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THE PRICE OF SILENCE

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ABSTRACT: This paper studies the causal impact of street noise on housing prices. It focuses on a very dense urban environment and its entire soundscape, using granular data on listed flats and street noise. We employ a combination of hedonic price and fixed effects model, exploiting the regular grid shape of the Eixample district, in Barcelona. Our results indicate that doubling the perceived street noise generates an average depreciation of 3.4% on sales and 2% on rents. We show that the lower semi-elasticity with which the rental market adjusts for the negative externality is associated with a higher turnover of tenants in louder streets. Moreover, we collect several pieces of evidence which suggest that the effect is not driven by sorting by neighbors. Lastly, we use our results to perform two cost-benefit analyses of policies which help reducing noise. Based on our findings, we formulate policy recommendations and highlight specific interventions that can mitigate the negative impact of urban noise.

JEL Codes: R31, R41
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1 Introduction

Noise has long been underappreciated as an urban externality, partly due to decades of urban planning decisions that prioritized private car use over other modes of transport. These historical preferences have shaped cities in ways that continue to influence how street space is allocated and used today. In many urban areas, the legacy of car-centric planning has led to densely built environments where exposure to traffic noise remains widespread. Yet, as concerns over urban livability have grown, the conversation is shifting. Globally, there is a renewed push to reduce car traffic and reclaim urban space for pedestrians and cyclists.

From an economic perspective, high population density implies greater exposure to negative externalities in urban areas (Carozzi & Roth, 2023). However, for the same reason, cities are also the places where policies aimed at mitigating these externalities can yield the greatest benefits. For example, density implies shorter travel distances and greater potential for the adoption of sustainable transport modes, resulting in reductions in both noise and air pollution. This is known as the "density trade-off" (Duranton & Puga, 2020). For this reason, the shift toward more livable environments is occurring primarily in urban areas, where we observe a surge in initiatives that rethink the use of space within cities. The city of Barcelona, which serves as the empirical setting of our analysis, has gained a prominent role in this debate through initiatives aimed at curbing road traffic and improving environmental quality.

Among the costs derived from car-oriented urban development, noise is arguably the one that has historically received the least attention in public discourse, especially when compared to pollution, congestion, and traffic accidents. Nonetheless, noise pollution causes annoyance and is associated with long-term negative health consequences (Argys, Averett, & Yang, 2020; Boes, Nüesch, & Stillman, 2013; Münzel et al., 2018). Moreover, noise increases violent crimes (Hener, 2022), and decreases human cognition (Thompson et al., 2022) and workplace productivity (Dean, 2024). The European Environmental Agency (2020) estimates that in 2019, at least 20% of the EU population was living in areas with high noise levels. Barcelona, one of the densest cities in Europe, is particularly affected: street noise is both high and pervasive across the urban landscape. In our data, covering the period from 2009 to 2017, nearly none of the street segments recorded an average noise level below the threshold recommended by the World Health Organization.

This is changing, however, as noise pollution has begun to receive increasing attention in recent years. In Spain, noise is the most frequently cited environmental issue related to housing (INE, 2023). The shift in attention to noise pollution is also institutional. At the European level, the EU requires cities to systematically monitor environmental noise under the Environmental Noise Directive, and the "population exposed to high noise levels" has become a key indicator tracked by the European Environment Agency. Municipalities are increasingly expected to demonstrate progress in reducing noise levels, and performance metrics based on these indicators are likely to become central to the evaluation of environmental and health outcomes. As local authorities begin to recognize noise as a major negative externality affecting quality of life, quantifying its impact becomes essential for supporting evidence-based policy design.

In this paper we study what is the causal effect of street noise on housing prices. We do so through a hedonic price model combined with an identification strategy which exploits the morphology of the streets of the Eixample district, in the city of Barcelona. We exploit spatial and temporal variation in noise levels and housing prices at a very granular level. Specifically, we use the variation within very small and regular buildings' blocks which characterize this area. Isolating the effect of interest is not straightforward. Higher noise levels often relate to higher accessibility or higher amenities, which positively capitalize into housing prices and act as confounding factors. The orthogonal structure of the street network of the Eixample creates grid cells of around 120x120 m within which local amenities can be safely assumed to be common to all properties. Yet, depending on the side of the block on which they are placed, houses are exposed to different noise levels. We exploit this within-block variation in order to isolate the effect of noise on housing prices and retrieve the willingness to pay for quieter streets.

We find that doubling the perceived level of noise, measured as an increase of 10 decibels (dB) and equivalent to 14% of the average noise level in the Eixample, results in an average depreciation of 3.4% on sales and 2% on rents. Given the average price per m^2 and the average size of listed flats in our sample, these effects translate into a reduction of 16,483 € and 27 € on sales and rents, respectively. The decapitalization gets larger with higher changes in noise, and it showcases some degree of non-linearity over the noise range. These results are robust to alternative noise measures and buildings' blocks definition, as well as restricted sample years and a wider orthogonal sample. Moreover, we show that our identification strategy based on within-block variation successfully captures local (dis)amenity. Indeed, when we add further street characteristics which are correlated to both noise and prices, our main results do not change.

Throughout the whole analysis, we find that the average price semi-elasticity to noise is higher for sales than for rents. We identify several reasons to rationalize the different responsiveness between selling prices and rents. The main one is the higher tightness which characterizes the rental market. Second, different socio-demographic characteristics between an average profile of buyers and renters may imply different order of priorities with respect to the environmental characteristics of a flat. Third, renters have higher asymmetric information, as buyers are more likely to perform a thorough inspection of the flat before buying. Fourth, there may be expected capital gains from investing in quieter streets. While we are not able to precisely identify the contribution of each of these factors to the different discount rate between sales and rents, they all point towards negative environmental externalities affecting homeowners and tenants differently. This result has important implications on distributional effects and environmental inequalities.

We collect several pieces of evidence which indicate that sorting by neighbors is not the underlying mechanism. Lower prices on noisier streets may indeed create clusters of residents with distinct socio-demographic characteristics. Over time, this clustering could lead to neighbor-based sorting. If this occurs, we risk confusing the effect of noise with homophily—the tendency for people to group with similar individuals, in this case, their neighbors. Using different proxies for residents' income we suggest that sorting is not driving our results. Moreover, using the number of published listings at the street section level, we collect evidence of higher turnover in the rental market for flats placed in louder streets. We argue that this reflects the flexibility of the rental market, within which mobility is higher. While this may be either a cause or a consequence of the lower decapitalization observed in the rental market compared to the selling market, it adds further support to the conclusion that noise is a salient disamenity which generates distaste for the location.

The heterogeneity analysis reveals that evening and night noise have an effect higher than the average, while day-time noise has a lower-than-average effect. We perform an exercise in which we look at several sources of noise and we find no statistically different effects across pedestrian, nightlife and traffic noise. We exploit the presence of both internal and external flats in the Eixample to show that the depreciation is driven by the latter. This confirms our results, as the internal flats are not exposed to the street noise. Similarly, we find that flats at lower floors are the ones driving the effect.

Lastly, we use our results to estimate expected costs and benefits of two policies which help reducing noise in the city of Barcelona. First, we look at an hypothetical repaving of the whole district of the Eixample with materials which reduce noise and heat absorption. We show that this policy would become welfare-improving within two years from investment. However, when benchmarked against the objectives set by the current Acoustic Zoning and the levels recommended by the WHO, this policy would still be insufficient to reach good levels of acoustic quality. Second, we perform another cost-benefit analysis on a 2022 policy providing grants for windows replacement in noisy streets. Also in this second case the benefits outweigh the costs. Nevertheless, we stress that an ideal policy should aim at reducing noise at the source and not only address the perception of noise as experienced inside the houses. In addition, this policy is regressive as it is a direct transfer of public resources to private homeowners.

The economic literature studying the effect of noise on housing prices has focused on different and specific sources of noise such as aircraft (Boes & Nüesch, 2011; Zheng, Peng, & Hu, 2020), railroad noise (Ahlfeldt, Nitsch, & Wendland, 2019; Diao, Li, Sing, & Zhan, 2023; Thiel, 2022) and road traffic (Brandt & Maennig, 2011; Swoboda, Nega, & Timm, 2015; von Graevenitz, 2018). Other parts of the literature have covered the trade-off between accessibility and the negative externality of noise emitted by busses (Fan, Teo, & Wan, 2021), as well as the effect of mitigation policies on prices (Lindgren, 2021; Moretti & Wheeler, 2024).

Our contribution to the literature is threefold. First, our paper is the first one to study the capitalization effect of the overall street noise on housing prices in a very densely populated urban context. Our area of analysis is a central district of one of the densest cities in Europe where street noise is generally high and a widespread issue across all streets. Different from von Graevenitz (2018), which is the study which is closest to ours, we do not limit the sample to major roads only, but consider the whole street network and therefore all sources of noise which contribute to the urban soundscape.

Second, we add to the literature which combines hedonic price models with spatial fixed effects. We do so by adopting an innovative type of fixed effects which exploits the setting provided by a specific street morphology. In particular, the grid-shaped street network of the Eixample district creates cells which are small, regular and homogeneous enough to represent a good natural space for within-comparison. This allow us to disentangle the effect of interest from observable and unobservable confounding factors which are often a threat to identification in the literature. Although we also benefit from urban features which are unique to this district, such as the presence of internal and external flats, our strategy is replicable in other settings in which the three mentioned conditions are met (i.e. where small, regular, and homogeneous comparison groups are identifiable).

Third, we make a further contribution to the literature by analyzing how the negative externality of noise is capitalized into both sales and rents (Grainger, 2012). Most of the literature studying noise uniquely focuses on the former. By including both, we can study how the capitalization of negative externalities differs across markets with different levels of tightness and asymmetric information. Buyers and tenants are different in terms of effort put into the choice of the unit, as well as temporal horizon considered. Moreover, given the different socio-demographic composition which tends to characterize the two groups, this can have important implications for distributional effects and environmental inequality.

Our results have important policy implications. First, we suggest that spatially broader, rather than localized interventions, are better suited to reduce noise level in dense urban environments while, at the same time, avoiding spatial inequalities and, potentially, gentrification. Second, an ideal policy should aim at achieving objective reductions in street noise more than targeting perceived noise within the flats. In addition, policies involving direct transfers to homeowners should be avoided for their regressive implications. Third, our results point towards widening the scope of public policies with respect to the most relevant sources. While nightlife is often the most addressed issue in cities, we do not find clear evidence of the prevalence of the burden it creates with respect to other sources. Our analysis suggests that targeting noise from motorized traffic would yield larger reductions in average noise levels, thus significantly contributing to healthier standards of acoustic quality. Examples of recommended policies include measures such as reducing private vehicle use in favor of public transport and active modes, lowering speed limits, tightening vehicle noise regulations and their enforcement, spatially broad low-emission zones or pedestrianized areas, promoting the transition to electric vehicles, and improving road surfaces.

The remainder of this paper is structured as follows. Section 2 presents the geographical setting of the analysis and Section 3 the data we use. The empirical framework is then explained in details in Section 4, and Section 5 presents the results. Section 6 contains the cost-benefit analysis of two public policies, and Section 7 identifies some guidelines for policy recommendations. Section 8 concludes.

2 Geographical setting

For identification purposes explained in detail in Section 3, our analysis will focus on the Eixample district. The Eixample is one of the ten districts of Barcelona. It lies in the middle of the city[1], and it covers an area of 7.5 km^2 (7.32% of the area of the city). In 2021, 16% (about 270,000 people) of the city's population was living in this area. There are several reasons why this unique setting benefits the internal validity of our results.

First, as shown in Figure 1, the street network of this district follows a regular and orthogonal structure. Each grid cell formed by the street intersections (on average sized around 120x120 m) contains buildings' blocks which will be critical in our estimation[2]. This type of urban

[1] Figure A1 shows the central position of this district within the city.

[2] See Figure A2 for a birdeye picture of the district.

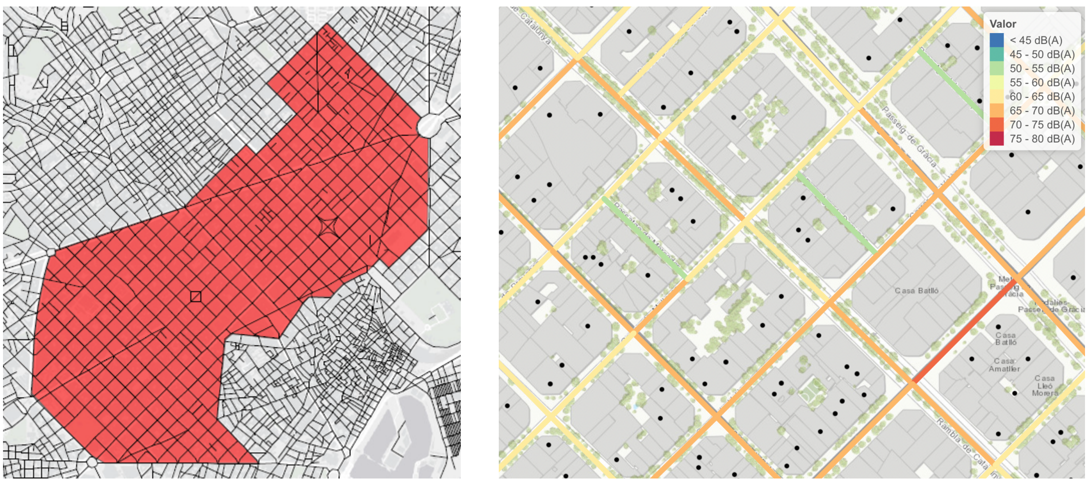
morphology implies that flats within the same block are all in very close and constant distance (subject to the same local (dis)amenities) while, at the same time, exposed to different streets' noise. A very distinctive element of the Eixample is the presence of external and internal flats. While the former face the street, the latter face the inner court of the buildings' block[3].

Second, the regularity of this district is also reflected in the homogeneity of urban features and socio-demographic characteristics. As Table A1 shows, when compared to other districts, the Eixample has lower variation in terms of both streets and buildings characteristics, as well as socio-demographics aspects[4]. The relative homogeneity in urban features helps us limiting the threat of unobservable characteristics (such as criminality or tidyness of the street) which could vary at the street segment level and which are likely correlated with noise. Similarly, the relative low variation in socio-demographics variables limits the scope of sorting by neighbors (Bayer, Ferreira, & McMillan, 2007; Diamond, 2016; Guerrieri, Hartley, & Hurst, 2013). The presence of either unobservable characteristics correlated to noise and prices, or sorting by neighbors would bias our estimation. Lastly, the Eixample is the district with the highest concentration of the loudest streets, as we show in the following section.

