer transactions, whereas a price decline resulting from an increase in supply would imply higher transaction volumes. Although I have no information on listings, I examine the effect of air pollution on the number of transactions within a neighborhood. My preferred hypothesis is that higher air pollution levels might lead to potential buyers waiting longer to decide to buy a house and to be more reluctant to engage in lengthy negotiations. If this is the case, I expect the number of transactions to be negatively related to air pollution. To test for this formally, I estimate the following model:

$$T_{g,d,t} = \gamma_0 + \gamma_1 \frac{1}{3} \sum_{s=t-2}^t \ln NO2_{g,d,s}^* + \gamma_2 \frac{1}{3} \sum_{s=t-2}^t N_{g,d,s} + \gamma_4 \frac{1}{3} \sum_{s=t-2}^t W_{g,d,s} + \alpha_g + \alpha_y + \alpha(y_t * I_{A>1.5\%}) + \omega_{i,g,d,t}, \quad (4)$$

where  $T_{g,d,t}$  is the natural logarithm of the number of transactions in neighborhood  $g$ , in district  $d$  and month  $t$ , and  $\ln NO2_{g,d,s}^*$  is the predicted ambient concentration estimated using the following model, which differs from equation (2) as it does not include housing characteristics as control variables:

$$\frac{1}{3} \sum_{s=t-2}^t \ln NO2_{g,d,s} = \gamma_0 + \gamma_1 \frac{1}{3} \sum_{s=t-2}^t \ln Z_{g,d,s} + \gamma_2 \frac{1}{3} \sum_{s=t-2}^t N_{g,d,s} + \gamma_4 \frac{1}{3} \sum_{s=t-2}^t W_{g,d,s} + \alpha_g + \alpha_y + \alpha(y_t * I_{A>1.5\%}) + \omega_{i,g,d,t}. \quad (5)$$

All other variables are as defined before and standard errors are also clustered

at the neighborhood level.

Table 6: Effect of air pollution on the number of transactions in a neighborhood

| Dep. Var: $\ln(\text{Transaction})$   | (1)                   |
|---------------------------------------|-----------------------|
|                                       | $> \text{mean}(NO_2)$ |
| $\ln(\text{Pollution})$ last 3 months | -3.186**<br>(1.413)   |
| Observations                          | 3,770                 |
| R-squared                             | 0.616                 |
| First-stage F statistic               | 6,969                 |
| <hr/>                                 |                       |
| House characteristics                 |                       |
| Neighborhood                          | ✓                     |
| Bad Weather Index                     | ✓                     |
| Year                                  | ✓                     |
| Airbnb(Districts) $\times$ Year       | ✓                     |

The dependent variable is the natural logarithm of the number of transactions. The specification is estimated using instrumental variables. The coefficient of interest captures the change in transaction volume when average air pollution over the last three months is above the mean. The specification includes neighborhood characteristic (population density, number of establishments such as health care and education), a bad weather index based on temperature, wind and precipitation, year and neighborhood fixed effects and a linear time trend interacted with a high-Airbnb-intensity district indicator (threshold: 1.5%). Robust standard errors in parentheses are clustered by neighborhood. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10%, respectively. Sources: Author' calculations using Land Registry records (Registrars of Property of Spain, 2014-2020), air pollution (Council of Madrid, 2014-2020a), neighborhood data (Council of Madrid, 2014-2020b) (Council of Madrid, 2014-2020c) (Inside Airbnb, 2022), thermal inversion (Copernicus Climate Data Store, 2014-2020) and weather variables (Store, 2014-2020).

Lopez and Tzur-Ilan (2023) find that peak pollution in the rental market is associated with longer duration of listing and fewer available properties, indicating a reduction in overall transactions. In line with this evidence, I examine how the relationship between air pollution and transaction volume evolves when pollution levels exceed the mean (see Table 6). Results indicate that housing transactions are negatively affected when air pollution levels surpass the mean. Specifically, a 1% increase in air pollution corresponds to a 3.19% decline in the number of housing transactions.<sup>27</sup> This pattern suggests that, in relatively pol-

<sup>27</sup>In low- $NO_2$  areas, an increase in pollution may prompt individuals to put their properties on the market. Residents of already high pollution areas may still perceive those neighborhoods as relatively less polluted and thus more attractive. This could increase transaction volumes when pollution increases in low- $NO_2$  areas without necessarily affecting prices. As Anenberg and Bayer (2020) show, housing prices may remain unchanged even when transactions rise because buyers and sellers face market frictions—for example, when a homeowner must sell before purchasing a new property or temporarily holds two properties—these frictions can amplify fluctuations in transaction volumes without putting pressure on prices.

luted areas, additional pollution primarily operates through the demand side: fewer households are willing to move into these areas, rather than existing residents increasing the supply of properties for sale.

## 5 Conclusion

This paper examines the causal effects of air pollution on housing prices from detailed transaction data, combined with air pollution data for Madrid. Using thermal inversion, an exogenous meteorological phenomenon, as an instrument I am able to address endogeneity concerns which could arise as changes in urban amenities, such as expanded public transport networks and a growing preference for a neighborhood may jointly affect air pollution and housing prices. My analysis shows that housing prices decrease by 0.65% when air pollution increases by 10%, a reduction of €1,327 for the average house. These findings are robust to alternative measures of air pollution, bad weather indices, and additional controls for seasonality.

To account for the timing of sales and purchases of houses, I compute mean air pollution over the three, six and nine months prior to each transaction, finding stronger effects for longer time horizons: the above-mentioned price differences increasing to €2,553 when considering a nine months' horizon. In line with previous studies, I also find air pollution to have non-linear effects, with strong negative effects on housing prices in highly polluted areas (Cai et al., 2024; Mikula and Pytliková, 2021). I also find stronger effect for neighborhoods with more high-educated and high-income individuals and for those with a relatively more children aged 0 to 14.

Finally, exploring market mechanisms, as pollution increases in already high polluted areas, the number of transactions per neighborhood decreases, potentially putting downward pressure on prices.

My study faces two limitations to be considered when interpreting the results. First, I do not have information on either the current conditions of the house nor the floor of the apartment, which are both important variables for determining housing prices. Having access to these variables would likely increase the precision of my estimates. Second, given that surveys show that people are aware of and concerned about air pollution, incorporating subjective assessments of air quality at the neighborhood level (Mínguez et al., 2013; Chasco and Gallo, 2013) into the model could be an interesting road for future research.

