The Traffic Noise Externality: Costs, Incidence and Policy Implications

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Abstract

Traffic noise is an understudied and potentially costly negative externality. More than 48 million Americans live in census tracts with medium or high traffic noise levels. Low-income and minority households are disproportionately represented in neighborhoods near major roads and, as a result, experience significantly higher noise exposure. Despite its potentially large economic toll and unequal distribution, the aggregate costs, incidence, and policy implications of traffic noise have received limited attention in economics. In this paper, we quantify the economic cost of traffic noise by estimating its effect on housing demand. Using quasi-exogenous variation from the construction of noise barriers, we find that reduced traffic noise exposure leads to significant increases in house prices. In the five years prior to barrier construction, we observe no differential trends in property values; after construction, however, prices increase immediately. Within 100 meters of a new barrier, house prices rise by 9.7%, with smaller effects at greater distances. These effects are larger in areas where barriers reduce noise the most, suggesting that homebuyers are willing to pay an economically meaningful amount for each decibel of reduced exposure. These results are not driven by changes in local air pollution, views or new construction. We use these estimates to calculate the aggregate cost of traffic noise at $90.6 billion nationwide. The burden of traffic noise, as a share of family income, is disproportionately borne by lower socioeconomic status (SES) households. Finally, we discuss two policy responses: a socially efficient Pigouvian tax of $984 per internal combustion engine vehicle, and the widespread adoption of electric vehicles, which could generate $77.9 billion in noise reduction benefits concentrated among low-SES families.

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1 Introduction

Traffic noise is an understudied and potentially costly negative externality. More than 48 million Americans live in census tracts with medium or high traffic noise levels. Low-income and minority households are disproportionately represented in neighborhoods near major roads and, as a result, experience significantly higher noise exposure. Noise has been linked to a wealth of physical and mental health conditions (WHO, 2017). Despite its potentially large economic toll and unequal distribution, the aggregate costs, incidence, and policy implications of traffic noise have received limited attention in economics.

In this paper, we quantify the economic cost of traffic noise by estimating its effect on homebuyers' willingness to pay for quieter environments. Using quasi-experimental variation based on the construction of noise barriers, we find that reduced traffic noise exposure leads to significant increases in house prices. Our estimates indicate that buyers are willing to pay an economically meaningful amount for each decibel of reduced noise. We use these estimates to quantify the aggregate cost of the traffic noise externality and examine its distribution. For the U.S. as a whole, we estimate the total cost of traffic noise at $90.6 billion – an economically significant burden. This burden, measured as a share of family income, is substantially higher for low-income households than for high-income ones, suggesting that traffic noise is a regressive externality. In terms of policy, we discuss two interventions: a socially efficient Pigouvian tax of $984 per internal combustion engine vehicle, and the widespread adoption of electric vehicles, which could generate $77.9 billion in noise reduction benefits concentrated among low-SES families.

Our empirical analysis is based on transaction-level housing price data from CoreLogic, tract-level traffic noise data from the U.S. Department of Transportation National Transportation Noise Map, and sound barriers data from the Florida Department of Transportation (FDOT) barriers inventory. We focus much of the analysis on Florida because it has the most accurate data on sound barriers and provides information on barriers that were proposed but not built.

In the first part of the paper, we estimate the causal effect of traffic noise on house prices. We first use a difference-in-differences model that compares changes in prices following the construction of a sound barrier for properties located 0—500 m from the traffic (and on the relevant side of the barrier) with changes in prices for properties located 500–1500 m from traffic (and on the relevant side of the barrier). The definition of the control group is based on the physics of the spatial decay of noise. We focus on properties on the noise-abated side of the barrier and use those on the opposite side for a placebo test. Second, we estimate a triple-difference model that uses information on barriers that were proposed but not built. We "match" each of the barriers that were proposed but not built to a barrier that was

actually constructed. This allows us to condition on a richer set of controls that absorb any time-varying barrier-specific and distance-bin-specific heterogeneity. Identification of this model comes from comparing the before and after price changes near and far away from the barrier experienced by properties near constructed and proposed barriers.

In the five years before the barrier construction, we observe no differential pre-trends between properties in the treated and control group. In retrospect, this is probably not too surprising. Since the control group and the treatment group are geographically close, most local amenities that can affect local housing demand – school quality, crime, street cleanliness, etc. – should be balanced, if not in levels then at least in changes. After construction, we observe an immediate and largely permanent increase in property values. For houses within 100 m of the barrier, the estimated price increase is 9.7%. The estimated effects for houses 100—200, 200—300 and 300—400 m from the barrier decline with distance. For distances above 400 m, we find no statistically significant effect. Estimates of the difference-in-differences and triple-difference models are similar. In additional models, we focus on repeated sales of the same property to control for property fixed effects and find slightly larger estimates.

To assess whether the increases in home prices increases in the amount of noise abatement, we use information on each barrier's efficacy. Interacting our effects with the expected decibels of noise reduction due to the barrier, we find that the price increases quadratically in noise reduction.