Figure 1: The Eixample district

(a) Orthogonal structure of streets

(b) Graphical illustration of the variation used



Source: City Council of Barcelona, Idealista

3 Data

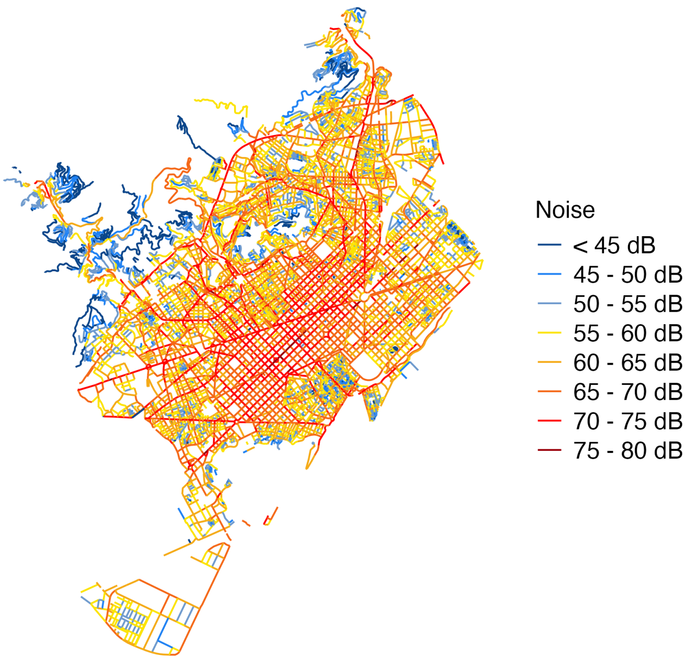
In order to estimate the effect of street noise on housing prices, we use granular data on noise exposure and housing prices, as well as a number of control variables. Noise is defined as unwanted or harmful outdoor sound created by human activities. Following the European Commission's

[3]This peculiarity is due to the design of the district by Ildefonso Cerdà in 1859 (el "Plà Cerdà "). The idea for this expansion of the city (the "Eixample") was to secure equal access to green spaces and hygene through air ventilation. This is why Cerdà designed building blocks which were supposed to host gardens in the inner court and only be built over two or three sides. His meticulous plans were not strictly followed during the implementation, and over time the majority of the blocks were built up and many of the central courtyards closed off. Nowadays, some inner courts have been built to house parking spaces, while some blocks hide playgrounds.

[4]The Eixample ranks within the first three districts with lowest variation for 12 out of the 15 variables presented.

2002/49/EC directive (European Commission, 2002), noise was recognized as one of the main environmental problems in Europe. Since then, Member States are required to collect data every five years and establish action plans to limit noise pollution in urban areas with more than 100.000 inhabitants. Information on noise and its effects should also be made available to the public. The City Council of Barcelona releases strategic noise maps (SNM) at the street section level[5], which are openly available to the public[6] for the years 2009, 2012 and 2017. These maps serve to *"globally assess the population's exposure to noise produced by different noise sources in a given area"*. Figures 2 and A3 show how the data looks like for the whole city in 2017 for day and night, respectively.

Figure 2: Noise map 2017, daytime



Source: City Council of Barcelona

The assessment of the noise level is carried out employing two different methods: real measurements and simulations. The real measurements are carried out with fixed and mobile sensors[7]. Specifically, fixed and mobile sensors register long-term and short-term readings, respectively[8]. Long-term measures (at least 24 hours long) establish the temporary evolution of noise during the day. Short-term readings (at least 15 minutes long) assess the daily noise level and its source (Barcelona City Council, 2017). Starting from these real readings, and following recommendations from the European Union (EU Monitor), computation methods (i.e. propagation models)

[5]A street section is any part of a street which lies in between two intersections (120 meters on average in the Eixample).

[6]The maps are downloadable from the Open Data website of the city of Barcelona

[7]109 fixed and 2,309 mobile sensors in 2009, 75 fixed and 1,703 mobile sensors in 2017. Information not available for 2012.Figure A4 presents an example of the two types of sensors.

[8]Both measures are carried out taking into account weather conditions, wind, and other events that might interfere with the measurement.

are applied to obtain the noise level for the whole street network. These models account for the topography of the area, the height of the buildings, land use and noise barriers. Noise levels are estimated at a fixed height of 4 meters above ground.

Noise levels or sound pressure are expressed in the decibel (dB) scale. The A-weighted decibel scale (dB(A)), the unit of measure in which the SNM are provided, adjusts the sensitivity of the meter to the human ear and it is therefore adopted to express annoyance. Throughout this paper, we will refer to dB(A) with simply dB for simplicity. The common noise indicator laid out by the European Commission's 2002/49/EC directive is the L_{den} (day-evening-night noise indicator), which is meant to represent the overall annoyance. It is a weighted average of L_d, L_e and L_n, which mean annoyance by day (between 7am and 9pm), evening (between 9 pm and 11 pm) and night (between 11pm and 7am), respectively[9]. Noise levels come in ranges of 5 dB each, so that each street section falls within one of these 8 categories: <45dB, 45-50dB, 50-55dB, 55-60dB, 60-65dB, 65-70dB, 70-75dB, or 75-80dB. As the human ear is able to handle a large range of noises, the decibel scale is a logarithmic transformation with base 10 of the perceived annoyance. This scale is more manageable, but this also implies that the interpretation of the levels and their difference is not straightforward. Each 10 dB increase means a factor 10 increase in the sound power, which by the human hear is generally perceived as a sound which is twice as loud. The smallest change in loudness perceivable by most people is 3 dB, which in objective terms means doubling the sound power (Ballou, 2008). Table A2 presents the decibel equivalent of some common sounds. 0 dB is the hearing threshold (near complete silence), while the threshold of pain[10] lies between 120-140 dB. In order to avoid harmful health effects, the WHO recommends long-term exposure to noise to be below 53 dB during the day and 45 dB during the night (European Environmental Agency, 2020).

Figure A5 in the Appendix presents the distribution of street sections into the different categories, both for the whole city and for the Eixample district[11]. First, one can observe that the distribution of the last sample year (2017) is less rightly-skewed than the other years, indicating an average reduction in noise[12]. Second, noise levels at night are lower, as expected. Third, the distributions in the Eixample are all more right-skewed than the whole city. This reflects the high concentration of high noise levels as suggested by Figure 2. The average noise level in the Eixample over the whole sample period is in the range 70-75 dB. In all years, almost none of the street segments of this district registered an average noise level below the threshold recommended by the WHO[13].

Figure A6 shows the distribution of noise by source in the year 2017. Interestingly, these

[9]In order to give more relevance to the annoyance during evening and night hours, usually rest and sleep hours, L_e and L_n are increased by 5 and 10 dB, respectively. Thus, the formula for L_{den} reads as follows:

$$L_{den} = 10log\frac{1}{T}(T_d 10^{\frac{L_{day}}{10}} + T_e 10^{\frac{L_e+5}{10}} + T_n 10^{\frac{L_n+10}{10}})$$

where T_d, T_e, T_n are the length of the day (14h), evening (2h) and night (8h) periods. T is the total length of a day (24h).

[10]The level of sound at which the listener begins to feel physical pain.

[11]The density has been smoothed for graphical representation. Note that the noise variable is a categorical one and not a continuous one as the density graph may suggest.

[12]However, when taking the mid-value of each range, the mean noise level barely changed over the sample years, especially in the Eixample.

[13]In 2017 the share of street segments below this threshold was 1.4%.

graphs reveal that the noise levels emitted by nightlife and pedestrians are mostly concentrated in the left tail of the distribution. On the other hand, traffic produces sounds which are much higher, especially in the Eixample. Table A3 shows correlation coefficients between noise and some street characteristics. Louder streets in the Eixample are on average wider, with more vehicles and bus lines passing through. They also have more nightlife activities. Moreover, streets with bi-directional traffic are louder than those which drive downhill (towards the sea), uphill (towards the hills) and those which are for pedestrians only. There is no significant difference between bi-directional streets and those which drive north-south, which give access to the biggest motorway which connect the city to the rest of the metropolitan area. Cycle lanes do not correlate with street noise.

Data on housing prices are gathered from *idealista*, the major real estate platform used in Spain. Specifically, we have all listings (both rents and sales) in the city of Barcelona posted in the month of December of each year between 2007 and 2019. The characteristics of the listings include the exact location of the dwelling, size, floor number, condition (new/second hand), number of rooms, presence of air conditioning and lift or boxroom and the type of property (studio, penthouse, duplex).

We clean observations from likely unrealistic listings[14] as well as outliers[15]. Figure A7 presents the evolution of prices since the first sample year, as well as the number of listings by year in the Eixample district. Following the outbreak of the financial crisis, prices fell until 2013 and began to recover starting in 2015 for rents and in 2017 for sales. The number of listings was quite low at the beginning of our sample period. It more than doubled between 2010 and 2011 and kept growing until 2017. Over these years, one can observe a difference in the composition of listings between rents and sales. While at the beginning units were mostly advestised for rents, this changed in the last couple of years of the sample, with a predominant role of sales.

Through the Cadaster of the city of Barcelona, we match each listing to the building it belongs to. This way, we obtain information about the age of the building, as well as the solar azimuth angle of its facade and the height of the opposite building (to proxy for exposure to natural light and views). This also allows to identify the buildings' block in which the house is placed, which will be key for our identification strategy. We assign each building to the closest street section. This determines the noise levels to which it is exposed, as well as a number of control variables (the number of trees, m^2 of parks within 50 meters, the absolute gradient and the width)[16][17]. We match each year in the noise sample (2009, 2012, 2017) to listings of the same year, as well as the preceding and following one[18]. This implies that we drop from the

[14] Following Garcia-López, Jofre-Monseny, Martínez-Mazza, and Segú (2020), we drop listings for sale with a size lower than 20 m^2 and price lower than 10,000 €. When advertised for rent, we keep observations with a monthly price between 100 € and 30,000 €.

[15] We drop observations with prices per m^2 above the 99^{th} percentile. This is 11,511 € per m^2 for sales and 38 € per m^2 for rents.

[16] We run a robustness check for houses in buildings which lie on an intersection, as it is not clear which noise level they are most exposed to.

[17] The sources from which we retrieve this information are the following: trees come form the Open Data Portal of the city; parks are obtained from Open Street Map; the gradient is computed from the elevation raster provided by the Geographic and Cartographic Institute of Catalonia; the width is computed through the street network and the Cadaster of the city.

[18] We assign the 2009 noise values to the units listed in 2008, 2009, and 2010; the 2012 values to those listed in 2011, 2012, and 2013; the 2017 values to those of 2016, 2017 and 2018. The underlying assumption is that noise exposure for each street segment does not vary drastically across subsequent years. Looking at the tem-

analysis postings of the years 2007, 2014, 2015 and 2019.

Figure A8 plots the distribution, mean and standard deviation of prices per m^2 by noise, as well as the number of listings in each range. First, one can observe that the great majority of observations lies on streets with relatively high noise levels. This is consistent with Figure A5, which shows that there is very few streets with noise during the day lower than 55 dB. Moreover, streets within the three lowest categories of noise are internal and mostly pedestrian streets, which pass through blocks (see Figure A9). As these streets might not be comparable to the rest and given the very low number of observations, we drop them from our sample of analysis. In a robustness check we include the whole range of noise. Focusing on noise ranges above 55 dB, the distribution of prices is quite balanced, meaning that there is a large variation in prices over all categories of noise. Moreover, the distributions look very normal on sales. For rents, they are slightly more left-skewed. Second, we observe a trend in the mean price which is increasing in noise. This is consistent with confounding factors which are correlated to noise and that positively capitalize into housing prices. The empirical framework we lay out aims at isolating the effect of the negative externality of noise from that of its correlated factors.

Throughout the analysis, we also use other data which come from different sources. Specifically, from the Open Data Portal, we obtain measures of air pollution, the census of commercial activities, cycle lanes and counting from traffic sensors. From the Metropolitan Transportation company of Barcelona, we download data on bus lines, while the direction of traffic of each street section is manually digitized.

The final sample has to 19,886 sales and 21,559 rents in the Eixample spread over 963 street sections and 434 blocks. Table A4 presents, for each year in the sample, the mean and standard deviation of price per m^2, as well as the number of observations.

4 Empirical framework

Hedonic price models have been used for long as a revealed-preference method which allows to evaluate the willingness to pay for environmental factors (Rosen, 1974). However, hedonic price models alone often only retrieve correlations. The main threat to an accurate estimation of the economic value of amenities is that they are often correlated to each other and to unobservable characteristics (Kuminoff, Parmeter, & Pope, 2010).

In our case, the main threat to the identification of the causal effect of noise on housing prices is that noise levels often represent other local characteristics which also influence housing prices. As an example, one can think about accessibility. On one hand, a higher noise level would reduce the price of the house, as noise pollution is a disamenity. On the other hand, a higher noise level might be related to higher accessibility, thus pointing towards an increase in the price of the dwelling (Ahlfeldt et al., 2019; Diao et al., 2023; Fan et al., 2021; Thiel, 2022). In other words, as shown in Table A3 noise levels are correlated to street traffic. Streets with more traffic are

poral evolution of noise values, it seems plausible to assume so. In fact, noise levels by street sections are highly correlated over time. In particular, the noise levels of 2009 and 2012 have a correlation coefficient of 0.97, while between 2012 and 2017 the coefficient is 0.74. We perform a robustness check in which we only keep observations of houses listed in the exact same year as the sample years of the noise data.

likely to represent connection axes between important areas of the city (for example, between residential areas and jobs centers). The same intuition can be extended to public transport accessibility, i.e. proximity to a train station or a bus stop (if the fleet is not electric) and to consumption amenities. Thus, noise represents a negative externality, but it also reflects the connectivity and attractiveness of the area. Both aspects are likely to affect housing prices in opposite directions. Disentangling them and isolating the real impact of noise on housing prices is not straightforward.

Our strategy leverages the variation in noise intensity at very granular levels. We exploit the orthogonal structure and the homogeneous square blocks of the Eixample district, using variation in noise levels within the same building block (i.e. areas of about 120x120 m)[19]. We do so by including blocks fixed effects in our regressions. The underlying hypothesis is that properties within the same block enjoy the same local characteristics. Still, depending on the side of the block on which the property is placed, it is exposed to different noise levels. In other words, we can safely assume that accessibility (through the street or the public transport network) is constant for all properties within the same block. Similarly, differences in school access[20], crime rates, consumption amenities, closeness to touristic attractions, and any other element which might directly affect housing prices, are arguably negligible[21]. Within such small blocks, the price effect of these local (dis)amenities is common to all properties and it is captured by the block fixed effect. By including an interaction term between the block and the year fixed effect, we allow (un)observable block characteristics to vary over time. Figure 1b visually shows the orthogonal structure of the Eixample district and it helps understanding our empirical strategy. Table A5 reports the variation which our estimation relies on. We observe an average number of listings per block of 36.28 for sales and 50.37 for rents[22]. Figure 3 plots, for each noise range, the mean and standard deviation of the difference between the price per m^2 of each flat and the mean of the block it belongs to, as a percentage of the block mean. The aim of this exercise is to graphically explore whether houses in noisier or quieter streets are systematically over- or under-priced with respect to the block mean. Both graphs represent a descriptive evidence of a trend of the price differential which is initially increasing in noise, but which then steadily declines as streets become louder.

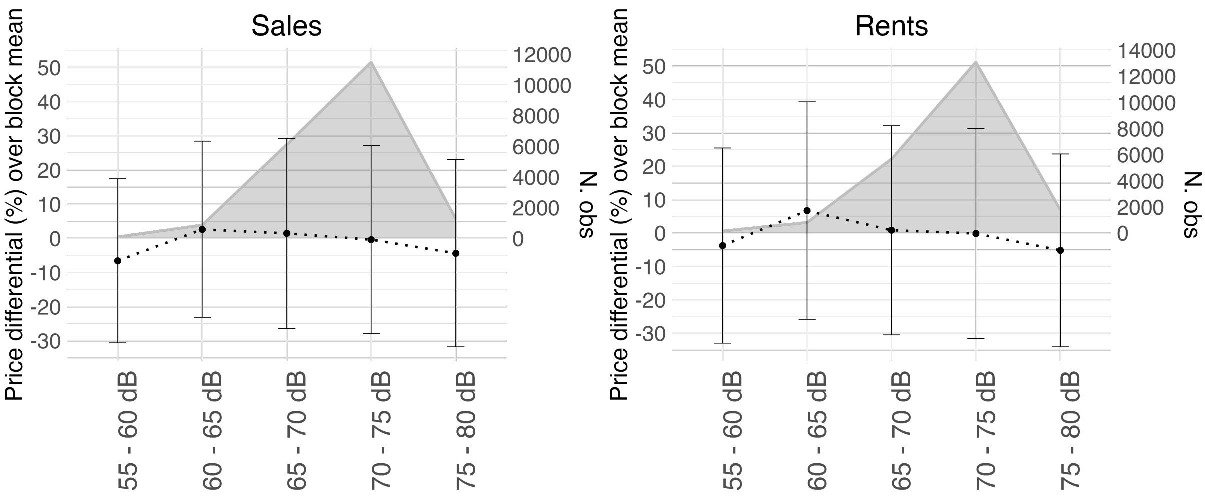
[19] As a robustness check, we also use a 2x2 moving blocks definition, in which the block is defined by groups of blocks of 2x2. This has the advantage of increasing the within-block variation in noise while keeping the local (dis)amenities fixed. Figure A10 illustrates how we define the 2x2 blocks.In another robustness check, we include areas of the city which belong to other districts and which are also characterized by a very regular grid shape, similar to the Eixample. Figure A11 maps this area, which includes parts of the district of Sant Martí and Sant Andreu.