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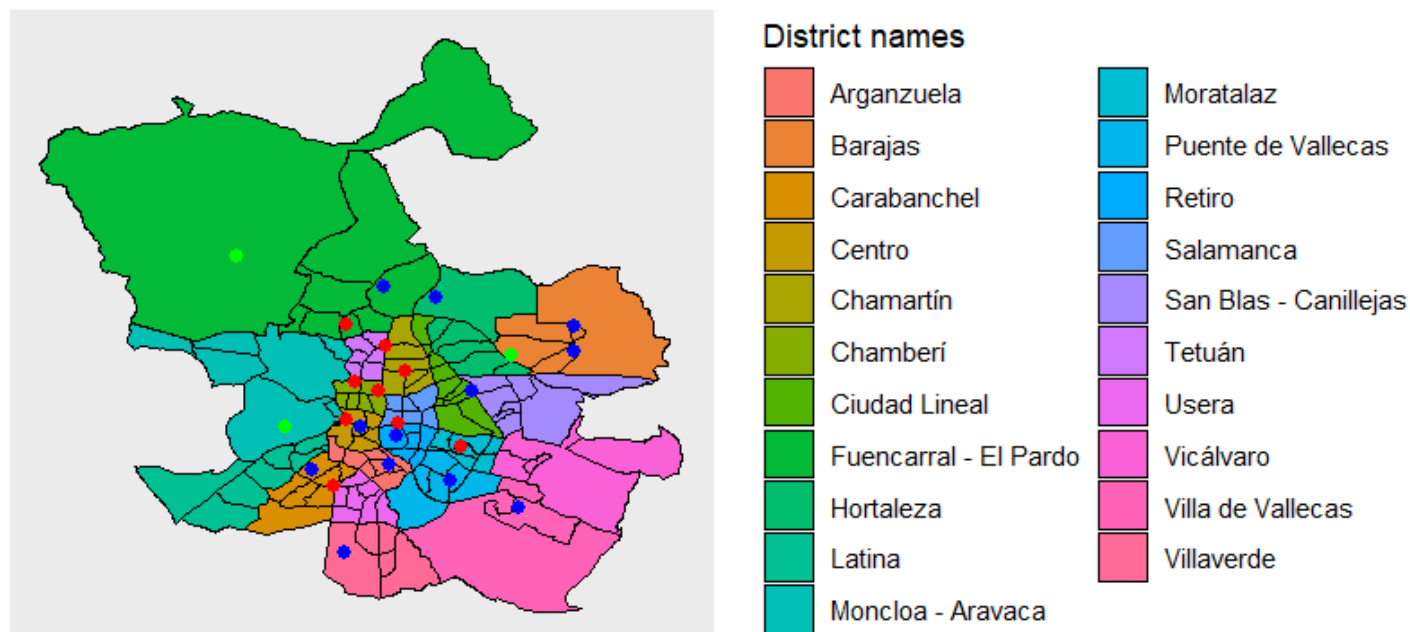
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# A Appendix

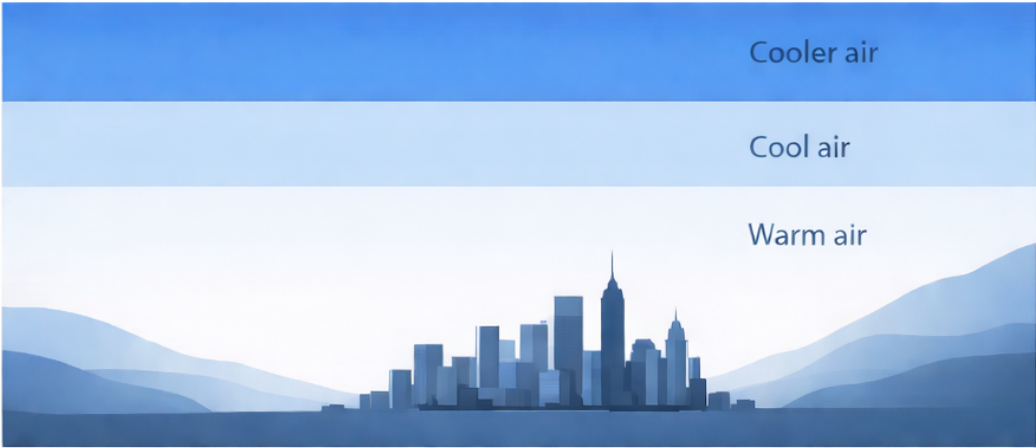
Figure A.1: Distribution of pollution monitors and districts across Madrid



Source: Own elaboration based on Council of Madrid (2014-2020a)

This figure show the distribution of districts and neighborhoods in Madrid and the location of pollution monitors. Traffic monitors are shown in red, urban background monitors in blue, and suburban monitors in green.

Figure A.2: Comparison of air movement during normal and inversion conditions



**Normal pattern**

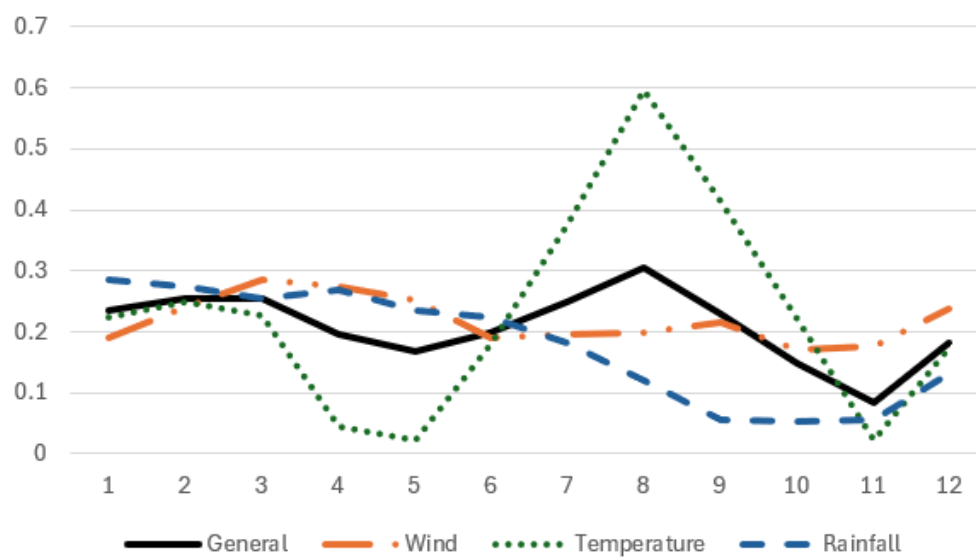


**Thermal inversion**

Source: Own elaboration

During normal conditions temperature decreases with altitude, but under thermal inversion the relationship is altered and a warm inversion layer appears.