The construction of a sound barrier may reduce not only noise exposure but also air pollution. It may also improve visual amenities by blocking views of the road. If so, our estimates could conflate the effects of noise reduction with improvements in air quality or views. To assess the role of air pollution, we use data on wind direction and speed. If air quality improvements were driving our results, we would expect larger price effects for properties located downwind of traffic, where pollution is higher, and in areas with lower wind speeds, where pollutants tend to linger. However, we find little evidence consistent with this pattern. To assess the role of improved views, we test whether the estimated effect of a barrier is smaller for properties whose view of the road was already obstructed by trees. If a tree canopy blocks the view of the road, the additional visual benefit from a sound barrier should be limited. Empirically, we find no evidence that the presence of roadside trees diminishes the barrier's effect on property values. We also consider whether our results could be explained by changes in unobserved housing quality due to new construction. We find that few new homes are built following barrier construction – likely because of limited undeveloped land in treated neighborhoods – suggesting a minimal role for endogenous supply changes.

In the second part of the paper, we combine our estimates of the causal effect of traffic

noise on property values with spatially granular data on noise exposure by census tract to quantify the total economic cost of the traffic noise externality. To examine how this burden is distributed, we relate the tract-level cost estimates to socioeconomic characteristics, including median family income, the poverty rate and the share of the population that is Black.

If we scale the cost of the externality as a share of median family income, we find that the correlation with median family income is negative while the correlations with the share of Black residents and the poverty rate are positive. Based on this measure, the externality is to be "regressive," meaning that its incidence is larger for low-SES tracts. This reflects the fact that low-SES families are overrepresented in tracts that are more exposed to traffic noise. However, if we scale the cost of the externality in per-capita terms, we uncover the opposite correlations: the per-capita cost is larger for tracts with higher median income, lower poverty rates and a lower share of black individuals. Based on this measure, the externality appears "progressive," meaning that its incidence is larger on high-SES families. The reason is that, despite being less exposed to noise, high-SES tracts have a higher per-capita cost because they have higher baseline property values.

To assess how large is the aggregate cost of the noise externality, we aggregate our tract-level estimates to the state-level for Florida and, under some additional assumptions, the entire United States. We estimate that for Florida, the cost of the externality amounts to $7.9 billion. For the United States as a whole, the cost of the externality amounts to $90.6 billion. Since these measures are based on the effect on property values, not annual rents, they need to be interpreted as a stock, not a flow.

In the final part of the paper, we discuss the policy implications of our findings. One approach to internalize the externality is to tax vehicles in proportion to the noise they generate. We estimate that the socially efficient Pigouvian tax would take the form of a one-time levy of $984 per internal combustion engine (ICE) vehicle.

An alternative policy is to subsidize electric vehicle (EV) adoption. EVs generate less traffic noise than traditional vehicles because electric engines are significantly quieter than ICEs. Estimates from the engineering literature suggest that replacing all ICE vehicles with EVs would reduce traffic noise by an average of 7.1 decibels in areas immediately adjacent to roads – a reduction similar to the 7 decibels achieved by sound barriers in our sample. Based on our estimates of the cost of traffic noise, we calculate that universal EV adoption would generate aggregate noise reduction benefits of $6.2 billion in Florida and $77.9 billion nationwide. As a share of family income or property values, these benefits would be concentrated among low-socioeconomic status (SES) households.

Finally, we estimate that the external benefits of the average EV in terms of noise reduc-

tion (relative to an ICE) are $774. This estimate does not include the forgone local costs of air pollution and global costs of CO2. As a point of reference, consider that the Inflation Reduction Act (IRA) passed by the Biden administration in 2021 provided a $7500 tax credit for EV buyers.

The paper is organized as follows. Section 2 describes the existing literature and Section 3 describe the data. Section 4 discusses the research design. The estimates of the effect of noise on prices are in Section 5. Section 6 quantifies the total cost of the externality and its incidence. Section 7 discusses Pigouvian taxes and the benefits of electric vehicles. Section 8 concludes.

2 Literature on Effect of Noise on Housing Prices

To be added

3 Data

We combine data on property prices, traffic noise, sound barriers and neighborhood characteristics for the state of Florida.

3.1 Sources

Property Prices and Characteristics. Data on house prices and characteristics come from two CoreLogic datasets: transactions data spanning the period from 1990 to 2022, and assessor data from 2006 and 2022. The transaction data include detailed information on individual property transactions, such as sale date, sale price, buyer and seller characteristics. The assessor data contain information on property characteristics, including year built, building area, land area and land use category. The unit of observation is a parcel, which in the data is equivalent to a tax unit (the level at which property taxes are paid). We include single family homes, condos, apartments and duplex. We exclude mobile homes, buildings with 5 stories or more and buildings with 3 units or more. We include only arm's length transactions with a sale price greater than $1000 and less than $7.5 million.[1]

Sound Barriers. Sound barriers are structures built beside roads to reduce noise diffusion. Since 1963, the Federal-aid Highway Program run by the US Departments of Transportation has helped states to fund the construction of sound barriers, with the cost of the barrier typically split between the federal and the state Department of Transportation. The

[1]Single family residences and condos in multi-unit buildings have their own parcel ID, while co-ops and multi-unit apartment buildings have a single parcel ID. Since we restrict our sample to buildings that have 1 or 2 units, we don't expect this to be an important issue.

process to identify the location where the barriers are built is based on a formula: a site is considered for a barrier if the traffic noise is projected to exceed 67 decibels (dB) during the noisiest hour of the day and it is "reasonable and feasible" to reduce it by at least 5 dB for some percentage of homes. In practice, what constitutes "reasonable" is likely interpreted in different ways by each state.