[20] In contrast to the U.S. context, school eligibility in Barcelona does not strictly follow residential assignment. Admission is based on a points system in which proximity is only one of several criteria, and families have some flexibility in school choice. Moreover, the catchment areas used for school assignments are substantially larger than our unit of analysis. As such, differences in school access are unlikely to explain price differentials at the block level.

[21] We perform some robustness checks in which we include further controls for observable amenities at the street section level (bus, subway and train stops, cycle lane, number of restaurants and air pollution) to show that the estimation strategy based on within-block variation already captures the relevant local (dis)amenities.

[22] If we consider within block-year variation only, which is the variation we exploit in our preferred empirical model, we still use an average number of listings of 21.42 for sales and 20.59 for rents.

Figure 3: Price differentials over the block mean (%) by noise



Note: This graphs show, for each noise range, the mean and standard deviation of price differentials with respect to the block mean (in percentage, on the left axis). The right axis shows the number of observations in each range.

To identify the effect of street noise on housing prices we estimate the following repeated cross-section fixed-effect model:

$$log(Price_{isjt}) = \beta_0 + \beta_1 Noise_{st} + \beta_2 X_i + \beta_3 Z_s + \omega_j \cdot \tau_t + \epsilon_i \quad (1)$$

Where $log(Price_{isjt})$ is the log of the price per m^2 of unit i, on street segment s and block j, listed in year t[23]. $Noise_{st}$ is the noise range in year t of the street segment s on which the property is placed. X_i is a vector controlling for unit i characteristics such as floor number, size (m^2), number of rooms, presence of air conditioning, lift and boxroom, condition of property (new/second hand), type of unit (studio/penthouse/duplex) and age of the building. It also includes the height of the building in front and the azimuth angle of the facade of the building, which precisely controls for the flat's orientation (e.g., North, North-East, East, etc.), an important factor potentially affecting differently housing prices of listings on different sides of the block. Additionally, we also include the interaction between the height of the building in front, the azimuth angle, and the floor number to proxy for exposure to natural light and views. Z_s controls for street segment characteristics, such as the gradient, the width, the number of trees and the m^2 of urban parks within 50 m from the street's centroid. These variables are assumed to be time-invariant. ω_j and τ_t are block and year fixed effects, respectively. We use robust standard erros and cluster them at the block level[24].

In the baseline specification, $Noise_{st}$ is L_{den} (the weighted average of all annoyance levels over the whole day). We assign $Noise_{st}$ a numerical value between 4 and 8 for each noise bin and interpret β_1 as the effect on prices for each change of 5 dB. The reason why the scale starts

[23]We use price per m^2 instead of the total price because it is a more standardized measure. Throughout the rest of the paper, price and price per m^2 will be used interchangeably.

[24]Results are robust to the definition of clustering at higher levels, such as census tracts and Basic Statistical Areas (AEB). AEB are geographical areas whose size is between that of a census tract and a neighborhood. There are 36 AEBs within the Eixample.

at 4 is that we exclude the first three lowest categories of noise, as those observations belong to internal and mostly pedestrian streets that might not be comparable to the rest, as explained in Section 3. In the robustness which uses the full range of noise, the range of L_{den} will be from 1 to 8. We also adopt a couple of alternative definitions of $Noise_{st}$. First, we define $Noise_{st}$ as the mid-value of each range[25]. This implies that the coefficient β_1 captures the noise effect on prices for each 1 dB change. Second, we include it in eq. (1) as a categorical variable, with base level 75 - 80 dB, the highest category. This allows us to study whether the effect is non-linear over the noise range.

Moreover, we perform several heterogeneity analyses. First, $Noise_{st}$ assumes different values depending on the time of the day and the source of noise. Next, we look at the heterogeneity of the effect depending on floor height, as the same objective measure of street noise might be perceived differently by residents of lower and higher floors. We then exploit the unique feature of the blocks of the Eixample, which have both internal and external flats - facing the inner court or the street, respectively. After having performed a series of robustness checks, we go further and we exclude any evidence of sorting by neighbors generated by noise, which confirms that our results are effectively driven by noise. Lastly, we look at the effect on turnover, as residents who directly experienced noise might decide to move faster than others.

5 Results

5.1 Baseline results

The results of the estimation of equation 1 are reported in Table 1. Throughout columns 1 to 6 we gradually add controls and fixed effects. Specifically, in column 1 we simply regress the noise level on the log of listed prices. Column 2 adds year fixed effects. Without controlling for local (dis)amenities common to the whole block, the effect is positive and significant. This reflects the omitted variable bias mentioned above: noisier streets represent relevant connection axes within the street network and higher consumption amenities. When block fixed effects are added, which implies we only use within-block variation in noise (thus keeping local (dis)amenities constant) the effect turns negative (column 3). The change in the sign between columns 2 and 3 suggests that our empirical framework successfully addresses the omitted variable bias. Column 4, which includes the interaction between block and year fixed effects, allows unobservable characteristics common to the buildings block to change over time. Column 5 and 6 add house and street characteristics, respectively. Our preferred specification is column 6. On average, moving from one range of noise exposure to the next one (i.e. increasing noise level by 5 dB) induces a depreciation of 1.7% on sales' prices and 1% on rents' prices[26].

Table A7 use the continuous definition of $Noise_{st}$ as the mid-value of each range. As expected, the results are consistent with our baseline definition of noise. As β_1 is interpreted as the effect for each change of 1 dB, the coefficients are equivalent. Specifically, we estimate effects

[25] To each of the five ranges in the data we assign the following mid-values: 57.5 to "55 - 60 dB"; 62.5 to "60 - 65 dB"; 67.5 to "65 - 70 dB"; 72.5 to "70 - 75 dB"; 77.5 to "75 - 80 dB".

[26] Table A6 show that the results are mostly robust to alternative levels of clustering of the standard errors. The coefficient on sales loses significance when standard errors are clustered at the neighborhood level. However, this is expected, as the Eixample contains only eight neighborhoods.

which are one-fifth of our baseline results (-0.3% on sales and -0.2% on rents). A more meaningful way to interpret the magnitude of the coefficients is considering a doubling of the noise annoyance. As explained above, doubling the sound annoyance translates to a 10 dB increase. This would imply an average effect on sales' prices of -3.4% and -2% on rents' prices. Given the average price per m^2 and the average size of listed flats in our sample[27], these effects translate into a reduction of 16,483 € and 27 € on sales and rents, respectively.

These effects are consistent with what is found by the literature which estimates an effect of an explicit reduction of decibels on prices. While the effects of aircraft, rail and metro noise tend to be sligthly larger (ranging from 0.3% to 0.6% for each dB change), the effects of road noise are closer in magnitude (0.23% and 0.27% on sales' prices for each dB change, as found in Brandt and Maennig (2011) and Swoboda et al. (2015), respectively). Moreover, we note that the effects found in context of low population density and single-family houses tend to be larger than those found in more densely populated urban areas[28].

Table 1: Effect of Street Noise on Housing Prices

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Sales						
Noise	0.026**	0.039***	-0.016**	-0.014**	-0.014**	-0.017**
	(0.010)	(0.010)	(0.007)	(0.007)	(0.007)	(0.007)
N	19886	19886	19886	19886	19886	19886
R-squared	0.003	0.171	0.447	0.498	0.579	0.580
Panel B: Rents						
Noise	0.018**	0.031***	-0.004	-0.009	-0.008	-0.010*
	(0.009)	(0.008)	(0.006)	(0.007)	(0.006)	(0.006)
N	21559	21559	21559	21558	21558	21558
R-squared	0.001	0.244	0.391	0.432	0.576	0.576
Year FE		Yes	Yes			
Block FE			Yes			
Block x Year FE				Yes	Yes	Yes
House controls					Yes	Yes
Street controls						Yes

Note: Columns gradually add fixed effects. Noise is assigned one numerical value (from 4 to 8) for each noise range. Each unitary change in noise is interpreted as a change of 5 dB. Standard errors clustered at the block level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[27]The average posted price in our estimation sample is 4,450.76 € per m^2 for sales and 14.93 € per m^2 for rents, while the average size is 109 m^2 for sales and 90 m^2 for rents.

[28]von Graevenitz (2018) estimates, for each 1 dB change, a semi-elasticity of sales' prices which ranges between -0.2% and -0.6% on apartments and between -0.5% and -1.4% on single-family houses.

Noise affects sales more than rents.[29] First, the rental market in Barcelona is much tighter than the selling market. According to *idealista*, the average number of leads for listings (i.e. number of people interested) in December 2023 was more than 10 times higher for rents than for sales (Idealista.com, 2023a). Over our sample period, prices in the Eixample increased much more for rents (18%) than for sales (12%). Second, socio-demographic characteristics may explain the difference[30]. Buyers are on average older, richer and more likely to have children (Idealista.com, 2023b). When asked to rank their priorities, 85% of renters state that price is the most important factor to consider. This suggestive evidence illustrates how, on average, socio-demographics may imply different ranks of priorities. While buyers may weight quietness more than price, the same may not hold for renters. Third, it might be due to asymmetric information. An interested buyer is likely to conduct a more thorough inspection of the flat, which makes her more aware of the noise exposure it is subject to. Lastly, as Ahlfeldt et al. (2019) show, the value attached to amenities has been increasing over time. Therefore, the investment decision embedded in the acquisition of a house may include expected capital gains from quieter streets. Given the fact that we use listed prices, the implicit assumption we are making is that the supply internalizes these factors, either by anticipating them or by adjusting to the demand.

Our baseline model assumes that the effect is linear over the whole range of noise. In order to study possible non-linearities, we use $Noise_{st}$ as a categorical variable and set the baseline to the highest noise level of 75 - 80 dB. Figure 4 plots the results. It shows that the magnitude of the effect on prices gets bigger with bigger changes in noise. On sales, the difference between being on the noisiest streets compared to being located on a street with the second highest noise level implies an appreciation of 5%. However, across the mid-ranges (between 55-60 dB and 70-75 dB), the effect for each additional change in 5 dB is lower in magnitude (between 0.5% and 1.5% more than the effect of the first 5 dB change), and it follows a linear trend. On rents, differences compared to the highest noise range are less pronounced until the 55-60 dB range. The effect increases in this category, which is a lower noise level than what is observed for sales. Therefore, rents showcase a non-linear trend over the noise range, suggesting that they are less responsive to changes in noise levels. This is consistent with the higher market tightness of the rental market and the resulting lower price elasticity of rents. In Table A8 we include the whole range of noise, including the three lowest categories. Linear results are robust (although slightly higher in magnitude). Figure A12 shows the categorical results. While the coefficients on the highest ranges do not change, the low number of observations in the first three categories makes the estimation very noisy, which reflects in large standard errors.

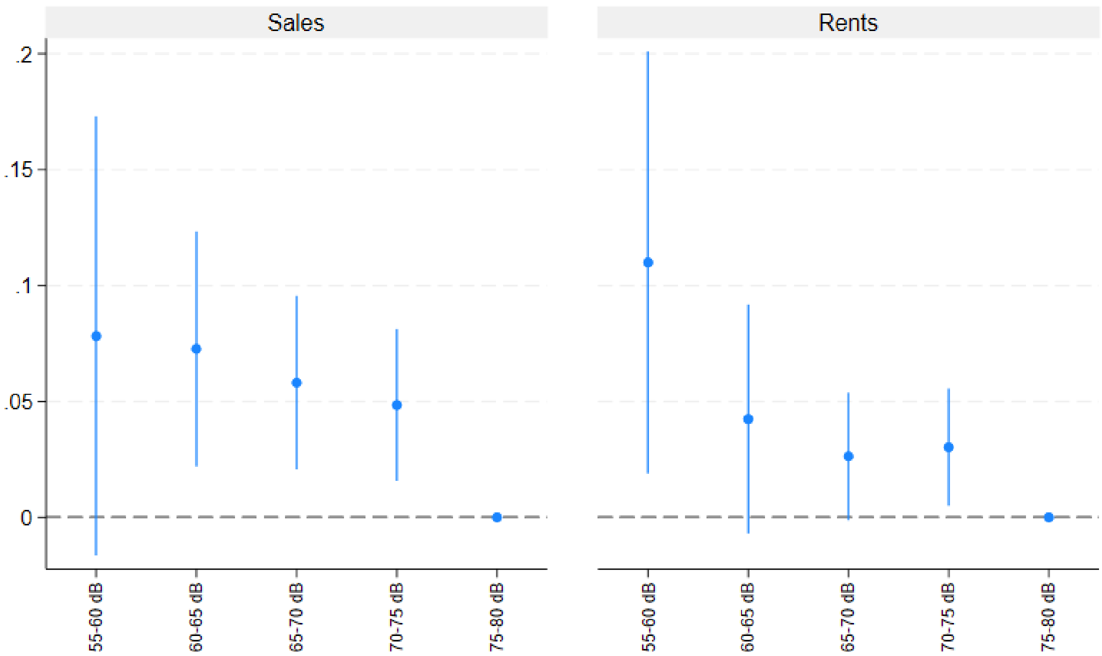
In the appendix we show that our main results hold when we perform a series of robustness checks. First, we use an alternative "2x2 moving block" definition, which includes four neighbouring blocks instead of one single block. This model allows us to increase within-block variation. Second, we run a robustness check in which we restrict the sample to the listings which are published only on the same year as the noise sample years. In fact, our baseline sample, which includes, for each sample year of the noise dataset (2009, 2012, 2017), all listings of the previous

[29]This is in line with what is documented by Grainger (2012), who shows that prices of owner-occupied houses are more responsive to reductions in air pollution than rents. This might be due to several reasons.

[30]Grainger (2012) shows that the different elasticity of sales and rents persists even after a stratification by income.

and following year, might contain some measurement error if the true noise level changed year by year. While our aim is to increase the sample size, this could also decrease the precision of the estimation. Finally, by including additional street characteristics which we are able to observe, we show that our estimation strategy which exploits within-block variation already captures local (dis)amenities of the area and the coefficient on noise does not change. We include simple proxies for accessibility defined as the presence of a bus, subway, train stop or cycle lane in the street section, consumption amenities (bars with live shows, pubs and clubs) as well as air pollution at the street section level. The inclusion of additional street characteristics which are correlated to noise does not change the estimated effect of noise on prices[31].

Figure 4: Results with $Noise_{st}$ as categorical variable



Note: These plots show non-linearities in the effect of noise on prices, especially on rents. We use a categorical variable and set the baseline level to the maximum noise range (75-80 dB). Standard errors are clustered at the block level and confidence intervals are at the 95% confidence level.