Figure A.3: Variability of weather indices across months for 2017



Source: Own calculation based on Store (2014-2020)

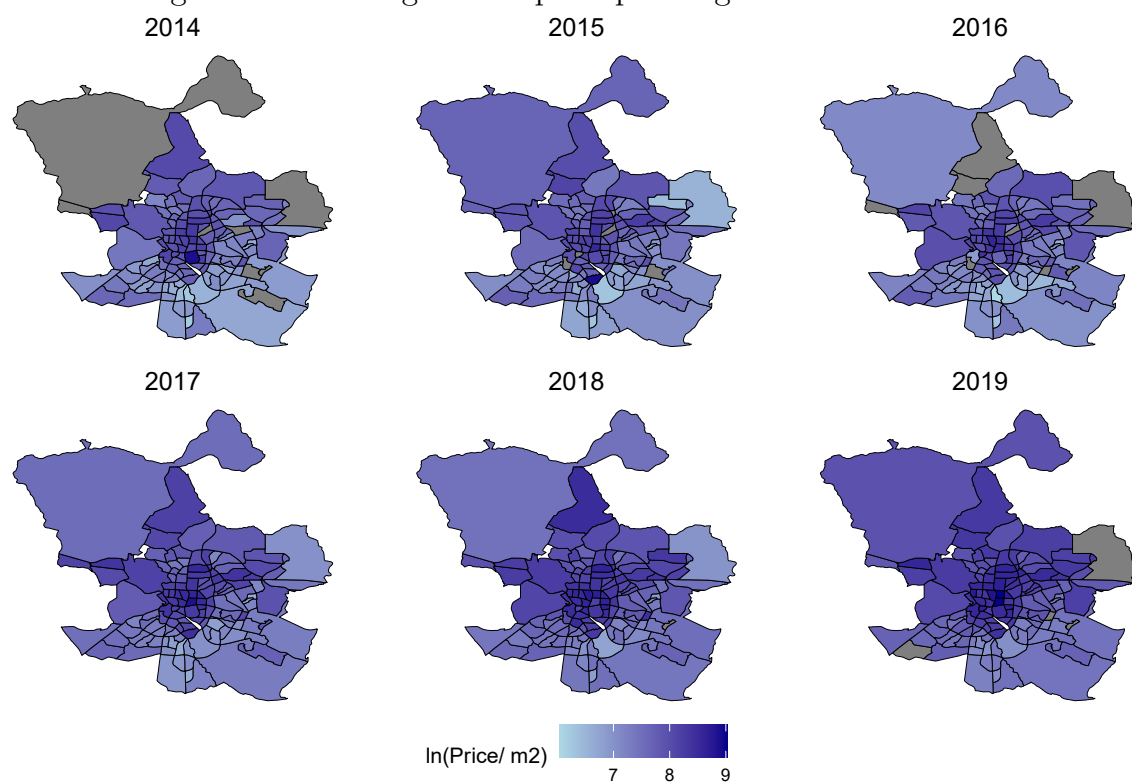
This figure show the variation of weather indices across months, the solid black line show the general index that is constructed as the mean of the wind, temperature and rainfall index. 2017 is selected as a representative year to illustrate differences across months.

Table A.1: Airbnb concentration by districts

| Districts             | Airbnb totals | Entire home | Nº households | % total Airbnb | % entire home |
|-----------------------|---------------|-------------|---------------|----------------|---------------|
| Centro                | 9,334         | 6,881       | 69,504        | 13.43          | 9.9           |
| Salamanca             | 1,419         | 1,113       | 63,001        | 2.25           | 1.77          |
| Chamberí              | 1,257         | 802         | 61,936        | 2.03           | 1.29          |
| Arganzuela            | 1,078         | 658         | 65,479        | 1.65           | 1             |
| Retiro                | 747           | 470         | 48,880        | 1.53           | 0.96          |
| Tetuán                | 984           | 640         | 67,073        | 1.47           | 0.95          |
| Chamartín             | 603           | 406         | 58,413        | 1.03           | 0.7           |
| Moncloa - Aravaca     | 604           | 306         | 46,361        | 1.3            | 0.66          |
| Carabanchel           | 732           | 338         | 96,871        | 0.76           | 0.35          |
| Usera                 | 353           | 177         | 50,285        | 0.7            | 0.35          |
| Ciudad Lineal         | 642           | 270         | 87,225        | 0.74           | 0.31          |
| Barajas               | 158           | 54          | 18,756        | 0.84           | 0.29          |
| San Blas - Canillejas | 472           | 176         | 60,551        | 0.78           | 0.29          |
| Hortaleza             | 446           | 211         | 72,104        | 0.62           | 0.29          |
| Puente de Vallecas    | 564           | 245         | 89,291        | 0.63           | 0.27          |
| Latina                | 550           | 198         | 95,756        | 0.57           | 0.21          |

Source: Inside Airbnb (2022) and Council of Madrid (2017). Note that on Airbnb it is possible to rent an entire house or just a room. % total Airbnb is the ratio of the total number of Airbnbs and the number of households. % entire home is the ratio of those Airbnbs that rent the entire house and the number of households.

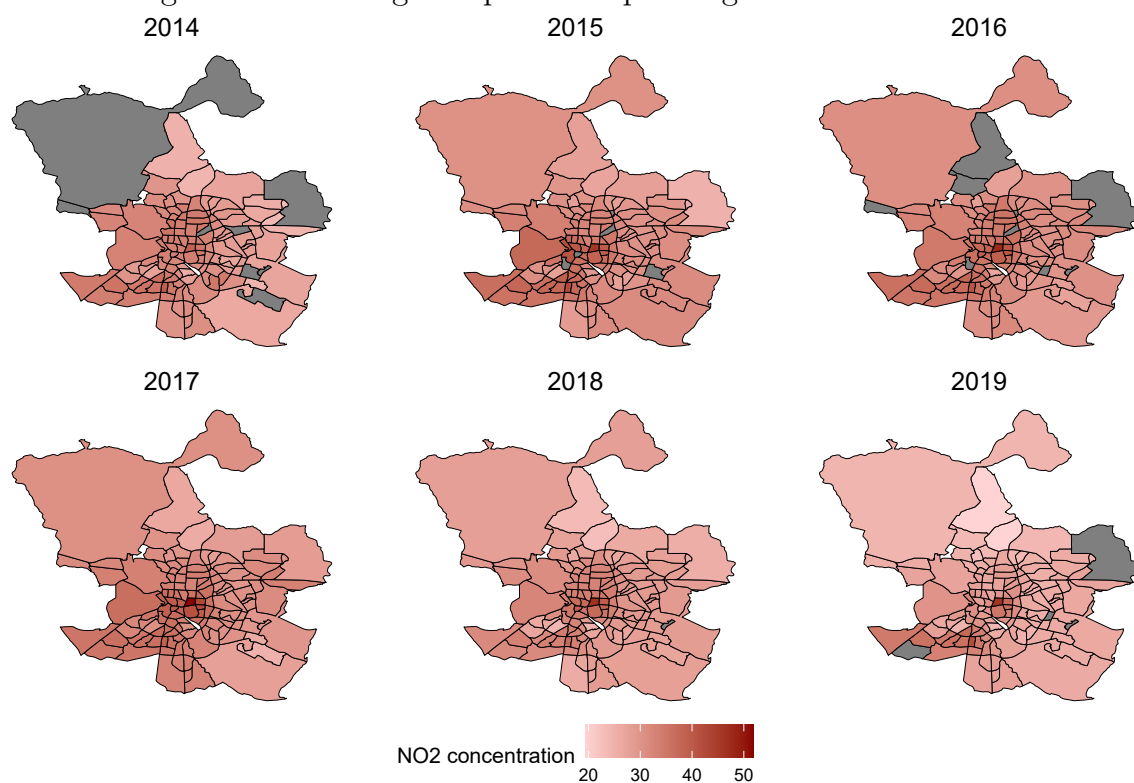
Figure A.4: Average house price per neighborhood over time