We focus on Florida because it has the most accurate data on sound barriers and it provides information on barriers that were proposed but not built. We obtained data on the exact location and date of construction of sound barriers from the Florida Department of Transportation (FDOT) barriers inventory. This dataset includes the universe of barriers built from 1988 to 2023 and offers detailed information on their characteristics (construction year, cost, materials, height, depth and length), as well as shapefiles indicating their precise locations.[2] Importantly for us, the dataset also provides the expected noise reduction measured in decibels (dB) for each barrier built. This information is an engineering estimate based on the barrier's height, depth and length and the construction materials used.[3] FDOT also provides information on barriers that were proposed but not built, which we use as an additional way to validate our estimates.

In our sample, there are $N = 1143$ barriers built between 1988 and 2022 and 497 barriers proposed but not built. Summary statistics are in Appendix Table A1. The average cost is \$741,000 and the average noise reduction is dB 7.15. Columns 3 reports means for barriers that were proposed but not built, and column 5 tests whether the means are different. The p-values indicate that the barriers built and those proposed but not built have similar costs, size and noise reduction. Proposed barriers are located in tracts with higher incomes, college share and white share of the population, though these differences are small e.g. a median family income of \$70,000 for constructed barriers versus \$73,000 for recommended barriers.

While we obtained barrier inventories for 47 other states from the US Department of Transportation Barriers Inventory, we found that the data quality is generally lower than Florida's because the starting and end points of each barrier appear often incomplete and measured with error. In addition, we are not aware of states other than Florida that make available information on barriers that were proposed but not built.

To be included in our analysis, a property needs to have its centroid within a buffer of length 1500 m drawn from the barrier on the relevant side of the barrier. This is illustrated in Figure 1 which shows an example of a barrier in Miami county and the corresponding properties. Since the average barrier has length 496 m, our analysis is based on rectangular-shaped "neighborhoods" with mean length 496 m and depth 1500 m. In our main analysis,

[2]The data can be found here: `https://www.geoplan.ufl.edu/noise-barrier-inventory/`.

[3]See Murphy and King (2014) for a discussion of sound barriers.

we include properties on the relevant side of the barrier. We use properties on the "wrong side" only for a placebo test as part of the robustness analysis.

To link home transactions to barriers and determine which side of the road a barrier was built on – thereby identifying which properties are affected – we use shapefiles of noise barriers and maps of Florida's road system from FDOT.[4] We overlay properties that were ever transacted in Florida from CoreLogic using the property's centroid from the assessor files. To do so, we first extract the end points of the barrier and construct a line segment between the points. This is a linear approximation to the barrier. The approximation will more accurately capture the barrier if it was built on a straight-away. It will be less accurate if the barrier is along a curve in the road. Second, we identify all properties that fall within the rectangle formed by the linear approximation and continuing 1500 m away in either direction of the barrier. To this sample, we add in properties that fall within a 200 m buffer of the barrier itself - using its continuous shape to do so. This procedure will include any properties along a curved barrier that may have been excluded by the linear approximation. We then calculate how far each property in this sample is from the actual noise barrier. We repeat this process for both barriers that were actually built, and those that have been proposed but not built yet. Finally we use information from FDOT on the locations of roads to determine which side of a highway a noise barrier was constructed.[5]

The final dataset contain all properties within 1500 m of a built or proposed barrier, on the "correct" and the "wrong" side. In total, our sample on the "correct side" includes 596,419 home sales that took place between 1990 and 2022. Summary statistics are in Appendix Table A2. The first column reports means computed on the full sample. The remaining columns report means for selected distance bins. These columns show that the observable characteristics of the properties in our sample and their census tracts are not exactly identical in all distance bins. On the other hand, most variables do not display a strong, monotonic correlation with distance. For example, the mean price fluctuates across bins, from $320,000 in the 0–100 m bin, to $280,000 in the 400–500 m bin, to $321,000 in the 900–1000 m bin and $306,000 in the 1400–1500 m bin. One exception is size, which appears to increase systematically with distance from 1,763 sq ft in the 0-100 m bin to 1,917 sq ft in the 1400-1500 bin. Heterogeneity in quality of properties is an important identification concern that we discuss in our empirical analysis below.

[4]The road data (from 2019) can be found here: `https://www.fdot.gov/statistics/gis/default.shtm#Roadway`.