5.2 Heterogeneous analysis

In order to understand what is driving the results, we perform four heterogeneity analyses. First, we differentiate noise by the time of the day. We estimate three versions of equation 1, replacing the total noise with different variables indicating the noise level for each street segment at day (7am-9pm), evening (9pm-11pm), and night (11pm-7am)[32].Table 2 presents the results with our

[31]We do not include these controls through the whole analysis as these variables are only defined for the last years of our sample period.

[32]The time ranges come with the data and it is not possible for us to redefine the time windows. We estimate three separate regressions instead of including all the three variables together in the same regression because the three different explanatory variables are highly correlated with each other (see Table A9).

preferred specification. The comparison reveals some degree of heterogeneity. On sales, evening and night noise have higher effects than the average L_{den} measure, while the coefficient on day-time noise is below the average. This is probably explained by the fact that evening and night hours are when most residents are more likely to be at home resting. For rents, the effects are all statistically insignificant.

Table 2: Heterogeneity by time

	(1) Sales	(2) Rents
Panel A: Day (7am - 9pm)		
Noise	-0.012*	-0.009
	(0.007)	(0.006)
Panel B: Evening (9pm - 11pm)		
Noise	-0.020***	-0.002
	(0.007)	(0.006)
Panel C: Night (11pm - 7am)		
Noise	-0.019***	-0.009
	(0.007)	(0.006)
N	19886	21558
Block x Year FE	Yes	Yes
House controls	Yes	Yes
Street controls	Yes	Yes

Note: Each panel estimates the effect of noise on prices at different times of the day. The first column shows the results on Sales and the second on Rents. Standard errors clustered at the block level in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The second heterogeneous analysis is by noise source. We use the categorisation included in the data for 2017. It allows to distinguish between traffic, railway, industrial, recreational, and pedestrian noise. We exclude from the analysis railway and industrial noise, since we do not observe variation within the Eixample district and the noise exposure from those sources is negligible. Since this information is available only for 2017, we only use listings for the years 2016, 2017 and 2018. We estimate the following model:

$$
\begin{aligned}
log(Price_{isj}) =& \beta_0 + \beta_1 Noise_s^{Traffic} + \beta_2 Noise_s^{Pedestrian} + \\
&+ \beta_3 Noise_s^{Recreational} + \beta_4 X_i + \beta_5 Z_s + \omega_j + \epsilon_i
\end{aligned}
$$

$log(Price_{isj})$, X_i, Z_s, and ω_j are defined as in equation 1. We include different variables of noise referring to different sources[33] and no year fixed effects. The results are presented in Table 3. For consistency, column 1 and 3 present the baseline regressions using L_{den} on the

[33] The noise levels from the different sources are not highly correlated, so we include them all together in the same regression (see Table A10). In particular, note that pedestrian noise is negatively correlated to total and traffic noise, while it is positively correlated to recreational noise.

same restricted sample we use for the heterogeneous analysis by source. The coefficients are very similar to the full sample estimation. However, using only the geographical variation in noise of 2017 does not yield significant results[34]. The same happens in column 2 and 4, where we include the three different noise sources. Interestingly, the coefficient on pedestrian noise is positive[35]. In addition, while we cannot statistically distinguish the effects of traffic and nightlife noise, the negative coefficient for traffic noise is notably larger in magnitude. This finding is relevant, as while nightlife is often the most addressed issue in cities, we do not find clear evidence of the prevalence of the burden it creates with respect to other sources.

Table 3: Heterogeneity by source

	Sales		Rents	
	(1)	(2)	(3)	(4)
	Average	By source	Average	By source
Noise	-0.012		-0.010	
	(0.009)		(0.008)	
Road traffic noise (Total)		-0.010		-0.009
		(0.009)		(0.008)
Noise in pedestrian streets (Day)		0.011		0.000
		(0.014)		(0.015)
Recreational noise (Night)		0.001		-0.001
		(0.009)		(0.012)
N	11517	11517	10537	10537
R-squared	0.520	0.520	0.395	0.395
Block FE	Yes	Yes	Yes	Yes
House controls	Yes	Yes	Yes	Yes
Street controls	Yes	Yes	Yes	Yes

Note: This table reports how the effect of noise changes with its source (column 2 and 4). The estimation sample is restricted to 2017. Therefore, the columns 1 and 3 report the results of average noise on prices on the same estimation sample of 2017. Standard errors clustered at the block level in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The third heterogeneity analysis splits the sample between lower and higher floors. We define lower floors as those lower than the second, while higher floors are all floors above that. Lower floors are closer to the source of noise, while higher floors are further away. This implies that houses at lower floors are exposed to a higher perception of noise. The aim of this exercise is double. First, we ask whether the effect is driven by some floors rather than others. Second, this analysis can be informative about whether the main reason for the depreciation is the actual noise annoyance perceived from inside the flat or on the street itself, to which residents are exposed as soon as they leave the building. Table 4 presents the results. We find that lower floors

[34] Reducing the sample to one year limits the exploited variation to only the spatial variation, dropping the time variation.

[35] Koster, Pasidis, and van Ommeren (2019) shows that more pedestrians lead to an increase in commercial rents and vacancies. Yoshimura et al. (2022) looks at the effect of converting street use from vehicles to a walkable environment on the revenues of retail stores, finding a positive relationship. These effects can capitalise into the real estate market.

are driving the effect. On these observations, the effect is statistically significant and higher than average, while on higher floors we find no significant effect. If the driving mechanism was the annoyance perceived on the street (i.e. when residents are outside), the effect would be common to all floors. As this is not the case, we interpret this as evidence that the burden perceived from inside the flat is driving the depreciation.

Table 4: Heterogeneity by floor

	Sales		Rents	
	(1)	(2)	(3)	(4)
	Low	High	Low	High
Noise	-0.021**	-0.011	-0.018**	-0.010
	(0.008)	(0.010)	(0.008)	(0.007)
N	8582	11113	8918	12473
R-squared	0.59	0.64	0.57	0.64
Block x Year FE	Yes	Yes	Yes	Yes
House controls	Yes	Yes	Yes	Yes
Street controls	Yes	Yes	Yes	Yes

Note: This table reports the results split by floor height. Columns 1 and 3 shows the effect on floors lower than 2, and columns 2 and 4 shows the effect for flats on higher floors. Standard errors clustered at the block level in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The last heterogeneity follows a similar vein but exploits a unique feature of the Eixample district: the presence of both internal and external houses. Internal units are located in the same building but face the inner court, while external units face the street. Therefore, external flats are exposed to the measured street noise while the internal flats are not. Thus, this exercise also represents a placebo test. The location of the flat within the building is available in the *idealista* dataset only starting from 2018. Thus, on these observations, we estimate the following model:

$$log(Price_{isj}) = \beta_0 + \beta_1 Noise + \beta_2 External + \beta_3 Noise \cdot External + \beta_4 X_i + \beta_5 Z_s + \omega_j + \epsilon_i$$

Table 5 show the results. Column 1 reports the baseline coefficient estimated on the sample for which the flat orientation is available. On average, we find no statistically significant effect. Column 2 exploits the flat location. Once again, results are statistically significant only on sales. The first coefficient shows that noise has no effect on internal flats. External flats have higher prices than the internal ones, but the difference decreases as noise increases. The negative coefficient on the interacted term means that the average negative effect of noise on housing prices is driven by the external flats. This once again confirms that the effect we find is driven by noise perceived by residents inside the flat rather than noise on the street, which would be common to both internal and external flats.

Table 5: Heterogeneity by flat location

	Sales		Rents	
	(1)	(2)	(3)	(4)
	Average	By flat location	Average	By flat location
Noise	-0.011	0.026	-0.013	-0.010
	(0.012)	(0.023)	(0.017)	(0.045)
external=1		0.338**		0.040
		(0.150)		(0.292)
external=1 × Noise		-0.041*		-0.004
		(0.022)		(0.044)
N	3369	3369	2307	2307
R-squared	0.592	0.595	0.522	0.523
Block FE	Yes	Yes	Yes	Yes
House controls	Yes	Yes	Yes	Yes
Street controls	Yes	Yes	Yes	Yes

Note: This table reports the results split by flat location. The estimation sample is restricted to 2017. Columns 1 and 3 shows the effect of noise, independent of the flat location, within the same estimation sample as columns 2 and 4. These colums reports the effect of noise by flat location. Standard errors clustered at the AEB level in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.3 Additional results

5.3.1 Sorting by neighbors

If the lower prices in noisier streets induce a sorting which is persistent over time, path-dependence might generate another type of sorting, which is sorting by neighbors (Heblich, Trew, & Zylberberg, 2021). If this was the case and if this explained the lower prices in noisier streets, our results would be biased. Throughout the analysis so far, we already collected some pieces of evidence which make us exclude this issue. In particular, sorting by neighbors would show up across all floors, while the heterogeneity analysis only finds results on the lower ones. The same holds for the heterogeneity by flat location (internal vs external flats). If there was sorting by neighbors, louder streets would have lower prices both in internal as in external flats.

Unfortunately, we are not able to directly test for sorting by neighbors, as we do not observe socio-demographic characteristics at the street section level. However, one can imagine that sorting by neighbors would also be reflected in different house characteristics. For example, we could expect that residents' income is correlated to flat characteristics such as the size or presence of air condition. Moreover, we could also assume that the composition of the residents between home owners and renters is related to the average income. In order to test these conjectures we create a panel dataset at the block-side level and estimate the following regression:

$$\overline{Y}_{sjt} = \beta_0 + \beta_1 Noise_{st} + \beta_2 \overline{X}_{sjt} + \beta_3 Z_s + \omega_j \cdot \tau_t + \epsilon_{sjt}$$

where $\overline{Y}_{sjt}$ is either the average size of houses or the probability of having air condition at the block-side level sj in year t. $\overline{Y}_{sjt}$ also assumes the value of the share of the total number of listings which are rents. The model controls for the rest of average house characteristics $\overline{X}_{sjt}$ and street characteristics Z_s. As in the baseline strategy, we include the interaction between block and year fixed effect $\omega_j \cdot \tau_t$. Standard errors are clustered at the AEB level[36]. If noise induces sorting which reflects in average house characteristics or the composition of listings, it would be captured by the coefficients β_1. Table 6 presents the results. Since none of the coefficients is statistically different from zero, we interpret this exercise as another piece of evidence that sorting by neighors is not the driving mechanism behind the effect of noise on prices.

Table 6: Sorting variables

	Sales		Rents		
	log(Size)	Air condition	log(Size)	Air condition	Rents share
Noise	0.004	-0.010	-0.005	0.005	0.153
	(0.008)	(0.016)	(0.008)	(0.011)	(1.489)
N	3019	3019	3177	3177	3797
R-squared	0.764	0.444	0.783	0.469	0.426
Block x Year FE	Yes	Yes	Yes	Yes	Yes
House controls	Yes	Yes	Yes	Yes	Yes
Street controls	Yes	Yes	Yes	Yes	Yes

Note: This table examines whether noise affects average house characteristics at the street section level. Columns 1 and 2 refer to listings for sale, while columns 3 and 4 refer to rents. The last column is the ratio of listings for rents over the total number of listings published at the street section level in a given year. Standard errors clustered at the AEB level in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.3.2 Effect on quantities

Another way through which the market may internalize the negative externality of noise, besides prices, is quantities. In this section, we explore whether the "distaste" for noise is visible in the number of listings on the market. This is more likely to be the case for rents than for sales for two main reasons. First, rents are more mobile than homeowners because of the temporary nature of the contract. Second, as our previous results show, the semi-elasticity of prices with respect to noise is higher on sales than on rents. If the rental market does not fully internalize the negative externality, we may observe systematical differences in the quantities demanded and supplied in noisier streets compared to quieter ones. We can think of three things that may happen.First, listings may remain longer on the market before finding a tenant or a buyer. Second, tenants may decide to move out more often. Third, landlords may prefer to rent out the dwelling instead of residing there. All these three potential scenarios would result in a higher number of listings on the market in noisier streets than in quieter ones. Moreover, all of them can be interpreted as a "distaste" for noise.

In order to test for these hypotheses, we aggregate the number of listings of each type in a panel dataset at the block-side level and estimate the following model:

$$N.Listings_{sjt} = \beta_0 + \beta_1 Noise_{st} + \beta_2 \overline{X}_{sjt} + \beta_3 Z_s + \omega_j \cdot \tau_t + \epsilon_{sjt}$$

[36]In the block-side level panel models, standard errors are clustered at the AEB level to avoid the problem of fixed effects being nested within clusters.

where $N.Listings_{sjt}$ is the number of listings of each type published in block-side sj in year t. As in the previous specification, this regression includes average house characteristics, street characteristics and the interaction between block and year fixed effects. Standard erros are clustered at the AEB level[37]. This sample is a balanced panel dataset of all block-sides which have at least one observation of any type over the sample years. When no listing of the other type appers in a given year, $N.Listings$ equals zero. This explains the different number of observations compared to the previous results on sorting by neighbors. Table 7 (columns 1 and 2) present the results. It shows that within block and year, there are on average 0.33 more listings for rents published on louder streets than in 5dB quieter streets. Given the sample mean, the coefficient corresponds to 5.7% more listings.

In order to rule out that these effects are driven simply by the existing stock of dwellings, we estimate a similar regression using data from the Spanish Cadaster. At the block-side level, we create a cross-sectional dataset with the number of residential dwellings and noise levels in 2017. We then estimate the following regression:

$$Stock_{sj} = \beta_0 + \beta_1 Noise_s + \beta_2 Z_s + \omega_j + \epsilon_{sj}$$

in which $Stock_{sj}$ is the number of flats in street s and on block j. Results in Table 7, column 3, show that, within block, there is no statistically significant difference in the stock of dwellings. Therefore, we exclude that the effect of noise on the number of listings on the market is driven by a systematically different stock of houses.

Table 7: Results on number of listings and stock of dwellings

	N.Listings		Stock
	Sales	Rents	
	(1)	(2)	(3)
Noise	0.206	0.333*	-0.601
	(0.219)	(0.191)	(2.927)
N	6450	6450	1484
R-squared	0.402	0.479	0.517
Block FE			Yes
Block x Year FE	Yes	Yes	
House controls	Yes	Yes	
Street controls	Yes	Yes	Yes
Mean Y	5.258	5.824	73.405

Note: This table examines whether noise affects the total number of listings posted at the street section level. Column 3 reports the effect on the stock of flats, as calculated through the Spanish Cadaster. Standard errors clustered at the block level in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[37] In the block-side level panel models, standard errors are clustered at the AEB level to avoid the problem of fixed effects being nested within clusters.

Althogh we are not able to disentangle the three above-mentioned potential scenarios from each other, these results suggest that, given market prices, the negative externality of noise still represents a disamenity which reflects into different quantities supplied and demanded in louder streets compared to quieter ones. While we are not able to observe neither the time listings spend on the market nor turnover, the high tightness of the rental market makes us more inclined towards the second scenario than the first one. The third scenario, in which units are disproportionately more advertised for rents on noisier streets than on quieter ones, would be reflected in a higher rents share. As we do not find statistically significant effects in our previous results on sorting (Table 6, column 6), we conjecture that what is likely explaining these results is a higher turnover of tenants in louder streets compared to quieter ones.

6 Cost-benefit analysis

In this section, we use our estimated capitalization effects and apply them to make two policy evaluations, comparing the estimated expected benefits and costs of two policies aimed at reducing noise. We focus on sales and exclude rents for the sake of this exercise, as this is the most salient price depreciation we find. The main reasons are two. First, our results show an effect which is more stable on sales than on rents. Second, given the nature of our data, the estimation of yearly benefits is clearer with selling offers than with listings for monthly rents. Moreover, the policies we analyse also affect temperatures. As we only use estimates on the capitalization of noise, the benefits we calculate represent a conservative estimation.