Source: Registrars of Property of Spain (2014-2020)

This figure shows the variation in house prices as recorded in May for 2014-2019. Neighborhoods with higher house prices are shown in darker shades of blue. May is selected as a representative month to illustrate differences across years.

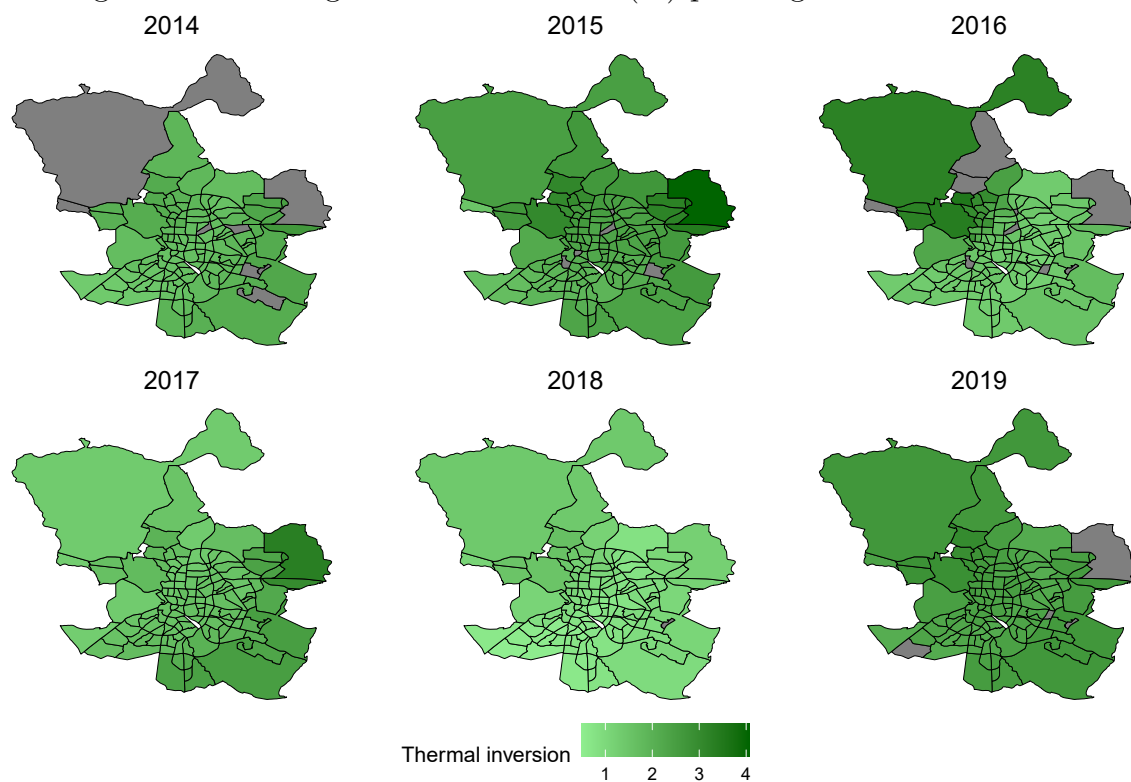
Figure A.5: Average air pollution per neighborhood over time



Source: Council of Madrid (2014-2020a)

This figure shows the variation in air pollution as recorded in May for 2014-2019. Neighborhoods with higher air pollution are shown in darker shades of red. May is selected as a representative month to illustrate differences across years.

Figure A.6: Average thermal inversion (%) per neighborhood over time



Source: Copernicus Climate Data Store (2014-2020)

This figure shows the variation in thermal inversions as recorded in May for 2014-2019. Neighborhoods with higher level of thermal inversion are shown in darker shades of green. May is selected as a representative month to illustrate differences across years.

Table A.2: Explained variation of air pollution

| Dependent variable: Log $NO_2$ concentration |              |              |                   |      |                   |                   |  |
|----------------------------------------------|--------------|--------------|-------------------|------|-------------------|-------------------|--|
| $R^2$                                        | House chars. | Neighborhood | Bad Weather Index | Year | Dist(Airbnb)*year | Thermal inversion |  |
| 0.043                                        | ✓            |              |                   |      |                   |                   |  |
| 0.13                                         | ✓            | ✓            |                   |      |                   |                   |  |
| 0.134                                        | ✓            | ✓            | ✓                 |      |                   |                   |  |
| 0.196                                        | ✓            | ✓            | ✓                 | ✓    |                   |                   |  |
| 0.196                                        | ✓            | ✓            | ✓                 | ✓    | ✓                 |                   |  |
| 0.752                                        | ✓            | ✓            | ✓                 | ✓    | ✓                 | ✓                 |  |

This table shows the  $R^2$  values from equation (2) where the dependent variable is the natural logarithm of  $NO_2$  and controls are added sequentially. Sources: Author' calculations using Land Registry records (Registrars of Property of Spain, 2014-2020), year of construction from Moral-Carcedo (2024), air pollution (Council of Madrid, 2014-2020a), neighborhood data (Council of Madrid, 2014-2020b) (Council of Madrid, 2014-2020c) (Inside Airbnb, 2022), thermal inversion (Copernicus Climate Data Store, 2014-2020) and weather variables (Store, 2014-2020).