[5]To determine the relevant side of the road on which properties are affected by the barrier, we sum the total length of roadway within 100 m of the barrier. We take the side that has more road length as the "wrong"-side. We use this in a placebo analysis. The "correct" side is where there is less road next to the barrier. If neither buffer contains any roadways, then we take a 200 m buffer and perform the same calculation.

Appendix Figure A3 shows the distribution of the years when the barriers were built (upper panel) and when the transactions took place (bottom panel).

Noise Exposure and Neighborhood Characteristics. To measure baseline traffic noise exposure by census tract, we rely on the 2020 U.S. Department of Transportation National Transportation Noise Map. This dataset provides model-based estimates of tract-level noise levels generated by aviation, rail and road traffic. For our analysis, we focus specifically on noise emanating from road traffic. As an example, Appendix Figure A2 shows the noise map for the Miami region. Murphy and King (2014) offers a methodological discussion of noise mapping and its limitations. Finally, we incorporate census tract-level information on socioeconomic characteristics – median family income, poverty rates, and racial composition – from the American Community Survey (ACS) for the period 2015–2019 and using 2010 tract boundaries.

3.2 Correlation Between Noise Exposure and Neighborhood Characteristics

To understand which demographics are more exposed to traffic noise, we start by documenting the correlation between noise in a census tract and the socioeconomic characteristics of its residents. Figure 2 shows the within-county correlation between traffic noise and median family income (top) and black share (bottom) in Florida. In this Figure, the unit of observation is a Census tract and both the axes are measured in deviation from the relevant county mean. The Figure illustrates the fact that Census tracts with a high exposure to noise tend to have lower median income and a higher minority share.

Table 1 reports mean neighborhood characteristics, by level of noise exposure, in deviation from the county mean. The unit of observation is, again, a census tract. However, for this descriptive evidence, we rely on a 2020 census tract-level dataset assembled from the Transportation Noise Map by Seto and Huang (2023) with national coverage. Neighborhood demographics come from the 2016–2020 ACS to align with the 2020 boundaries.[6] The top panel includes tracts in Florida. For comparison, the bottom panel includes all tracts in the U.S.

Tracts with a high level of noise exposure (dB above 50 in column 1) have lower median property values, median family income and share of college educated residents compared to tracts with medium and low levels of noise exposure (dB between 46 and 50 and below 46 in columns 2 and 3, respectively). They also have higher poverty rates, Black and urban shares of the population and mean density. Notably, the relation between noise and socioeconomic characteristics appears generally similar between the U.S. and Florida. For example, moving

[6]We also use the 2020 TIGER Shapefiles to calculate the area within 2020 census tract boundaries in order to measure population density.

from column (1) to column (3) raises median family income from -13.2 to 6.4 in the U.S. and from -12.5 to 6.7 in Florida. It also raises the share of college educated residents from -2.7 to 1.1 in the U.S. and -2.7 to 1.5 in Florida. The corresponding numbers for the poverty rates are 4.0 and -1.9 for the US and 3.7 and -1.6 for Florida. The similarity between the US and Florida in the correlation between noise and socioeconomic characteristics is helpful in assessing the external validity of our estimates based on Florida data. The last row in each panel shows the fraction of tracts that are exposed to very high level of noise (dB $>$ 90).

For comparison, Appendix Table A3 reports similar statistics without adjusting for county mean. Here the correlation between noise and socioeconomic characteristics is weaker. This suggests that when comparing neighborhoods within a county there is a strong negative correlation between noise and socioeconomic characteristics, and when comparing counties the correlation is more muted. This reflects the fact that wealthy urban counties tend to be denser and noisier than rural counties. At the same time, rich suburban neighborhoods within each county tend to be quieter than poorer urban core neighborhoods.

4 Research Design

Figure 3 shows the cross-sectional correlation between traffic noise exposure and median property values after conditioning on county fixed effects. The level of observation in this figure is a census tract and the sample consists of all the 4,212 census tracts in Florida. For our measure of noise exposure, we use the maximum traffic noise of any location in the census tract. The negative correlation indicates that tracts with higher noise exposure have lower median property values. The slope is -0.007 (0.0001), indicating that one additional decibel is associated with a 0.7 percent lower property values.

This correlation is difficult to interpret causally, since properties and residents in tracts that are exposed to noise could have worse unobservables. For example, properties near freeways or major roads may be of lower quality and enjoy worse amenities than properties further away. Similarly, tracts near freeways or major roads may be exposed to higher crime, more blight or more air pollution than tracts in quieter areas. As discussed above, tracts that are exposed to noise are empirically denser, more urban and have higher poverty rates (Table 1). Thus, the negative slope in Figure 3 could simply reflect the presence of omitted variables correlated with noise.