6.1 Street re-pavement policy

First, we evaluate the welfare benefits of a hypothetical full re-pavement of the Eixample with materials which have been shown to decrease noise. As a benchmark of what should be the objective of such a policy, we use two reference points. The first one is the so-called Acoustic Zoning, with which the local administration sets the maximum level of noise which can be registered in each street section of the city (acoustic sensitivity zones). In some areas, these limits are meant to be strictly respected. In the other areas, they represent an objective for acoustic quality. The municipal environmental regulation (Barcelona City Council, 2011) establishes that, when the registered acoustic levels are above the maximum allowed within the relevant acoustic zone, measures should be adopted in order to reach the maximum levels. The current Acoustic Zoning, updated in 2022[38], divide the streets of the Eixample into three categories, with maximum acoustic levels during the day of 60 dB and 65 dB. The second one is the WHO recommended level for a healthy acoustic environment, which is set to 53 dB L_{den} (day-evening-night noise exposure) and 45 dB during the night.

Taking the last available Strategic Noise Maps (2017) and using the mid-value of each noise range, streets of the Eixample exceed the noise limits set in the current Acoustic Zoning by an average of 3.7 dB during the day[39]. 83% of the streets exceed the limits, of which 57% register a noise power which is almost double the limit (+2.5 dB) and 42% exceed the maximum by at least

[38]The current acoustic zone map can be found here.

[39]Taking the lowest or the highest value of each noise range, streets exceed the acoustic limits by 1.2 dB and 6.2 dB, respectively.

7.5 dB. The WHO recommended limits for a healthy acoustic environment are more stringent. The average reduction required to reach the recommended level of L_{den} is 16 dB and practically all streets of the Eixample exceed it.

As a potential policy to reduce noise, we will first consider a re-paving of the whole surface of the streets of the Eixample with a special material which reduces noise as well as heat absorption. Barcelona tested these materials in a short length of street in 2021 as a pilot project within the framework of the Life Heatland project, started in Murcia (in southern Spain). In 2024, the repaving was extended to a longer fraction of street[40]. Results from the pilot project initiated in Murcia show that the new material reduced noise by 3 dB and surface temperatures by 7 °C (Freire, Grau, & Ayerra, 2021). Given the cost incurred in Murcia, we estimate what would be the cost of repaving the whole Eixample. We then compare it to the expected benefits computed using our estimated capitalization effects of noise on housing prices. The assumption is that the intervention would reduce noise levels by 3 dB in all streets. To benchmark the effectiveness of the policy, we compare it to the objectives established by the Acoustic Zoning and the recommended levels by the WHO.

The first pilot project testing these materials costed 1.24 million € for 22,000 m^2 of new pavement. The Eixample has a total surface of streets of 1.5 million m^2 (Barcelona City Council, 2021). Assuming the costs incurred in Murcia would be maintained in Barcelona, the cost of repaving the whole Eixample with noise-reducing materials would be of around 84.3 million €[41]. Our results indicate an average capitalization effect of 1.7% for each 5 dB decrease in street noise. This implies, as confirmed by the estimation with the continuous noise measure, that a decrease of 3 dB induces a 0.9-1% increase in the selling price of houses. At the aggregate level, basing the inference on the same 2017 sample which we use for our analysis, this translates to around 22.3 million €. One should keep in mind that our data collects listings of flats on the market in the month of December of each year. This means that not all units listed at that moment will be sold in the same month, implying that multiplying the monthly aggregate value for 12 months would highly overestimate the benefits. According to real estate agencies (Tinsa, 2017), in 2017 houses were sold after an average of 4.3 months in Barcelona. Assuming December is a representative month of the year in terms of published listings, the aggregate benefits of a reduction of 3 dB in noise in every street of the Eixample would have amounted to around 67 million € over the whole year. Comparing the estimated benefits to the costs of repaving the whole district, 80% of the costs would be covered in the first year after investment. In less than two years, the policy would start to be welfare improving.

This simple analysis has the advantage of helping to understand the meaning of the magnitude of the price discount we find in Barcelona's housing market, although we need to read these results with a grain of salt. The approximations about the number of houses sold during the whole year lacks some precision. As our data only offer a snapshot of the month of December, we can not be sure about the yearly numbers. In addition, the material used in the repaving not only reduces noise, but it also decreases the heat absorption and therefore temperatures. These benefits are

[40] Read here about the 2021 pilot project and the 2024 expansion.

[41] As a comparison to real municipal investments, the "Pla Endreça", a set of measures directed towards the maintenance of the public space (approved in 2024), allocated 29 million € to the repaving of 600,000 m^2 asphalt. According to these numbers, repaving the whole Eixample with normal asphalt would cost around 72.5 million €.

not taken into account in our cost-benefit analysis.

Comparing the estimated impact on noise of this policy to the benchmark tells us that a 3 dB reduction would still fall short of reaching the objectives set in the current Acoustic Zoning and the standards recommended by the WHO. Compared to the average reduction needed in 2017 to reach the current limits, 3 dB represents the 80%[42] of this gap. When compared to the WHO standards, 3 dB is only 19% of the average wedge between the 2017 values and the health recommendations. This suggests that this policy, despite being welfare improving, would not be sufficient in order to reach high standards of acoustic quality.

6.2 Subsidy for window replacements

We perform a second analysis of a real policy implemented in Barcelona to reduce perceived noise within flats in noisy streets. Specifically, in 2022 the Barcelona's city hall launched a call offering grants for windows replacement in acoustically stressed areas[43]. The aim of the call was to provide a subsidy for window replacement for residents in street with a noise exposure higher than 65 dB. A maximum amount of 3,000 € per flat would have been provided to install new windows with an acoustic insulation value of at least 30 dB. We check whether this policy has been efficient in monetary terms, computing costs and benefits from the sample of flats listed for sales in Idealista in December 2017[44]. In this sense, we compare the public cost, the total amount of subsidies, with the increased housing value induced by the reduction in perceived noise within the flat. For the cost, we will assume a fixed cost of 3000 € per flat, which corresponds to the amount of public resources allocated for the grant. This probably underestimates the real cost of the intervention, which is complemented by a private cost borne by the owner. Unluckily, estimating the total cost would be impossible since it depends on the number of windows to be replaced, the size of the window, the type of chosen glass and frame and other factors we can not account for. In any case, we believe the public cost is a good parameter to look at, as this is the total amount of public resources allocated to the noise reduction by this specific policy. The call expressly conditioned the subsidy to the installation of new windows with an acoustic insulation value (Rw) of at least 30 dB. The Rw value is an index that measures a window's ability to reduce external noise, suggesting how much noise the window can block. The exercise of imputing the acoustic insulation value to a specific window type is challenging, as this value depends on the glass type (single, double, triple, laminated, etc.), the window frame material, the size of the window, the type of window opening, and the building façade. As reference, we will set to 30 dB the level of absorbed noise from the newly installed windows, since this is the minimum value necessary to get the subsidy. This would correspond to a good 6mm double glass window. We cannot consider this value as the overall reduction in perceived noise within the flat after the window renewal, as we need to consider that the existing windows before the replacement were already reducing the external noise. We assume the previous window to be a normal basic window, such as a single 4mm glass with an old frame. It is difficult to estimate the

[42] 48% when considering the upper bound of each range. When considering the lower bound, 3 dB is more than double the reduction needed.

[43] See the call here.

[44] We use the listings for 2017 because this is the closest year to the call for which a strategic noise map is available.

exact acoustic insulation value of this window type, because, as mentioned above, it depends on many factors. Generally, we can attribute to this kind of window an Rw value between 26 and 28 dB. We will use the middle point of the range (27 dB) as noise reduction of the old window. Based on this decision, the window replacement would induce a 3 dB reduction in perceived noise within the flat.

Based on these assumptions, we can compute costs and benefits the subsidies. As for the cost, we consider only the public fixed cost of 3,000 € per flat. The computation is straightforward: out of the total amount of flats listed for sale in December 2017, 3,925 flats were located in street segments with a noise level above the 65 dB limit. We will assume that all owners of these flats apply and get the grant, as they are entitled to receive it. Considering a fixed cost of 3,000 € per flat, the public cost for the policy for this specific sample of flats would amount to 11,775,000 €. As it comes to quantifying the benefit, we refer to it as the increased value of the house driven by the reduction in perceived noise within the flat thanks to the new window. As we mentioned above, the lower bound to receive the subsidy (30 dB acoustic noise reduction) would imply a 3 dB reduction in the perceived noise within the flat. Given the flats considered and their average price, applying the estimated coefficient in our main analysis[45] we can quantify the overall increased market value for those flats to be 19,259,243 €. In this second analysis, we do not extrapolate yearly values, as we use this sample to simulate a potential group of homeowners entitled to apply for the grant[46]. According to these figures, the benefits are 1.64 times higher than the cost, suggesting that the policy has been worth implementing.

We perform an alternative cost-benefit analysis in which we condition the subsidy on the age of the building and on the floor, as we find our result to be more salient for lower floors. Specifically, we do the same computation exercises for the 1712 listed flats in December 2017, which are not only in street segments with a noise level of at least 65dB but are also located in buildings constructed before the year 2000[47] and at the second floor or lower[48]. In this case, the policy would be even more efficient, as the benefits would have been 2.26 times higher than the costs. In addition, limiting the number of owners that could apply for the grant would have also the advantage of abating the public cost of the policy by more than half[49]. Thus, we suggest that future policies should target directly the flats for which the noise reduction would be more salient to reduce the public expenditure and make the policy more efficient when comparing benefits and costs.

Finally, we note that this policy is not aimed at reducing the objective street noise, but only the noise perceived from inside the house. This means that the externality of noise is not tackled directly, since the level of objective noise on the street would not change. Given that the level of 65 dB is extremely high, we believe reducing this value directly would be preferable, as people would still experience extreme levels of noise outside the house. In addition, this intervention is regressive, as it entails a direct transfer of public resources to private people which highly likely

[45] Our estimation with the continuous noise measure indicates an average capitalization effect of 0.9% for each 3 dB decrease in street noise.

[46] As both costs and benefits are unitary, obtaining yearly values implies multiplying both costs and benefits by a constant.

[47] Assuming that building constructed after the year 2000 are already equipped with decent quality windows.

[48] In this case, we employ the coefficient estimated for lower floors in the heterogeneity analysis to compute the overall benefit.

[49] The total public cost to replace the windows in this hypothetical case would be 5,163,000 €.

are richer than the average resident as they own at least one flat. We believe that policies which tackle the problem directly by reducing the objective noise at the source are preferrable for two reasons. First, they are more sustainable in the long term. Second, they do not entail a direct transfer of resources to homeowners[50], thus are less regressive.

7 Discussion and policy recommendations

The objective of this section is to summarize the policy-related aspects arising from our analysis and provide clear policy recommendations.

First, our results suggest that the effect of street noise on housing prices is highly localized. Policies aimed at reducing noise pollution will likely increase housing prices at a very local level, potentially exacerbating environmental inequalities within the city. We suggest public policies should aim at a general improvement in environmental conditions throughout the whole city rather than through very localized projects. This implication is aligned with what is often suggested by the economic literature which studies the causes and consequences of gentrification. In fact, our paper shows that a reduction in noise can potentially contribute to the gentrification process by raising housing prices.

Second, although much public debate and existing regulations focus on nightlife noise, our analysis does not find nightlife noise to be the main driver of real estate depreciation. In order to investigate more deeply this interesting ambivalence between traffic and nightlife noise, we analyze the noise levels registered by the newly published data on noise sensors[51]. By doing so, we identify two main priorities that we believe should be taken into account when designing policies: night-time noise and traffic. Figure 5 plots the density distribution of dB above the limit established by the 2022 Acustic zoning as registered by the sensors of the Eixample in 2022. As Panel 5a shows, night-time limits (which are lower than day-time limits) are exceeded more often than during the day. When splitting the sample by source, traffic exceeds the limits more often than footfall from leisure activities (footfall during the day, nightlife during the night. We call this source "Leisure") (Figure 5b). When intersecting these two dimensions, Figure 6 clearly shows that leisure activities exceed the limits mostly during the night, but traffic noise is above the limit in a consistent way both during the day and during the night. Given these statistics, we suggest that widening the focus to other sources of noise such as motorized vehicles would help decrease the average noise levels on a more general scale than nightlife noise only.

[50] The transfer would be only indirect, through increased housing prices for flats.

[51] This data collects the hourly noise levels registered by the sensors installed throughout the city for different sources of noise. We don't use this source in our main analysis because the number of sensors over the street network of the Eixample is very limited. In 2022, there were 60 sensors over the around 1,000 street sections of the Eixample. Sensors are placed in specific areas of the city according to the type of noise that they are aimed at capturing. Sensors which register nightlife noise are placed in areas with high footfall, both during the day and during the night. We categorize these sensors as "Leisure". Sensors aimed at measuring traffic noise are placed in streets where the prevalent source of noise is motorized vehicles. This data can be found here: https://opendata-ajuntament.barcelona.cat/data/es/dataset/xarxasoroll-equipsmonitor-dades.

Figure 5: Distribution of sensor measures above the limits

(a) (b)

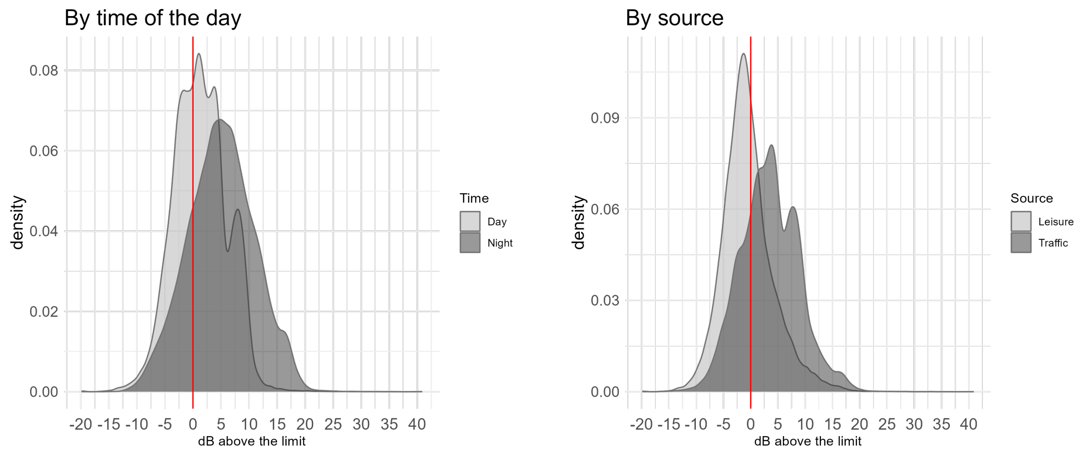
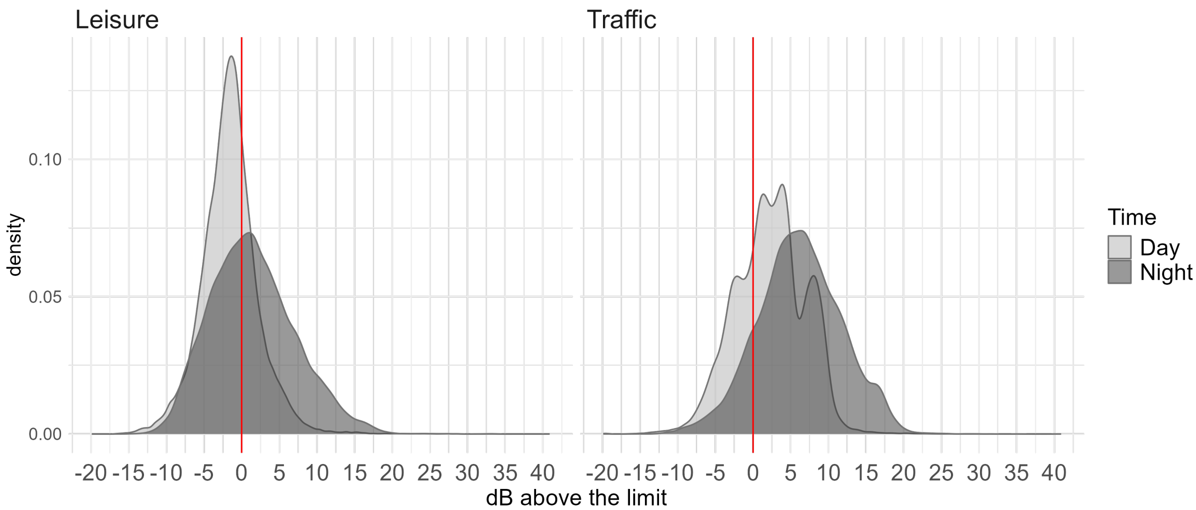


Figure 6: Distribution of sensor measures above the limits



Note: These density plots show the distribution of 2022 hourly noise measurements by source and by time of the day. The horizontal axis represents the difference between the registered noise and the limit set by the Acoustic Zone Maps in 2022. *Source*: City Council of Barcelona, own elaboration

Lastly, as detailed in the previous section, the ultimate goal of noise-reduction policies should be to reduce objective street noise, rather than merely reducing perceived noise inside houses.Differently, the externality of noise would not be tackled directly and people would still experience extremely high levels of noise in the street. In addition, reducing the perceived noise inside the flat through specific subsidies would be regressive, as it entails a direct transfer of public resources to private people which highly likely are richer than the average resident as they own at least one flat. We recommend prioritizing policies that directly reduce street noise at the source.