Table A.3: Effect of air pollution on housing prices including controls sequentially in an OLS model

| Dep. Var: $\ln(\text{price}/m^2)$<br>Pollution: Last 3 months |                                     | (1)      | (2)       | (3)       | (4)       | (5)       | (6)       |
|---------------------------------------------------------------|-------------------------------------|----------|-----------|-----------|-----------|-----------|-----------|
|                                                               | $\ln(\text{Pollution})$             | 0.097*** | 0.044***  | -0.005    | -0.002    | -0.002    | -0.053*** |
| Year of construction                                          | Built before 1960                   |          | 0.086***  | -0.183*** | -0.183*** | -0.183*** | -0.319*** |
|                                                               | Built between 1960 - 1975           |          | -0.249*** | -0.302*** | -0.301*** | -0.301*** | -0.279*** |
|                                                               | Built between 1975 - 2000           |          | -0.271*** | -0.306*** | -0.306*** | -0.306*** | -0.268*** |
|                                                               | Second- hand                        |          | 0.315***  | 0.222***  | 0.221***  | 0.221***  | 0.031**   |
| Property Type                                                 | Flat without annexes                |          | -0.176*** | -0.155*** | -0.156*** | -0.156*** | -0.089*** |
|                                                               | Semi-detached                       |          | -0.148*** | 0.001     | 0.001     | 0.001     | 0.110**   |
|                                                               | Detached                            |          | -0.068*** | 0.098     | 0.098     | 0.098     | 0.123**   |
| Property size                                                 | Less than 55 m <sup>2</sup>         |          | -0.128*** | -0.101*** | -0.100*** | -0.100*** | 0.184***  |
|                                                               | Between 55 and 75 m <sup>2</sup>    |          | -0.277*** | -0.224*** | -0.224*** | -0.224*** | 0.092***  |
|                                                               | Between 75 and 100 m <sup>2</sup>   |          | -0.254*** | -0.215*** | -0.215*** | -0.215*** | 0.019     |
| Activities CNAE                                               | Mean of human health                |          |           | 0.005     | 0.005     | 0.005     | -0.003**  |
|                                                               | Mean education                      |          |           | 0.001     | 0.001     | 0.001     | 0.002     |
|                                                               | Mean wholesale and retail           |          |           | -0.001*** | -0.001*** | -0.001*** | 0.000     |
|                                                               | Mean accommodation and food service |          |           | 0.002***  | 0.002***  | 0.002***  | -0.000    |
|                                                               | Mean other services                 |          |           | -0.002    | -0.002    | -0.002    | 0.002***  |
|                                                               | Mean entertainment and recreation   |          |           | -0.000    | -0.000    | -0.000    | -0.001    |
|                                                               | Population density                  |          |           | 0.001***  | 0.001***  | 0.001***  | 0.001     |
|                                                               | Bad Weather index                   |          |           |           | 0.292***  | 0.292***  | -0.304*** |
| Observations                                                  |                                     | 106,449  | 106,449   | 106,449   | 106,449   | 106,449   | 106,449   |
| R-squared                                                     |                                     | 0.002    | 0.135     | 0.240     | 0.241     | 0.241     | 0.581     |
| House characteristics                                         |                                     |          | ✓         | ✓         | ✓         | ✓         | ✓         |
| Neighborhood                                                  |                                     |          |           | ✓         | ✓         | ✓         | ✓         |
| Bad Weather Index                                             |                                     |          |           |           | ✓         | ✓         | ✓         |
| Year                                                          |                                     |          |           |           |           | ✓         | ✓         |
| Airbnb(Districts)×Year                                        |                                     |          |           |           |           |           | ✓         |

The dependent variable in all columns is the natural logarithm of housing prices per square meter. All specifications are estimated using OLS. In column (1), no controls are included; column (2) adds housing-characteristic (year of construction, built square meters, property type and whether it is new/second hand); column (3) incorporates neighborhood characteristic (population density, number of establishments such as health care and education) and fixed effects; column (4) introduces a bad weather index; and column (5) includes year fixed effects. Finally, column (6) includes a linear time trend interacted with a high-Airbnb-intensity district indicator (threshold: 1.5%), using the same set of controls as the baseline specification. Robust standard errors in parentheses are clustered by neighborhood in column (4) and (5). \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10%, respectively. Sources: Author' calculations using Land Registry records (Registrars of Property of Spain, 2014-2020), year of construction from Moral-Carcedo (2024), air pollution (Council of Madrid, 2014-2020a), neighborhood data (Council of Madrid, 2014-2020b) (Council of Madrid, 2014-2020c) (Inside Airbnb, 2022), thermal inversion (Copernicus Climate Data Store, 2014-2020) and weather variables (Store, 2014-2020).

Table A.4: Effect of air pollution on housing prices including controls sequentially in an IV model

| Dep. Var: $\ln(\text{price}/m^2)$<br>Pollution: Last 3 months |                                     | (1)      | (2)       | (3)       | (4)       | (5)       | (6)       |
|---------------------------------------------------------------|-------------------------------------|----------|-----------|-----------|-----------|-----------|-----------|
|                                                               | $\ln(\text{Pollution})$             | 0.041*** | 0.039***  | 0.058***  | 0.059***  | 0.059***  | -0.065*** |
| Year of construction                                          | Built before 1960                   |          | 0.086***  | -0.183*** | -0.183*** | -0.183*** | -0.319*** |
|                                                               | Built between 1960 - 1975           |          | -0.249*** | -0.302*** | -0.301*** | -0.301*** | -0.279*** |
|                                                               | Built between 1975 - 2000           |          | -0.271*** | -0.306*** | -0.306*** | -0.306*** | -0.268*** |
| Property Type                                                 | Second- hand                        |          | 0.315***  | 0.222***  | 0.221***  | 0.221***  | 0.031**   |
|                                                               | Flat without annexes                |          | -0.176*** | -0.155*** | -0.156*** | -0.156*** | -0.089*** |
|                                                               | Semi-detached                       |          | -0.148*** | 0.001     | 0.001     | 0.001     | 0.110**   |
| Property size                                                 | Detached                            |          | -0.068*** | 0.099     | 0.098     | 0.098     | 0.122**   |
|                                                               | Less than 55 m <sup>2</sup>         |          | -0.128*** | -0.101*** | -0.100*** | -0.100*** | 0.184***  |
|                                                               | Between 55 and 75 m <sup>2</sup>    |          | -0.277*** | -0.224*** | -0.224*** | -0.224*** | 0.092***  |
| Activities CNAE                                               | Between 75 and 100 m <sup>2</sup>   |          | -0.254*** | -0.215*** | -0.215*** | -0.215*** | 0.019     |
|                                                               | Mean of human health                |          |           | 0.005     | 0.005     | 0.005     | -0.003**  |
|                                                               | Mean education                      |          |           | 0.001     | 0.001     | 0.001     | 0.002     |
|                                                               | Mean wholesale and retail           |          |           | -0.001*** | -0.001*** | -0.001*** | 0.000     |
|                                                               | Mean accommodation and food service |          |           | 0.002***  | 0.002***  | 0.002***  | -0.000    |
|                                                               | Mean other services                 |          |           | -0.002    | -0.002    | -0.002    | 0.002***  |
|                                                               | Mean entertainment and recreation   |          |           | -0.000    | -0.000    | -0.000    | -0.001    |
|                                                               | Population density                  |          |           | 0.001***  | 0.001***  | 0.001***  | 0.001     |
|                                                               | Bad Weather index                   |          |           |           | 0.292***  | 0.292***  | -0.304*** |
| Observations                                                  |                                     | 106,449  | 106,449   | 106,449   | 106,449   | 106,449   | 106,449   |
| R-squared                                                     |                                     | 0.002    | 0.135     | 0.240     | 0.241     | 0.241     | 0.581     |
| House characteristics                                         |                                     |          | ✓         | ✓         | ✓         | ✓         | ✓         |
| Neighborhood                                                  |                                     |          |           | ✓         | ✓         | ✓         | ✓         |
| Bad Weather Index                                             |                                     |          |           |           | ✓         | ✓         | ✓         |
| Year                                                          |                                     |          |           |           |           | ✓         | ✓         |
| Airbnb(Districts)×Year                                        |                                     |          |           |           |           |           | ✓         |