4.1 Expected Effect of Barriers on Noise

Our empirical analysis uses changes in noise levels induced by the construction of sound barriers. Sound barriers are considered effective at reducing noise in nearby properties. Rochat (2016) estimates that the average noise reduction achieved by sound barriers in the

U.S. is 7dB in properties near the barrier. This figure is remarkably close to what we observe in our data. The mean expected noise reduction in our sample is 7.15 dB (Appendix Table A2 above). Since decibels are measured on a log scale, a 7 dB reduction implies a 39% reduction in the loudness of the noise.[7]

Noise decays quickly and non-linearly with distance. According to the "inverse square law" of noise, the intensity of a sound wave changes in inverse proportion to the square of the distance from the source. For our purposes, this implies that the noise reduction caused by a new sound barrier is expected to decay rapidly with distance from traffic. For properties that are immediately adjacent to busy roads, a sound barrier is expected to offer larger benefits than for properties that are further away. For the latter group, a sound barrier offers limited benefits because the initial level of traffic noise is low to begin with.

Table 2 illustrates this point by quantifying the expected effect of the average sound barrier on properties located at various distances from an average highway. Column 2 reports the expected noise level without a barrier. The entry in the first row is based on the fact that highway noise at a distance of 25 meters typically ranges from 70 dB to 80 dB, with a median of 76 dB (Corbisier, 2003). The other entries in column 2 are derived using the "inverse square law," which implies that a doubling of distance results in a 6 dB reduction in noise. Entries in column 3 report the noise level after construction of a noise barrier. Since the average barrier reduces traffic noise by 7 dB, entries in column 3 are simply equal to the ones in column 2 minus 7 dB. The magnitudes of entries in columns 2 and 3 are not immediately interpretable because they are measured in decibels. To make the magnitudes easier to interpret, in columns 4 and 5 we report how loud a property can expect to be using a scale 0 to 100, with 100 representing the level of loudness experienced at 25 m before the barrier (row 1, column 4).

Column 6 shows the expected change in loudness caused by the construction of the barrier measured on a 0 to 100 scale. Entries show that the expected change declines rapidly with distance. The expected change for properties that are 25 m from traffic is -38.5%, more than double the one for properties that are 100 m from traffic (-17.0%). In turn, the latter is more than double the one for properties that are 400 m from traffic (-7.4%). The last two columns provide some examples to help visualize the level of noise at each distance. It is clear that the benefits of the barrier are noticeable at shorter distances and become harder to detect at longer distances. For example, shifting from the noise level of a food mixer to that of a dishwasher (25 m) is likely to be very salient to home buyers and likely to affect housing demand. By contrast, the benefits for properties at distances 400 m or more appear

[7] A reduction of sound by 10 dB reduces the loudness of the sound by one half, while a reduction of sound by 20 dB reduces the loudness of the sound by three quarters.

less noticeable. For example, moving from the noise level of a refrigerator hum to that of a bird call is probably less salient for buyers and less likely to have significant impacts on housing demand.[8]

As a preliminary piece of exploratory evidence, we assess whether in our data we see evidence of the spatial decay in the effect of noise. Based on the noise engineering literature and the calculations in Table 2, we expect that, if there is an effect of new barriers on noise (and therefore prices), it is larger for properties near the barrier and rapidly drops to zero for properties further away. Our sample include properties that are within 1500 meters from the barrier and its relevant side. We divide the properties into 15 bins based on distance from the barrier: 0–100 m from the barrier, 100–200 m; 200–300 m, through 1400–1500 m. We estimate the change in price after the construction of the barrier compared to before the construction for each 100 m bin: 100–200 m; 200–300 m, through 1100–1200 m, relative to 1200–1500 m which is assumed to be far enough from traffic to be a safe control group, conditioning on a vector of barrier $\times$ event time fixed effects, barrier $\times$ distance bin fixed effects and building characteristics $\times$ year of sale fixed effects.

Appendix Figure A1 shows the estimates. Each dot quantifies the change in price following the construction of new barriers relative to 1200–1500 m away. The estimates exhibit a clear decay pattern with increasing distance from the barrier, consistent with the notion that noise declines with distance and therefore the benefits of a barrier also decline with distance. The effect appears to be statistically different from zero for properties that are less than 200 m from the barrier. At longer distances, we cannot reject that the effect is equal to zero. We test this directly by using variation in the timing of barrier constructions to see if prices change 500–1500 m away. These estimates rely on the event study estimation of de Chaisemartin and D'Haultfœuille (2024) and are plotted in Appendix Figure A4. We find no evidence of a change in transacted home prices beyond 500 m from the barrier.

4.2 Identification Assumptions

In our empirical analysis, we use two specifications to estimate the effect of noise exposure on transacted home prices.

(1) First, we use a difference-in-differences model that compares transaction prices in the five years after barrier construction with the five years prior, for properties plausibly affected by the new barrier and properties plausibly unaffected by the new barrier *within the same narrowly defined neighborhood*. Specifically, we compare changes in prices following the

[8]Our estimates should be thought of as conservative. The fact that doubling of distance results in a 6 dB reduction in noise is for an environment with no obstructions. Decay is likely even faster in our setting where building structures are present.

construction of a barrier for properties located 0–500 m from the traffic (and on the relevant side of the barrier) with changes in prices for properties located 500–1500 from traffic (and on the relevant side of the barrier). The definition of the control group is based on the assumption that the effect of the barrier is negligible for properties located more than 500 m from traffic because the change in noise induced by the barrier is negligible at distances greater than 500 m. This assumption is consistent with the physics of the spatial decay of noise illustrated in Table 2 and the empirical evidence in Appendix Figure A1. We focus on properties on the relevant side of the barrier and use those on the wrong side of the barrier for a placebo test.