Summarizing,we argue that effective policies should intervene on a broad area instead of being localized. Moreover, they should reduce objective noise on the street rather than perceived noise within the flat. Finally, policies aimed at reducing noise from motorized vehicles would help decrease the average noise levels on a more general scale than nightlife noise only. Effective policies might include reducing private vehicle traffic in favor of public transport and sustainable modes, speed reductions, stricter vehicle noise regulations and enforcement, large scale low emission zones or pedestrianizations, transition to electric vehicles, and road re-pavement.

8 Conclusion

In this paper, we evaluate the environmental externalities created by noise pollution. Doing so is informative about the burden they create on residents and the extent of the potential benefits created by policies tackling the issue. We do so by applying a hedonic price model combined with a peculiar feature of the urban morphology of the Eixample district, in Barcelona. Using posted prices of listings from *idealista* and a very granular dataset on noise pollution, this paper shows that noise is a negative externality which capitalizes into housing prices.

It adds to the literature by studying the whole soundscape of a urban environment with very high population density and where noise pollution is a generally widespread problem. We find that doubling the annoyance perceived by noise (an increase of 10 dB) induces a depreciation of 3.4% on sales' prices and 2% on monthly rent prices. Throughout the whole analysis, we find higher price semi-elasticity to noise on sale prices than on rents. This is consistent with the higher tightness of the rental market in Barcelona, its higher asymmetric information, the different socio-demographic profiles of buyers compared to renters and the expected capital gains from investing in quieter streets.We show that noise induces a higher turnover of tenants in louder streets compared to quieter ones, which is consistent with the relatively lower semi-elasticity of rents' prices compared to sales. The effect seems to be driven by the noise annoyance perceived from inside the house rather than by the one experienced on the street itself. Moreover, we exclude that the effect is driven by sorting by neighbors. Our results suggest that evening and night noise have an higher impact on the depreciation than day-time noise. However, we do not find evidence of a driving source of noise, as pedestrian, nightlife and traffic do not affect prices differently.

When comparing our results to the effect found in the literature for other related environmental factors, we find that the magnitudes are comparable to sizeable reductions in air pollution and congestion. Specifically, the capitalization implied by a 5 dB reduction is roughly equivalent to that of a decrease of 1 $\mu g/\mathrm{m}^3$ in the concentration of suspended particulates in the air[52] in the US (Grainger, 2012)[53]. However, when compared to recommended limits, the same magnitude implies very different relative changes. With respect to the WHO recommeded limits, a 5 dB reduction represents 5/53 of the level for noise exposure, while 1 $\mu g/\mathrm{m}^3$ of $PM_{2.5}$ is 1/5 of the level for exposure to $PM_{2.5}$[54]. Given the same capitalization effect for a smaller change in terms

[52] Annual average $PM_{2.5}$ concentration in the city of Barcelona decreased by 1 $\mu g/\mathrm{m}^3$ between 2012 and 2019.

[53] Grainger (2012) replicates the estimation strategy of Chay and Greenstone (2005) (who use data from the 1970s) in later years (between 1990 and 2000). Grainger (2012) finds a higher magnitude of results, and he argues that this is explained by increase in awareness of the detrimental effect of air pollution over time.

[54] The WHO recommended level of maximum annual $PM_{2.5}$ exposure is 5 $\mu g/\mathrm{m}^3$ (World Health Organization, 2021)

of health risk, we conclude that noise is more salient than air pollution, likely due to the higher annoyance it generates. Regarding traffic, Tang (2021) studies the impact of the introduction of the London Congestion Charge on property values. Using his estimates, we can approximate that the effect of 800 fewer vehicles per day in London is comparable to a reduction of 5 dB in our sample[55].

Our findings yield precise policy recommendations. Street noise reductions produce highly localized increases in housing prices, potentially exacerbating spatial inequalities and fueling gentrification. To avoid this, broad, city-wide interventions are preferable to spatially concentrated measures. Moreover, while public debate and regulations often focus on nightlife noise, targeting noise from motorized traffic would yield broader reductions in average noise levels. Lastly, we suggest that effective policies should prioritize reductions in street noise at the source, more than perceived noise from inside the flats. Examples of such policies include reducing private vehicle use in favor of public transport and active modes, lowering speed limits, strengthening vehicle noise regulations and enforcement, broad low-emission zones or pedestrianized areas, promoting the transition to electric vehicles, and improving road surfaces.

This study leaves room for further research, particularly on aspects that also represent its limitations. For example, our analysis is based on asked prices rather than final transaction prices. The key assumption is that landlords internalize the negative externality of noise into the asked price, adjusting it in response to demand. However, if bargaining occurs, it creates a wedge between the initial asked price and the final price agreed upon by the parties. On one hand, the above-mentioned market tightness leads us to believe that this issue is not a major concern for rents. Nevertheless, bargaining is more likely to occur on sales. If the result of the bargaining process is independent of noise, our results are unbiased. However, if the intensity of bargaining varies systematically directly with noise or with street characteristics that correlate with noise (e.g., consumption amenities, accessibility) or with noise itself, our estimates may be biased. There are two possible scenarios we can think of. In the first one, the intensity of bargaining increases with noise, as the buyer asks for a higher discount due to the negative externality. However, in the second one, the amenities which correlate to noise and which positively capitalize into housing prices act as an "insurance" for the seller, implying a decrease in the intensity of bargaining. We consider it more plausible that bargaining is responsive to noise than to amenities, as the former is highly specific to the street level, while the latter tends to be more stable at the block level. This would imply that, in the possible presence of noise-related bargaining, our estimates are more likely to represent a lower bound of the true effect: buyers in noisier streets would negotiate larger discounts, and the actual price gap between quieter and noisier streets would exceed the differences we observe in asked prices. That said, determining whether one of the two scenarios prevails and which one is an empirical question that remains open for future research. Another limitation of the data with respect to our analysis is the lack of information on noise insulation of the flat. Nevertheless, we believe that even if insulation is correlated to noise and affects prices, our estimated coefficients represent a lower-bound, as noise insulation would drive prices up. Finally, when it comes to traffic, noise is only one among

[55] In the case of Barcelona, 800 vehicles represent around 5% of the traffic circulating in the city on an average working day of 2019. Between 2019 and 2022, the number of vehicles in Barcelona decreased by around 12%.

several negative externalities it produces, including air pollution and congestion. Future research could aim at identifying whether and which of these externalities has a prevailing effect over the others.

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9 Appendix

A1 Robustness checks

A1.1 Alternative block definition

In order to increase within-block variation we use an alternative "2x2 moving block" definition, which includes four neighbouring blocks instead of one single block. In this way, each squared block belongs to four different groups, containing the neighboring units on all possible sides. Figure A10 illustrates how these blocks are defined. Table A11 shows that this alternative definition successfully increases the within-block variation in noise compared to the baseline definition (as reported in Table A5). This specification implies that the observations contained in each block are duplicated in the dataset, once for each group they belong to (on average 3.5). Therefore, we weight each observation by the inverse of its number of duplicates. Moreover, as each group contains several blocks, it is not possible to mantain the same clustering of the standard errors as in the baseline specification (at the block level). We increase the level of clustering to the Basic Statistical Area (AEB). However, this choice also presents some issues. When blocks are at the border between different AEBs, the 2x2 group contains several AEBs. We use alternative definitions of AEBs for clustering and show that results are robust. Table A12 show that the results are robust to this alternative definition of blocks. However, the higher clustering level results in a lower significance level of the results. Table A13 shows that the results are robust to alternative clusterings.

A1.2 Alternative samples

When including for each sample year of the noise dataset (2009, 2012, 2017) all listings of the previous and following year, we might generate some measurement error if the true noise level changed year by year. While our aim is to increase the sample size, this could also decrease the precision of the estimation. Therefore, we run a robustness check in which we restrict the sample to the listings which are published only on the same year as the noise sample years. Table A14 shows that the sample size decreases to around one third, but the results are mostly robust, especially on sales.

While the Eixample gives us the most confidence in terms of internal validity of our estimation, it is not the only area of the city which was built with a very regular grid shape. We define a wider "orthogonal sample" which includes all regular blocks of the city. This includes the Eixample and some parts of the districts of Sant Martí and Sant Andreu. Figure A11 maps the area included in this wider sample. Table A15 show that the results hold and the magnitude of the coefficients is slightly higher.

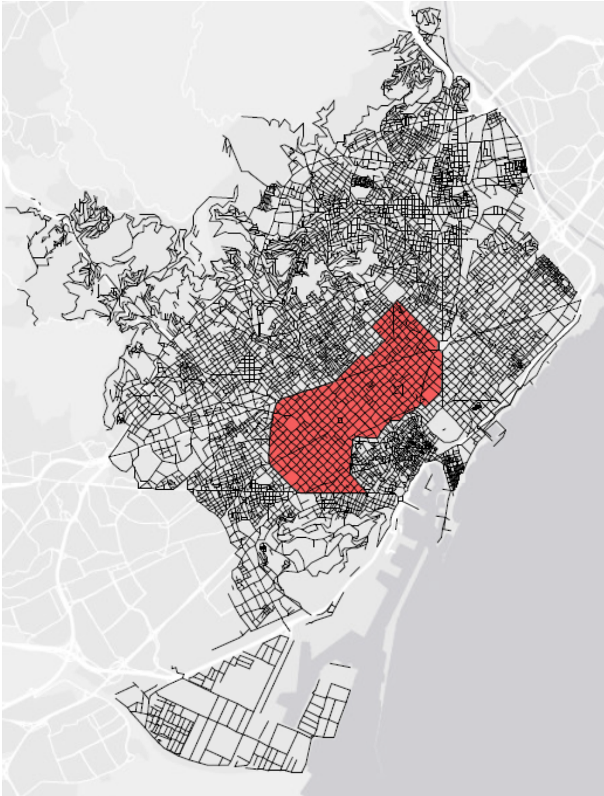
A1.3 Robustness to additional streets characteristics

By including additional street characteristics which we are able to observe, we show that our estimation strategy which exploits within-block variation already captures local (dis)amenities of the area and the coefficient on noise does not change. Unfortunately, we only have access to additional street-level characteristics in the last year of our sample period. Therefore, we are once again forced to perform this exercise limiting the sample to 2017. We include a simple proxies for accessibility defined as the presence of a bus, subway, train stop or cycle lane in the street section, consumption amenities (bars with live shows, pubs and clubs) as well as air pollution at the street section level. Table A16 show that the inclusion of additional street characteristics which are correlated to noise does not change the estimated effect of noise on prices. Across the two models, the coefficient on noise is not statistically different.

For buildings which lie on the corners of the blocks we are unsure about which noise level they are mostly exposed to, since they lie on intersections. Moreover, the noise level at the street section level may not precisely reflect the perceived noise in these buildings, as these intersections are where the traffic lights are located. Non-electric vehicles emit more noise accelerating than cruising. Additionally, engines expell more exhaust gases during acceleration. Therefore, the effect of noise in these houses may be higher than on those located towards the center of a street section. We run a robustness check in which we include a dummy for corner buildings and its interaction with noise. Table A17 shows that, on sales, the coefficient on noise in non-corner buildings is higher than the average, but that being on a corner does not affect prices, nor does the effect of noise differ from houses towards the center of the street section. We conclude that corner buildings are not driving the results. On rents, the effect is once again less stable and looses significance when controlling for corner buildings.