The dependent variable in all columns is the natural logarithm of housing prices per square meter. All specifications are estimated using instrumental variables. In column (1), no controls are included; column (2) adds housing-characteristic (year of construction, built square meters, property type and whether it is new/second hand); column (3) incorporates neighborhood characteristic (population density, number of establishments such as health care and education) and fixed effects; column (4) introduces a bad weather index; and column (5) includes year fixed effects. Finally, column (6) includes a linear time trend interacted with a high-Airbnb-intensity district indicator (threshold: 1.5%), using the same set of controls as the baseline specification. Robust standard errors in parentheses are clustered by neighborhood in column (4) and (5). \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10%, respectively. Sources: Author' calculations using Land Registry records (Registrars of Property of Spain, 2014-2020), year of construction from Moral-Carcedo (2024), air pollution (Council of Madrid, 2014-2020a), neighborhood data (Council of Madrid, 2014-2020b) (Council of Madrid, 2014-2020c) (Inside Airbnb, 2022), thermal inversion (Copernicus Climate Data Store, 2014-2020) and weather variables (Store, 2014-2020).

Table A.5: Robustness: Effect of air pollution on housing prices using alternative pollution measures

| Dep. Var: $\ln(\text{Price}/m^2)$     | (1)<br><i>Using mean of<br/>air pollution</i> | (2)<br><i>Log-Lin<br/>specification</i> | (3)<br><i>Inverse distance<br/>weighted average of<br/>the three closest<br/>monitors</i> | (4)<br><i>Closest monitor<br/>for air pollution</i> |
|---------------------------------------|-----------------------------------------------|-----------------------------------------|-------------------------------------------------------------------------------------------|-----------------------------------------------------|
| $\ln(\text{Pollution})$ last 3 months | -0.073***<br>(0.011)                          | -0.0017***<br>(0.000)                   | -0.080***<br>(0.012)                                                                      | -0.076***<br>(0.012)                                |
| Observations                          | 106,449                                       | 106,449                                 | 106,406                                                                                   | 106,406                                             |
| R-squared                             | 0.581                                         | 0.581                                   | 0.581                                                                                     | 0.581                                               |
| First-stage F statistic               | 3,394                                         | 7,583                                   | 2,365                                                                                     | 1,271                                               |
| House characteristics                 | ✓                                             | ✓                                       | ✓                                                                                         | ✓                                                   |
| Neighborhood                          | ✓                                             | ✓                                       | ✓                                                                                         | ✓                                                   |
| Bad Weather Index                     | ✓                                             | ✓                                       | ✓                                                                                         | ✓                                                   |
| Year                                  | ✓                                             | ✓                                       | ✓                                                                                         | ✓                                                   |
| Airbnb(Districts)×Year                | ✓                                             | ✓                                       | ✓                                                                                         | ✓                                                   |

The dependent variable in all columns is the natural logarithm of housing prices per square meter. All specifications are estimated using instrumental variables. In column (1), I use the daily mean of air pollution instead of the median employed in my baseline specification and in column (2) I use a Log-Lin specification. In columns (3) and (4), I rely on alternative pollution measures: (3) inverse-distance-weighted average of the three nearest monitoring stations, while (4) uses the reading from the single closest monitor. All columns include house characteristics (year of construction, built square meters, property type and whether it is new/second hand) and neighborhood characteristic (population density, number of establishments such as health care and education), a bad weather index based on temperature, wind and precipitation, year and neighborhood fixed effects and a linear time trend interacted with a high-Airbnb-intensity district indicator (threshold: 1.5%). \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10%, respectively. Sources: Author' calculations using Land Registry records (Registrars of Property of Spain, 2014-2020), year of construction from Moral-Carcedo (2024), air pollution (Council of Madrid, 2014-2020a), neighborhood data (Council of Madrid, 2014-2020b) (Council of Madrid, 2014-2020c) (Inside Airbnb, 2022), thermal inversion (Copernicus Climate Data Store, 2014-2020) and weather variables (Store, 2014-2020).

Table A.6: Robustness: Effect of air pollution on housing prices under alternative specifications for the bad-weather index

| Dep. Var:ln(Price/ m <sup>2</sup> ) | (1)                     | (2)                        |
|-------------------------------------|-------------------------|----------------------------|
|                                     | <i>Looser threshold</i> | <i>Stricter thresholds</i> |
| ln(Pollution) last 3 months         | -0.080***<br>(0.012)    | -0.065***<br>(0.009)       |
| Observations                        | 106,449                 | 106,449                    |
| R-squared                           | 0.581                   | 0.581                      |
| First-stage F statistic             | 3,403                   | 3,425                      |
| House characteristics               | ✓                       | ✓                          |
| Neighborhood                        | ✓                       | ✓                          |
| Bad Weather Index                   | ✓                       | ✓                          |
| Year                                | ✓                       | ✓                          |
| Airbnb(Districts)×Year              | ✓                       | ✓                          |

The dependent variable in all columns is the natural logarithm of housing prices per square meter. All specifications are estimated using instrumental variables. Columns (1) and (2) estimate the effect of average air pollution over the previous three months using alternative bad weather indices. Column (1) employs a looser index, defined by the top 50th percentile of rainfall and wind and the top and bottom 25th percentiles of temperature. Column (2) uses a stricter index, defined by the top 10th percentile of rainfall and wind and the top and bottom 5th percentiles of temperature. All columns include house characteristics (year of construction, built square meters, property type and whether it is new/second hand) and neighborhood characteristic (population density, number of establishments such as health care and education), a bad weather index based on temperature, wind and precipitation, year and neighborhood fixed effects and a linear time trend interacted with a high-Airbnb-intensity district indicator (threshold: 1.5%). Robust standard errors in parentheses are clustered by neighborhood. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10%, respectively. Sources: Sources: Author’ calculations using Land Registry records (Registrars of Property of Spain, 2014-2020), year of construction from Moral-Carcedo (2024), air pollution (Council of Madrid, 2014-2020a), neighborhood data (Council of Madrid, 2014-2020b) (Council of Madrid, 2014-2020c) (Inside Airbnb, 2022), thermal inversion (Copernicus Climate Data Store, 2014-2020) and weather variables (Store, 2014-2020).