Specifically, we estimate the following difference-in-differences model:

$$\begin{aligned}\log \rho_{it} = &\sum_{j \leq 500\text{m}} \mathbb{1}\{\text{dist} = j\} \cdot \mathbb{1}\{\tau \geq 0\} \cdot \beta_j \\ &+ \sum_{j} \left(\mathbb{1}\{\text{dist} = j\} \cdot \mathbb{1}\{\tau < -5\} \cdot \beta_j^0 + \cdot \mathbb{1}\{\text{dist} = j\} \cdot \mathbb{1}\{\tau > 5\} \cdot \beta_j^1 \right) \\ &+ \gamma_{b(i)d(i)} + \eta_{b(i)\tau} + x_{it}'\zeta + \varepsilon_{it} \quad (1)\end{aligned}$$

where the dependent variable ρ_{it} is the sale price of parcel i at time t in 2022 dollars; d is the distance bin; τ is the number of years since or to the year of the barrier construction; b indexes the barrier; $\gamma_{b(i)d(i)}$ is a vector of barrier $\times$ distance group fixed effects that for each barrier in our sample controls for permanent differences in prices across parcels that are closer or further away from a specific barrier; $\eta_{b(i)\tau}$ is a vector of barrier $\times$ event time fixed effects that control for localized trends in prices that may be correlated with the timing of the barrier construction. The barrier $\times$ event time fixed effects are identical to barrier $\times$ year fixed effects because each barrier only has one event timing. The vector x_{it} includes property-level controls: year built $\times$ year of sale fixed effects; log building area (continuous, with zero filled in for missing) $\times$ year of sale fixed effects; building area missing indicator $\times$ year of sale fixed effects; log land area $\times$ year of sale fixed effects; land area missing indicator $\times$ year of sale fixed effects; noise level (from traffic noise map) $\times$ year of sale fixed effects; no traffic noise indicator $\times$ year of sale fixed effects; land use category $\times$ year of sale fixed effects. Throughout the paper, we focus on the period that includes the 5 years before construction and the 5 years after construction. We keep in the estimation sample 10 years before and after – namely, $\tau < -5$ and $\tau > 5$ – and use a dummy for $\tau < -5$ interacted with distance and a dummy for $\tau > 5$ interacted with distance to absorb their direct effects: $\sum_j (\mathbb{1}\{\text{dist} = j\} \cdot \mathbb{1}\{\tau < -5\} \cdot \beta_j^0 + \mathbb{1}\{\text{dist} = j\} \cdot \mathbb{1}\{\tau > 5\} \cdot \beta_j^1)$.

The control group is geographically close to the treatment group. Recall that we use

rectangularly-shaped "neighborhoods" with mean length 496 m and depth 1500 m. The limited size implies that many local amenities are likely to be homogenously distributed over space within areas of this size. For example, amenities like school quality, crime and street cleanliness are likely to be similar. And even if they were not identical in levels, there are not obvious reasons to expect that their change over time are systematically correlated with the construction of new barriers. For example, it seems implausible that after the construction of a barrier, school quality, crime or street cleanliness would improve differentially more in the 0–500 m range compared to the 500–1500 m range.

Empirically, we find no evidence of differential pre-trends. In the years before the barrier construction, the movement of prices of properties located 0–500 m and 500–1500 m from the barriers are indistinguishable.

(2) To further probe the validity of our identification assumptions, we turn to a second specification. We estimate a triple-difference (DDD) model that uses barriers that have been proposed but not built to further strengthen our identification strategy. We "match" each of the barriers that were proposed but not built to a barrier that was actually constructed. In particular, barriers that were built are matched to their closest proposed (but not built) barrier that is at least 1000 m away. Having a matched barrier for each constructed barrier allows us to condition on a richer set of controls that absorb any time-varying barrier-specific and distance-bin-specific heterogeneity. Identification of the DDD model comes from comparing the before and after price changes near and far away from the barrier experienced by properties near constructed and proposed barriers.

Using the matched barriers, we estimate the following specification:

$$\log \rho_{it} = \sum_{j \leq 500\text{m}} \mathbb{1}\{\text{Barrier built}\} \cdot \mathbb{1}\{\text{dist} = j\} \cdot \mathbb{1}\{\tau \geq 0\} \cdot \beta_j$$
$$+ \sum_j \Big(\mathbb{1}\{\text{Barrier built}\} \cdot \mathbb{1}\{\text{dist} = j\} \cdot \mathbb{1}\{\tau < -5\} \cdot \beta_j^0 + \mathbb{1}\{\text{Barrier built}\} \cdot \mathbb{1}\{\text{dist} = j\} \cdot \mathbb{1}\{\tau > 5\} \cdot \beta_j^1 \Big)$$
$$+ \eta_{b(i)\tau} + \xi_{mj\tau} + \gamma_{b(i)d(i)} + x_{it}'\zeta + \varepsilon_{it} \quad (2)$$

The indicator $\mathbb{1}\{\text{Barrier built}\}$ denotes whether the barrier was actually constructed, rather than proposed. As before, we include controls x_{it}, barrier by distance bin fixed effects $\gamma_{b(i)d(i)}$ and barrier $\times$ event time fixed effects $\eta_{b(i)\tau}$. The parameters of interest are the β_j's and capture the price effects of built barriers in 100 m bands.