A2 Figures

Figure A1: The Eixample district and the city of Barcelona

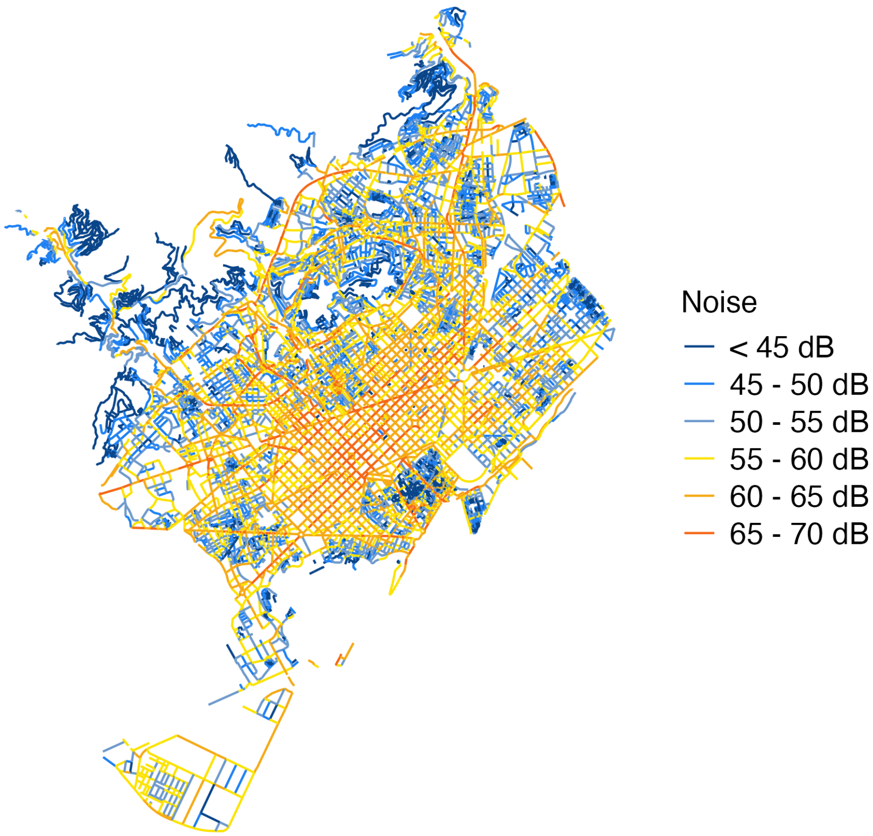


Source: City Council of Barcelona

Figure A2: Bird's-eye view of the Eixample District

Source: City Council of Barcelona

Figure A3: Strategic Noise Map 2017 - Night

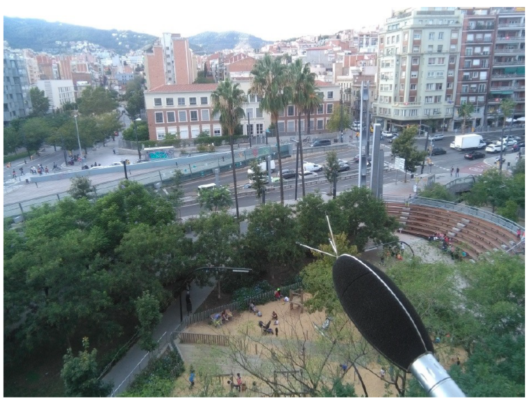


Source: City Council of Barcelona

Figure A4: Examples of sensors

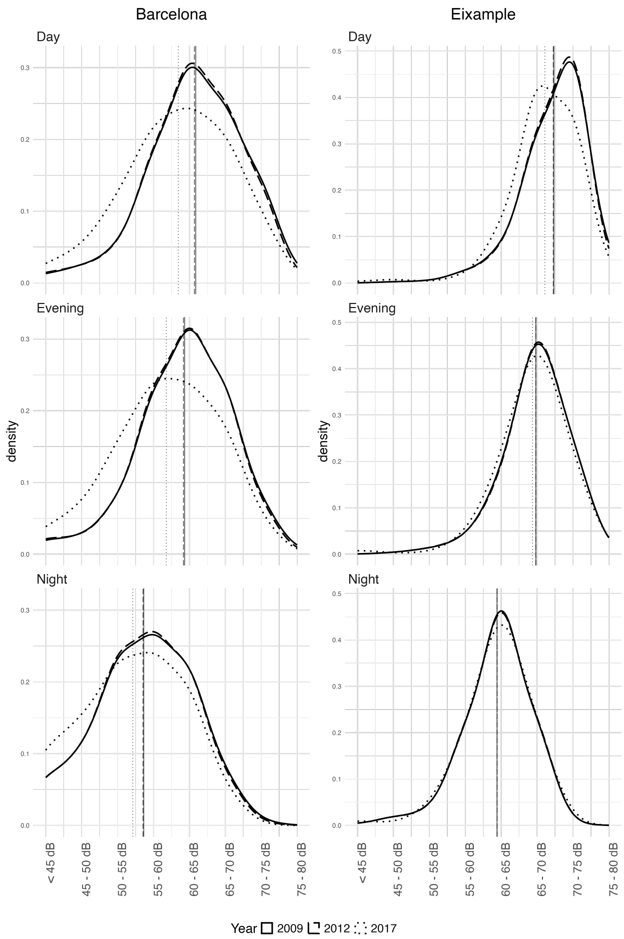
(a) Movable sensor for short-term noise readings

(b) Fixed sensor for long-term noise readings



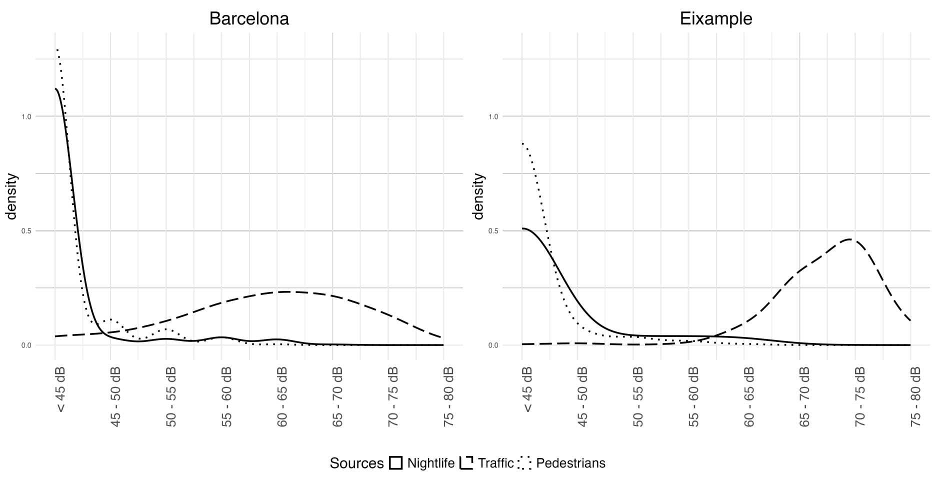
Source: City Council of Barcelona

Figure A5: Noise distributions by year and time of the day



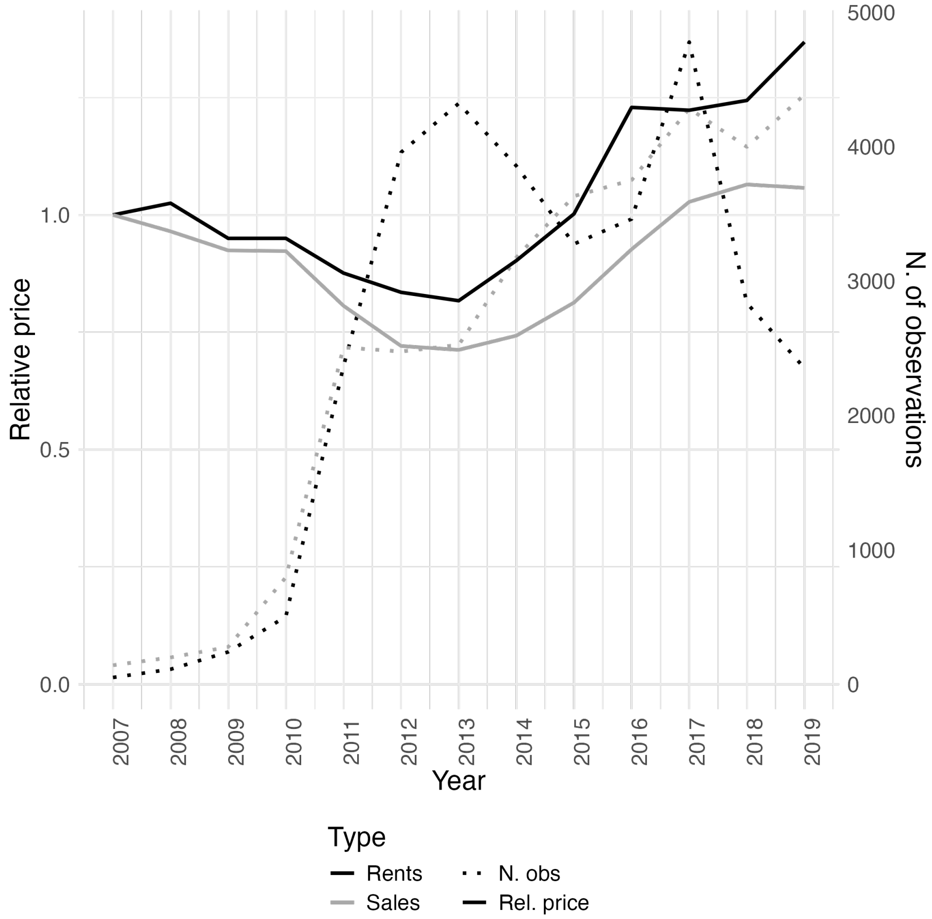
Source: City Council of Barcelona, own elaboration

Figure A6: Noise distributions by source



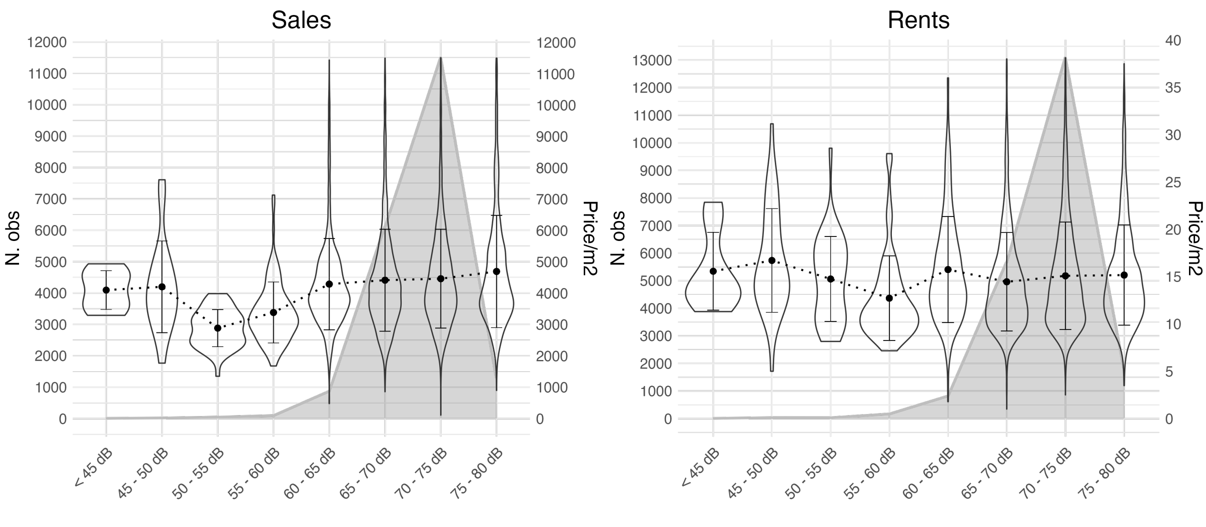
Source: City Council of Barcelona, own elaboration

Figure A7: Prices and listings over time - Eixample



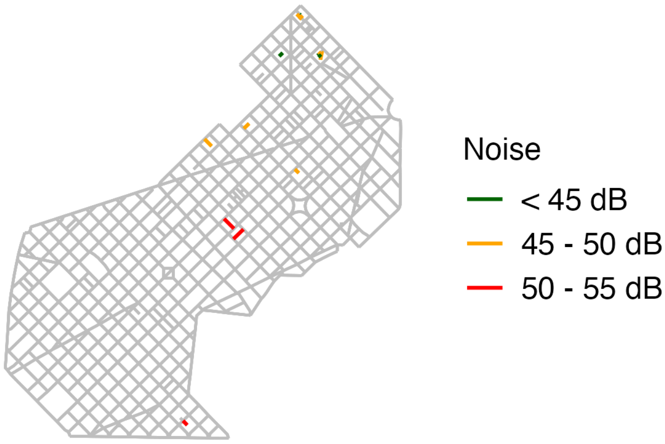
Source: Idealista, own elaboration

Figure A8: Distribution of prices and number of observations by noise level



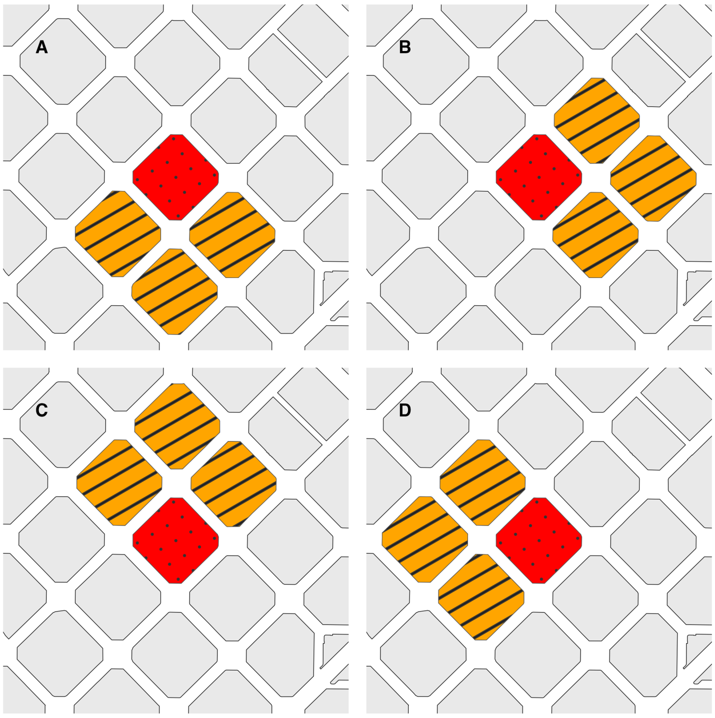
Note: This violin plot represents the distribution of prices. The points show the mean together with the standard deviation of prices within each noise range (on the right axis). The shade in the background plots the number of observations in each noise range (on the left axis). *Source*: Idealista, City Council of Barcelona

Figure A9: Streets within the three lowest ranges of noise



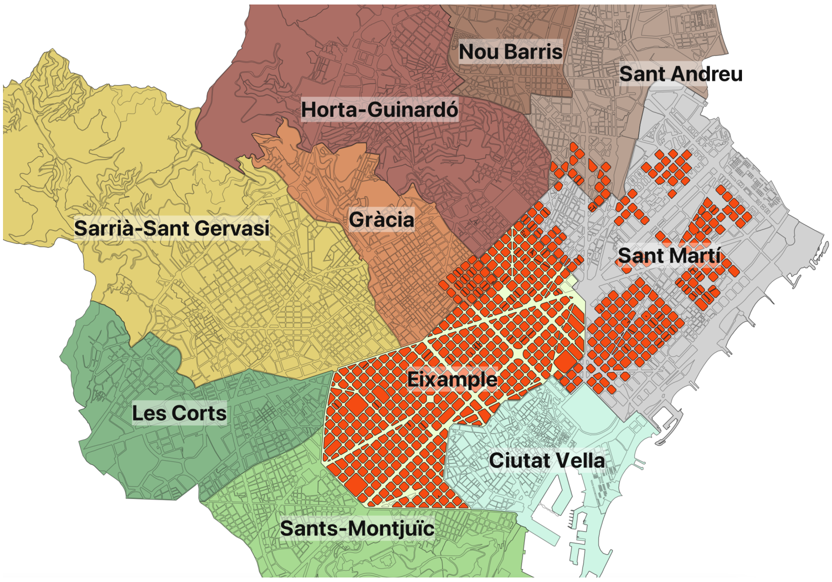
Source: City Council of Barcelona, own elaboration

Figure A10: Graphic illustration of the 2x2 block definition



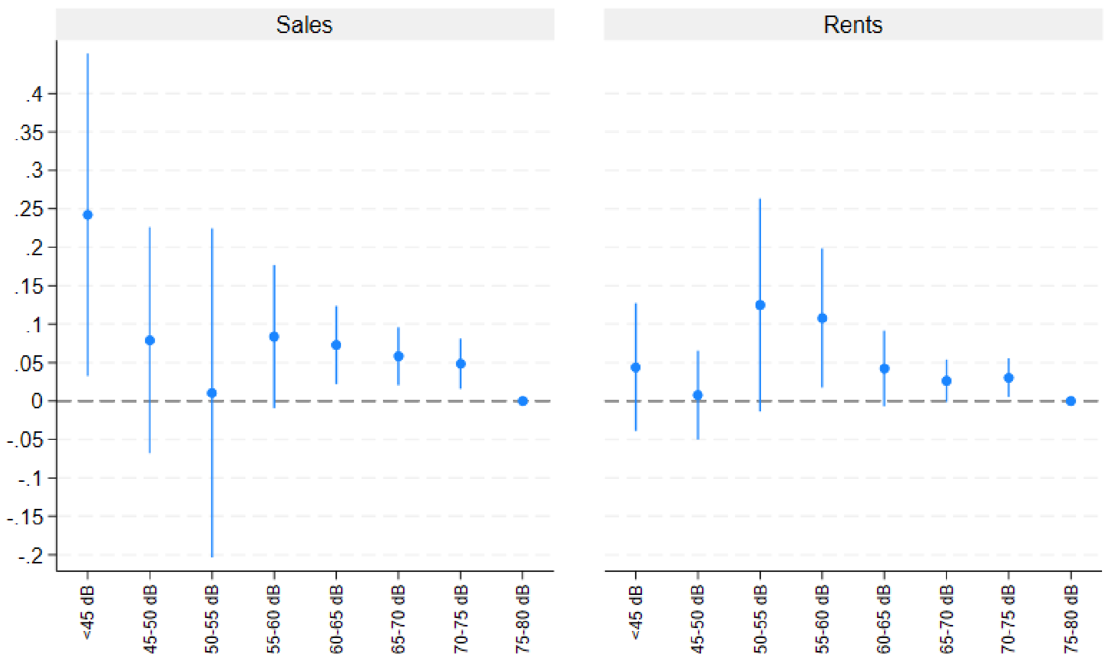
Note: This map illustrates the definition of the 2x2 moving block definition. Each block (represented by the red block) is assigned to groups of 4 contiguous blocks (represented by the orange blocks). Therefore, each block is assigned to group A, as well as to group B, C, and D. *Source:* City Council of Barcelona, own elaboration

Figure A11: Map of all orthogonal blocks



Note: This map shows the extent and structure of the wider orthogonal sample used for robustness check. As it shows, this sample selects areas outside of the Eixample district which are characterized by a very similar orthogonal, regular street morphology. *Source:* City Council of Barcelona, own elaboration

Figure A12: Results with $Noise_{st}$ as categorical variable



Note: These plots represent the results of a robustness check in which we include all noise ranges as categorical variables and set the baseline level to the maximum noise range (75-80 dB). Standard errors are clustered at the block level and confidence intervals are at the 95% confidence level.