Table A.7: Robustness: Effect of air pollution on housing prices after including eliminated monitors and excluding problematic districts

| Dep. Var: $\ln(\text{Price}/m^2)$ | (1)                              | (2)                                           | (3)                                           | (4)                                 |
|-----------------------------------|----------------------------------|-----------------------------------------------|-----------------------------------------------|-------------------------------------|
|                                   | <i>Including Retiro monitors</i> | <i>Including Retiro and suburban monitors</i> | <i>Excluding district 1 from October 2018</i> | <i>Excluding district 18 and 19</i> |
| $\ln(\text{Pollution})$           | -0.078***                        | -0.077***                                     | -0.067***                                     | -0.066***                           |
| last 3 months                     | (0.012)                          | (0.012)                                       | (0.009)                                       | (0.010)                             |
| Observations                      | 106,449                          | 106,449                                       | 104,602                                       | 102,263                             |
| R-squared                         | 0.581                            | 0.581                                         | 0.575                                         | 0.583                               |
| First-stage F statistic           | 3,783                            | 3,406                                         | 4,004                                         | 3,504                               |
| House characteristics             | ✓                                | ✓                                             | ✓                                             | ✓                                   |
| Neighborhood                      | ✓                                | ✓                                             | ✓                                             | ✓                                   |
| Bad Weather Index                 | ✓                                | ✓                                             | ✓                                             | ✓                                   |
| Year                              | ✓                                | ✓                                             | ✓                                             | ✓                                   |
| Airbnb(Districts) $\times$ Year   | ✓                                | ✓                                             | ✓                                             | ✓                                   |

The dependent variable in all columns is the natural logarithm of housing prices per square meter. All specifications are estimated using instrumental variables. For column (1), the Retiro monitor is included in the sample and in column (2) suburban and the Retiro monitors are included. In column (3), district 1 is eliminated from the sample from October 2018 due to the announcement and implementation of "Madrid Central" during that year. Finally, in column (4), districts 18 and 19 are eliminated from the sample for all the years due to the creation of new neighborhoods in these districts. All columns include house characteristics (year of construction, built square meters, property type and whether it is new/second hand) and neighborhood characteristic (population density, number of establishments such as health care and education), a bad weather index based on temperature, wind and precipitation, year and neighborhood fixed effects and a linear time trend interacted with a high-Airbnb-intensity district indicator (threshold: 1.5%). Robust standard errors in parentheses are clustered by neighborhood. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10%, respectively. Sources: Author' calculations using Land Registry records (Registrars of Property of Spain, 2014-2020), year of construction from Moral-Carcedo (2024), air pollution (Council of Madrid, 2014-2020a), neighborhood data (Council of Madrid, 2014-2020b) (Council of Madrid, 2014-2020c) (Inside Airbnb, 2022), thermal inversion (Copernicus Climate Data Store, 2014-2020) and weather variables (Store, 2014-2020).

Table A.8: Robustness: Effect of air pollution on housing prices including seasonal and traffic controls

| Dep. Var:ln(Price/ $m^2$ )  | (1)<br><i>Including a "hot/ cold<br/>season" control</i> | (2)<br><i>Including end-year<br/>dummy</i> | (3)<br><i>Traffic control</i> |
|-----------------------------|----------------------------------------------------------|--------------------------------------------|-------------------------------|
| ln(Pollution) last 3 months | -0.080**<br>(0.035)                                      | -0.108***<br>(0.010)                       | -0.065***<br>(0.010)          |
| Observations                | 106,449                                                  | 106,449                                    | 102,852                       |
| R-squared                   | 0.581                                                    | 0.581                                      | 0.572                         |
| First-stage F statistic     | 2,775                                                    | 3,028                                      | 3,419                         |
| House characteristics       | ✓                                                        | ✓                                          | ✓                             |
| Neighborhood                | ✓                                                        | ✓                                          | ✓                             |
| Bad Weather Index           | ✓                                                        | ✓                                          | ✓                             |
| Year                        | ✓                                                        | ✓                                          | ✓                             |
| Airbnb(Districts)×Year      | ✓                                                        | ✓                                          | ✓                             |

The dependent variable in all columns is the natural logarithm of housing prices per square meter. All specifications are estimated using instrumental variables. In column (1), I include a seasonal indicator equal to 1 for sales occurring in spring or summer and 0 otherwise. In column (2), I add a December dummy to capture end-of-year, tax-motivated sales and in column (3) I include a traffic variable mean occupation which represent the percentage of time a traffic detector is active. All columns include house characteristics (year of construction, built square meters, property type and whether it is new/second hand) and neighborhood characteristic (population density, number of establishments such as health care and education), a bad weather index based on temperature, wind and precipitation, year and neighborhood fixed effects and a linear time trend interacted with a high-Airbnb-intensity district indicator (threshold: 1.5%). Robust standard errors in parentheses are clustered by neighborhood. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10%, respectively. Sources: Author' calculations using Land Registry records (Registrars of Property of Spain, 2014-2020), year of construction from Moral-Carcedo (2024), air pollution (Council of Madrid, 2014-2020a), neighborhood data (Council of Madrid, 2014-2020b) (Council of Madrid, 2014-2020c) (Inside Airbnb, 2022), traffic data (Council of Madrid, 2014-2020d), thermal inversion (Copernicus Climate Data Store, 2014-2020) and weather variables (Store, 2014-2020).