Any time-varying and barrier-specific unobserved shocks that affect the price of properties are absorbed by $\eta_{b(i)\tau}$. Any distance-from-barrier and barrier-specific unobserved shocks that affect prices are also absorbed by $\gamma_{b(i)d(i)}$. A matched barrier for each constructed

barrier allows us to condition on match m × distance bin × event time fixed effects $\xi_{mj\tau}$. Identification now comes from the fact that for each event time, we observe the prices of properties affected by a constructed barrier and its paired proposed barrier. The control group for, say 0–100 m, are transactions that were 0–100 m away from the matched proposed barrier. This set of controls fully absorb any distance-specific time-varying unobserved shock that is correlated with barrier construction. Empirically, our estimates of the triple-difference are similar to the ones from the double-difference model.

Finally, in some models, we focus on repeated sales of the same property to control for property fixed effects. Comparing the same property over time allows us to test whether unobserved heterogeneity in housing quality biases our baseline estimates, although the sample is necessarily smaller because not all properties are transacted multiple times. We find that estimates are not sensitive to conditioning on property fixed effects.

5 Effect of Noise on Property Values

5.1 Graphical Evidence

To study the timing of the effect, we start with an event study that allows us to look at pre-trends and assess the validity of our identification assumption. We start with a single distance group $d^* = 0$–100 m. The omitted category is the 500–1500 m group and the controls are the same used in the model in equation 1:

$$\log \rho_{it} = \sum_{k \neq -1} \mathbb{1}\{\text{dist} = d^*\} \cdot \mathbb{1}\{\tau = k\} \cdot \alpha_k + \sum_{j \neq d^*,\ j \leq 500\text{m}} \mathbb{1}\{\text{dist} = j\} \cdot \mathbb{1}\{\tau \geq 0\} \cdot \tilde{\beta}_j$$
$$+ \sum_j \left(\mathbb{1}\{\text{dist} = j\} \cdot \mathbb{1}\{\tau < -5\} \cdot \beta_j^0 + \mathbb{1}\{\text{dist} = j\} \cdot \mathbb{1}\{\tau > 5\} \cdot \beta_j^1 \right) + \tilde{\gamma}_{b(i)d(i)} + \tilde{\eta}_{b(i)\tau} + x_{it}' \tilde{\zeta} + \tilde{\varepsilon}_{it} \tag{3}$$

The α_k are the parameters of interest for distance d^*, and we account for the direct effects $\tilde{\beta}_j$ on other distances within 500 m of the barrier. Throughout the paper we report standard errors clustered by barrier.

Figure 4 shows the event study estimates for properties that are 0–100 m from the barrier. Specifically, it shows the effect of the construction of new barriers on the price of properties that are 0–100 m from the barrier (and on the relevant side of the barrier) relative to properties that are 500–1500 m from the barrier (and on the same side of the barrier). In the five years before the construction of the barrier, we observe no obvious pre-trends in conditional property values. After the construction of the barrier, we observe an immediate increase in property values. The increase in the five years after construction ranges from 6

to 11%, with a mean equal to 6.7%.

Figure 5 shows the corresponding estimates for distance bins 100–200 m, 200–300 m, 300–400 m and 400–500 m. There appears to be an effect for distance bins 100–200m, although smaller than the one for the 0–100 m bin in Figure 4. The effect for distance bins 200–300 m and 300–400 m appears smaller and not statistically different form zero in most even times. Overall, this figure confirms that the price effects become smaller and less clearly detectable as we move away from the barrier, consistent with the notion that the treatment becomes smaller.

5.2 Baseline Estimates

Our baseline difference-in-differences estimates are presented in Table 3. The model is the one specified in equation 1. It includes five treated distance bins: d = 0–100 m, 100–200 m, 200–300 m, 300–400 m, and 400–500 m while the control group includes properties at distances 500–1500 m. It compares transactions in the five years after barrier construction with the five years prior, and for properties near to the barrier with those that were further than 500 m meters away.

In column (1), we condition on our "main" set of fixed effects which include barrier $\times$ distance bin fixed effects $\gamma_{b(i)d(i)}$, barrier $\times$ event time fixed effects $\eta_{b(i)\tau}$ and the vector x_{it} defined above. For houses situated within 100 m of the barrier, we find a 6.76% increase in sale prices, similar to what we observed in Figure 4. The estimated effect diminishes monotonically with distance, declining to 3.99% for houses 100–200 m away, 3.19% for houses 200–300 m away, and becoming statistically indistinguishable from zero for houses located 400 m or more from the barrier.