A3 Tables

Table A1: Within-district variation

	Eixample			Other districts (N = 9)		
AEB characteristics	Mean	Sd	N	Mean(Mean)	Mean(Sd)	Mean(N)
Urban features						
Mean street gradient	1.27	0.41	36	3.15	1.66	22
Mean street width	26.74	9.16	36	24.13	11.84	22
Mean street length	118.97	14.36	36	90.08	27.94	22
N. urban trees/km2	3,156.48	631.63	36	2,386.90	1,101.77	22
N. intersections/km2	76.44	29.48	36	167.47	89.80	22
Buildings' height	17.18	1.60	36	12.91	3.80	22
Buildings' constr. year	1942	11.62	36	1954	12.36	22
Population density (2009)	37,430.75	14,678.70	36	31,038.05	18,991.42	22
Socio-demographics						
% Foreign (2009)	19.08	3.22	36	18.62	6.83	22
% Pop. 16-45 yo (2009)	42.27	2.26	36	43.32	3.92	22
% w/o Studies (2009)	7.61	1.32	36	10.72	2.48	22
% w/ Primary studies (2009)	14.84	3.12	36	20.42	4.26	22
% w/ University studies (2009)	29.21	5.97	36	19.82	5.08	22
% Unemployed (2011)	5.65	0.51	36	6.74	0.93	22
Relative HH Income (2008)	116.13	34.34	36	105.69	43.21	22

Note: This table shows within-district variation in the Eixample compared to the mean within-district variation in the rest of the city. The starting unit of analysis is the AEB (Statistical Basic Area). These are geographic units between the census tracts and the neighborhoods. There is 233 in total in the city, 36 of which are in the Eixample. For consistency with the socio-demographic variables (which are only available at the AEB level), the rest of variables were also aggregated at the AEB level.

Table A2: The decibel (dB) scale

0 dB	Threshold of hearing
10 dB	Normal breathing
20 dB	Rustling leaves
30 dB	Ticking clock
40 dB	Library
50 dB	Rain
60 dB	A normal conversation
70 dB	Vacuum cleaner 3m away
80 dB	Heavy city traffic
90 dB	Passing motorcycle
100 dB	Ambulance 30m away
110 dB	Loud thunder
120 dB	Jet taking off 60m away
130 dB	Gunshot within 10m
140 dB	Gunshot within 1m

Source: European Environmental Agency (2020), SoundEar.com

Table A3: Noise correlations

Width	0.006***					
	(0.001)					
Nightlife		0.333***				
		(0.106)				
N. bus lines			0.150***			
			(0.013)			
Cycle lane				0.094		
				(0.058)		
ln(Traffic)					0.551***	
					(0.069)	
Pedestrianized						-1.652***
						(0.162)
Downhill						-0.391***
						(0.070)
Uphill						-0.221***
						(0.073)
South						-0.042
						(0.069)
North						0.017
						(0.074)
Double						0.000
						(.)
N	1107	1109	1109	1109	107	1075
R-squared	0.016	0.009	0.112	0.002	0.381	0.123

Note: This table shows simple correlations between noise and street characteristics. Nightlife refers to the number of nightlife activities present on the street section. These are defined as bars with live shows, pubs and clubs. N. bus lines is the number of different bus lines passing through the street. Cycle lane is a dummy for the presence of a cycle lane. Ln(Traffic) is the logarithm of the number of vehicles counted by sensors placed on the street. Pedestrianized, Downhill, Uphill, South and North are all different traffic direction of the street. The excluded category is Double, meaning bidirectional streets. Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Housing prices by year

	Sales	Rents
2008	4,657.77	14.69
	(1,271.49)	(3.95)
	185	98
2009	4,580.57	13.50
	(1,369.63)	(4.17)
	263	207
2010	4,577.82	13.55
	(1,391.41)	(4.31)
	711	417
2011	4,020.11	12.90
	(1,338.84)	(3.87)
	2,402	2,306
2012	3,537.87	12.31
	(1,320.35)	(3.76)
	2,380	3,840
2013	3,537.22	11.98
	(1,372.99)	(3.82)
	2,428	4,154
2016	4,491.57	17.22
	(1,585.61)	(5.91)
	3,610	3,283
2017	5,004.16	17.72
	(1,548.30)	(5.53)
	4,114	4,581
2018	5,199.05	17.79
	(1,554.96)	(5.91)
	3,793	2,673
Total	4,450.76	14.93
	(1,604.00)	(5.52)
	19,886	21,559

Note: This table shows the mean and the standard deviation (in parenthesis) of the price per m^2 of flats in the Eixample over the years included in our sample. Every third row reports the number of observations in the corresponding year.

Table A5: Within-block variation

	Sales				Rents			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Streets/block	3.58	1.23	1	11	3.70	1.19	1	12
Within block								
Obs/block	46.35	36.28	2	425	50.37	31.18	2	198
Obs/street	21.20	24.74	1	557	22.74	19.83	1	202
Noise/block	2.25	0.79	1	5	2.31	0.79	1	5
Within block x year								
Obs/block x year	18.33	21.42	2	380	20.59	17.68	1	126
Obs/street x year	9.27	15.03	1	534	10.02	10.79	1	146
Noise/block x year	1.72	0.67	1	4	1.81	0.68	1	4

Note: This table shows descriptive statistics within block and within block x year.These values represent the variation exploited in our estimation.

Table A6: Robustness to different clusterings

	(1)	(2)	(3)	(4)	(5)
Panel A: Sales					
Noise	-0.015***	-0.015**	-0.015**	-0.015**	-0.015
	(0.003)	(0.006)	(0.006)	(0.007)	(0.011)
N	19960	19960	19960	19960	19960
R-squared	0.580	0.580	0.580	0.580	0.580
Panel B: Rents					
Noise	-0.010***	-0.010*	-0.010	-0.010*	-0.010*
	(0.003)	(0.006)	(0.006)	(0.006)	(0.005)
N	21558	21558	21558	21558	21558
R-squared	0.576	0.576	0.576	0.576	0.576
Block x Year FE	Yes	Yes	Yes	Yes	Yes
House controls	Yes	Yes	Yes	Yes	Yes
Street controls	Yes	Yes	Yes	Yes	Yes
Robust se	Yes	Yes	Yes	Yes	Yes
Cluster se	No	Block	Census	AEB	Neigh

Note: Each column clusters standard errors at geographically increasing spatial levels. Clustered standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Results with mid-range

	Sales		Rents	
	(1) Baseline	(2) Continuous	(3) Baseline	(4) Continuous
Noise (range)	-0.017**		-0.010*	
	(0.007)		(0.006)	
Noise (mid-range)		-0.003**		-0.002*
		(0.001)		(0.001)
N	19886	19886	21558	21558
R-squared	0.580	0.580	0.576	0.576
Block x Year FE	Yes	Yes	Yes	Yes
House controls	Yes	Yes	Yes	Yes
Street controls	Yes	Yes	Yes	Yes

Note: This tables show results of the effect of noise on prices when defined as a numerical variable from 1 to 8 for each noise range (first row) and when each range is defined with the mid-range value. For the first row, a unitary change of noise is to be interpreted as a change of 5 dB. For the second row, each unitary change of noise represents a change of 1 dB. Standard errors clustered at the block level in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Robustness with whole range of noise

	Sales		Rents	
	(1) Noise > 3	(2) Whole range	(3) Noise > 3	(4) Whole range
Noise	-0.017**	-0.015**	-0.010*	-0.009*
	(0.007)	(0.006)	(0.006)	(0.005)
N	19886	19960	21558	21632
R-squared	0.580	0.580	0.576	0.576
Block x Year FE	Yes	Yes	Yes	Yes
House controls	Yes	Yes	Yes	Yes
Street controls	Yes	Yes	Yes	Yes

Note: This table shows how the estimated effect changes when the sample is limited to noise levels above the third range (50-55 dB, columns 1 and 3) compared to estimates using the whole range of noise (columns 2 and 4). Standard errors clustered at the block level in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Correlation among time ranges

	Total	Day	Evening	Night
Total	1	0.91	0.90	0.92
Day	0.91	1	0.92	0.87
Evening	0.90	0.92	1	0.92
Night	0.92	0.87	0.92	1

Note: This table shows correlation coefficients across noise over different times of the day.

Table A10: Correlation among sources

	Total	Traffic	Pedestrian	Recreational
Total	1	0.80	-0.12	0.17
Traffic	0.80	1	-0.3	-0.007
Pedestrian	-0.12	-0.3	1	0.32
Recreational	0.17	-0.007	0.32	1

Note: This table shows correlation coefficients across noise from different sources.

Table A11: Within-block variation

	Sales				Rents			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Streets/2x2 block	10.57	2.65	2	23	10.77	2.69	2	23
Blocks/2x2 block	3.54	0.77	1	6	3.54	0.77	1	6
Within 2x2 block								
Obs/2x2 block	167.65	92.38	5	930	185.29	85.91	6	574
Obs/street	21.43	24.96	1	557	23.03	20.14	1	205
Noise/2x2 block	3.10	0.76	1	5	3.15	0.76	1	5
Within 2x2 block x year								
Obs/2x2 block x year	56.53	56.72	1	821	62.03	54.92	1	397
Obs/street x year	9.14	15.01	1	534	9.83	10.89	1	148
Noise/2x2 block x year	2.36	0.77	1	5	2.39	0.79	1	5

Note: This table shows descriptive statistics within 2x2 block and within 2x2 block x year.These values represent the variation exploited in our estimation.

Table A12: Results with 2x2 block definition

	Sales		Rents	
	(1) Baseline	(2) 2x2 blocks	(3) Baseline	(4) 2x2 blocks
Noise	-0.017**	-0.017***	-0.010*	-0.009*
	(0.007)	(0.006)	(0.006)	(0.005)
N	19886	77166	21558	85285
R-squared	0.580	0.515	0.576	0.530
Block x Year FE	Yes	Yes	Yes	Yes
House controls	Yes	Yes	Yes	Yes
Street controls	Yes	Yes	Yes	Yes

Note: This table compares estimates with different definition of block. Column 1 and 3 use the natural definition of block (1x1). Column 2 and 4 use the 2x2 moving block definition. Standard errors clustered at the block level in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A13: Results with 2x2 blocks and alternative clustering

	(1)	(2)	(3)	(4)
Panel A: Sales				
Noise	-0.017**	-0.017**	-0.017**	-0.017**
	(0.008)	(0.008)	(0.007)	(0.008)
N	77166	77166	77166	77166
R-squared	0.515	0.515	0.515	0.515
Panel B: Rents				
Noise	-0.009	-0.009	-0.009	-0.009
	(0.005)	(0.006)	(0.006)	(0.006)
N	85285	85285	85285	85285
R-squared	0.530	0.530	0.530	0.530
Block x Year FE	Yes	Yes	Yes	Yes
House controls	Yes	Yes	Yes	Yes
Street controls	Yes	Yes	Yes	Yes
Clustering	AEB1	AEB2	AEB3	AEB4

Note: This table compares different clustering of standard errors. As the 2x2 moving block definition can include more than one Basic Statistical Area (AEB), we cluster standard errors at all possible AEBs. Clustered standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A14: Results on restricted sample years

	Sales		Rents	
	Baseline	Restricted years	Baseline	Restricted years
Noise	-0.017**	-0.021**	-0.010*	-0.007
	(0.007)	(0.010)	(0.006)	(0.008)
N	19886	6563	21558	8501
R-squared	0.580	0.668	0.576	0.632
Block x Year FE	Yes	Yes	Yes	Yes
House controls	Yes	Yes	Yes	Yes
Street controls	Yes	Yes	Yes	Yes

Note: This table compares estimates between a sample which matches listings of +-1 year with the respect to the noise data (columns 1 and 3) and one which restricts the match to the exact year only (column 2 and 4). Standard errors clustered at the block level in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A15: Results on orthogonal sample

	Sales		Rents	
	(1)	(2)	(3)	(4)
	Baseline	Orthogonal	Baseline	Orthogonal
Noise	-0.017**	-0.018***	-0.010*	-0.012**
	(0.007)	(0.007)	(0.006)	(0.005)
N	19886	21050	21558	22353
R-squared	0.580	0.590	0.576	0.583
Block x Year FE	Yes	Yes	Yes	Yes
House controls	Yes	Yes	Yes	Yes
Street controls	Yes	Yes	Yes	Yes

Note: This table compares estimate of the sample restricted to the Eixample district (baseline) to one which includes further orthogonal areas (Orthogonal). Standard errors clustered at the block level in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A16: Robustness to additional street controls

	Sales		Rents	
	(1)	(2)	(3)	(4)
	2017 only	+ Streets var	2017 only	+ Streets var
Noise	-0.012	-0.010	-0.010	-0.011
	(0.009)	(0.010)	(0.008)	(0.008)
Bus stops		0.004		0.002
		(0.004)		(0.004)
Subway		0.006		0.004
		(0.021)		(0.032)
Train		0.106*		0.016
		(0.056)		(0.037)
Cycle lane		-0.022**		0.011
		(0.010)		(0.012)
Bars		-0.001		-0.004
		(0.002)		(0.003)
PM2.5		-0.021		0.001
		(0.018)		(0.019)
N	11517	11517	10537	10537
R-squared	0.520	0.521	0.395	0.396
Block FE	Yes	Yes	Yes	Yes
House controls	Yes	Yes	Yes	Yes
Street controls	Yes	Yes	Yes	Yes

Note: This table compares estimates on the 2017 sample (columns 1 and 3) and adding street characteristics which may raise concerns of omitted variable bias. Standard errors clustered at the block level in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A17: Robustness with corner buildings

	Sales		Rents	
	(1) Baseline	(2) Corner dummy	(3) Baseline	(4) Corner dummy
Noise	-0.017**	-0.022***	-0.010*	-0.007
	(0.007)	(0.008)	(0.006)	(0.006)
Corner		-0.083		0.069
		(0.067)		(0.066)
Corner=1 × Noise		0.012		-0.010
		(0.010)		(0.010)
N	19886	19886	21558	21558
R-squared	0.580	0.580	0.576	0.576
Block x Year FE	Yes	Yes	Yes	Yes
House controls	Yes	Yes	Yes	Yes
Street controls	Yes	Yes	Yes	Yes

Note: This table examines whether the effect of noise on prices changes for flats at the corner of blocks. Standard errors clustered at the block level in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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