Table A.9: Robustness: Effect of air pollution on housing prices for old and new houses

| Dep. Var: $\ln(\text{Price}/m^2)$     | (1)                                 | (2)                                |
|---------------------------------------|-------------------------------------|------------------------------------|
|                                       | <i>Houses built before<br/>2000</i> | <i>Houses built after<br/>2000</i> |
| $\ln(\text{Pollution})$ last 3 months | -0.057***<br>(0.009)                | -0.079***<br>(0.026)               |
| Observations                          | 88163                               | 18286                              |
| R-squared                             | 0.600                               | 0.457                              |
| First-stage F statistic               | 3,217                               | 1,402                              |
| House characteristics                 | ✓                                   | ✓                                  |
| Neighborhood                          | ✓                                   | ✓                                  |
| Bad Weather Index                     | ✓                                   | ✓                                  |
| Year                                  | ✓                                   | ✓                                  |
| Airbnb(Districts) $\times$ Year       | ✓                                   | ✓                                  |

The dependent variable in all columns is the natural logarithm of housing prices per square meter. All specifications are estimated using instrumental variables. Column (1), includes houses built before 2000 and column (2) houses built after 2000. All columns include house characteristics (year of construction, built square meters, property type and whether it is new/second hand) and neighborhood characteristic (population density, number of establishments such as health care and education), a bad weather index based on temperature, wind and precipitation, year and neighborhood fixed effects and an interaction term between year and a linear time trend interacted with a high-Airbnb-intensity district indicator (threshold: 1.5%). Robust standard errors in parentheses are clustered by neighborhood. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10%, respectively. Sources: Author' calculations using Land Registry records (Registrars of Property of Spain, 2014-2020), year of construction from Moral-Carcedo (2024), air pollution (Council of Madrid, 2014-2020a), neighborhood data (Council of Madrid, 2014-2020b) (Council of Madrid, 2014-2020c) (Inside Airbnb, 2022), thermal inversion (Copernicus Climate Data Store, 2014-2020) and weather variables (Store, 2014-2020).

Table A.10: Robustness: Randomization inference of the impact of thermal inversion

| Dep. Var: $\ln(\text{Price}/m^2)$     |                      |
|---------------------------------------|----------------------|
| $\ln(\text{Pollution})$ last 3 months | -0.065***<br>(0.009) |
| Confidence interval at 1%             | [-32.15, 18.9]       |
| House characteristics                 | ✓                    |
| Neighborhood                          | ✓                    |
| Bad bad weather index                 | ✓                    |
| Year                                  | ✓                    |
| Airbnb(Districts) $\times$ Year       | ✓                    |

The dependent variable is the natural logarithm of housing prices per square meter. The specification is estimated using instrumental variables. This table shows the confidence interval at 1% where thermal inversions are randomly assigned 500 times within neighborhood-year pairs. All columns include house characteristics (year of construction, built square meters, property type and whether it is new/second hand) and neighborhood characteristic (population density, number of establishments such as health care and education), a bad weather index based on temperature, wind and precipitation, year and neighborhood fixed effects and an interaction term between year and a group of districts with an Airbnb rental share above 1.5%. Sources: Author' calculations using Land Registry records (Registrars of Property of Spain, 2014-2020), year of construction from Moral-Carcedo (2024), air pollution (Council of Madrid, 2014-2020a), neighborhood data (Council of Madrid, 2014-2020b) (Council of Madrid, 2014-2020c) (Inside Airbnb, 2022), thermal inversion (Copernicus Climate Data Store, 2014-2020) and weather variables (Store, 2014-2020).

Table A.11: Robustness: Heterogeneity in the effect of air pollution on housing prices for quality houses and foreigners

| Dep. Var: $\ln(\text{Price}/m^2)$     | (1)<br>Bottom 25%    | (2)<br>Top 25%       |
|---------------------------------------|----------------------|----------------------|
| 1. Quality houses:                    |                      |                      |
| $\ln(\text{Pollution})$ last 3 months | -0.018<br>(0.013)    | -0.026***<br>(0.007) |
| Observations                          | 26,610               | 26,610               |
| R-squared                             | 0.314                | 0.491                |
| First-stage F statistic               | 1,842                | 1,642                |
| 2. Foreign except EU and OECD:        |                      |                      |
| $\ln(\text{Pollution})$ last 3 months | -0.071***<br>(0.018) | -0.037*<br>(0.021)   |
| Observations                          | 13,575               | 32,943               |
| R-squared                             | 0.403                | 0.513                |
| First-stage F statistic               | 1,445                | 1,021                |

The dependent variable in all columns is the natural logarithm of housing prices per square meter. All specifications are estimated using instrumental variables. Each panel reports results for a different sample split. Panel 1 divides neighborhoods by quality houses and panel 2 by foreign except EU and OECD. Column (1) reports estimates for observations in the bottom quartile, while column (2) reports estimates for those in the top quartile. All columns include house characteristics (year of construction, built square meters, property type and whether it is new/second hand) and neighborhood characteristic (population density, number of establishments such as health care and education), a bad weather index based on temperature, wind and precipitation, year and neighborhood fixed effects and an interaction term between year and a linear time trend interacted with a high-Airbnb-intensity district indicator (threshold: 1.5%). Robust standard errors in parentheses are clustered by neighborhood. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10%, respectively. Sources: Author' calculations using Land Registry records (Registrars of Property of Spain, 2014-2020), year of construction from Moral-Carcedo (2024), air pollution (Council of Madrid, 2014-2020a), neighborhood data (Council of Madrid, 2014-2020b) (Council of Madrid, 2014-2020c) (Inside Airbnb, 2022) (Council of Madrid, 2017), thermal inversion (Copernicus Climate Data Store, 2014-2020) and weather variables (Store, 2014-2020).

## B Appendix

The Spanish legislation on air quality is closely related to the European regulation. Current laws on this topic are: Law 34/2007, that updates the legal basis for the assessment and management of air quality in Spain and has the aim of achieving optimum levels of air quality and a Royal Decree 102/2011, which legislates a national air quality index to inform citizens, in a clear and homogeneous manner throughout the national territory, about the quality of the air at any given moment.

This national index defines six categories of air quality: good, reasonably good, fair, unfavorable, very unfavorable, and extremely unfavorable. The pollutants considered in the index are: Suspended Particulate Matter smaller than 10 micrometers ( $PM_{10}$ ), Suspended Particulate Matter smaller than 2.5 micrometers ( $PM_{2.5}$ ), Troposphere Ozone ( $O_3$ ), Nitrogen Dioxide ( $NO_2$ ) and Sulfur Dioxide ( $SO_2$ ).

In this paper, I use  $NO_2$  levels for air pollution, as it is one of the main pollutants in the national index, but also used by the United States Environmental Protection Agency and the World Health Organization in their pollution indices.  $NO_2$  is a gas, which is emitted in the combustion processes carried out by motor vehicles and in high temperature industrial and electricity generation. It is easily recognized by its reddish-brown color and its characteristic pungent odor which increases the potential for awareness among individuals and house buyers. The European air quality directive has set two limit values for nitrogen dioxide ( $NO_2$ ) for the protection of human health: the  $NO_2$  hourly mean value may not exceed 200 micrograms per cubic meter ( $\mu g/m^3$ ) more than 18 times in a year and the  $NO_2$  annual mean value may not exceed 40  $\mu g/m^3$ . During my study period, these limit were exceeded in every year. For example, in 2017, 16 monitoring stations recorded annual mean concentrations above 40  $\mu g/m^3$ , and the hourly limit of 200  $\mu g/m^3$  was exceeded 183 times.

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