In column (2), we add parcel fixed effects which fully absorb time-invariant heterogeneity. Thus, in this specification we compare the change in price experienced by *the same property* after barrier construction (relative to before) for properties that are close to the barrier (relative to further away). The effective sample size drops from 594,936 to 474,033 because not all properties experience multiple sales. The estimated effects are larger than those in column 1, indicating that if anything, unobserved heterogeneity in time-invariant parcel characteristics biases estimates in column 1 downward. For houses within 100 m of the barrier, the estimated effect increases to 8.59%. For houses 100–200 and 200–300 m from the barrier, the estimated effects increase to 5.79% and 4.41%, respectively. In this specification, the effect on properties 300–400 m from the barrier is marginally statistically significant.

Columns (3) through (6) report estimates from a larger sample that includes properties near barriers that were proposed for construction, but have yet to be built. The sample nearly doubles to 1,093,205 transactions. Note that at this stage we have not yet matched barriers

that were proposed but not built to barriers that were actually built. Here, we simply add properties near recommended barriers to the control group. Since later we match the two types of barriers, we report estimates in columns (3) through (6) for reference, to provide a sense of how the inclusion of barriers not built affects the difference-in-differences estimates. The model in column (4) conditions on property fixed effects. The coefficients are similar to the ones in column (2). For houses within 100 m of the barrier, the estimated effect is 8.84%. For houses 100–200, 200–300 and 300–400 m from the barrier, the estimated effects are 6.33%, 4.39% and 4.58%, respectively.

One may be concerned that properties near traffic differ from properties further away in unobserved ways and that the effect of these unobserved factors on house prices is time-varying. For example, properties near traffic could have lower unobserved quality than those further away. Models in columns (2) and (4) account for time-invariant heterogeneity across distance bins, as they include distance group and parcel effects. Thus, if houses 0–100 m from a barrier have permanently lower unobserved quality than houses 100–200 m away, this heterogeneity is fully accounted for by distance group and parcel controls. But models in columns (2) and (4) do not account for the possibility that the price of house quality may be changing over time.

To address this concern, the models in columns 5 and 6 include a set of distance $\times$ year fixed effects. This specification accounts for distance specific trends in unobserved determinants of house prices. The coefficients in column (5) are larger than the corresponding coefficients in column (3) and the coefficients in column (6) are larger than the corresponding coefficients in column (4). This finding suggests that unobserved shocks that change the desirability of properties close to traffic relative to properties further away are not the main drivers of our estimates.[9]

In Table 3, the sample of barriers that were proposed but not built are simply added to the estimation sample as a control group. In Table 4, we estimate the DDD model of equation 2. We "match" each of the barriers that were proposed but not built to a barrier that was built to further strengthen our identification strategy. The sample size is greater in Table 4 relative to Table 3 because there are more built than proposed barriers. Recall that we report standard errors clustered by barrier.

In column (1) we condition on barrier $\times$ event time fixed effects $\eta_{b(i)\tau}$. In this model any time-varying and barrier-specific unobserved shocks that affect the price of properties are absorbed. Column (2) controls for match m $\times$ distance bin $\times$ event time fixed effects $\xi_{mj\tau}$. Identification comes from the fact that for each event time, we observe the prices of properties

[9]For completeness, in Appendix Figure A5 we show estimates of the effect on transacted home prices for proposed (but not built) barriers. As expected, no effect is detectable.

affected by a constructed barrier and its paired proposed barrier. The control group for, say 0—100 m, are transactions that were 0-100 m away from the matched proposed barrier. Finally, in column (3) we estimate the full DDD specification. It includes both barrier by event time ($\eta_{b(i)\tau}$) and match × distance bin × event time fixed effects ($\xi_{mj\tau}$). Identification comes from comparing the before and after price changes near and far away from the barrier experienced by properties near constructed and proposed barriers.

Overall, Tables 3 and 4 indicate that within 100m of the barrier, the construction of a new barrier raises property values by 6.7%–10.3% and 7.0%–9.6%, respectively, and by a smaller amount 100–300 m from the barrier. Thus, we conclude that the estimates appear generally stable across specifications within each table and across tables.

Since our data report the construction cost of each barrier, we can compute the marginal value of public funds (MVPF), defined as the property value appreciation over costs (Hendren and Sprung-Keyser, 2020). In the 0–100 m range, the average MVPF for barriers that were built amounts to 1.7, while the MVPF for barriers proposed but not built is 1.3. This is to be considered as a back-of-the-envelope calculation that ignores property taxes. Property taxes would reduce both the social benefits (since some of the home value increase gets taxed), and the social costs (since property taxes end up in local government coffers).

Since barriers raise property values, it is reasonable to ask: why do private homeowners and developers not build barriers everywhere there is a noisy road? In urban centers with sidewalks and retail establishments, this is often practically infeasible. Outside cities, we suspect that one limiting factor is that the land next to the highway where barriers can be built is state-owned. (Barriers are most effective when placed directly next to the sound source). A separate constraint is likely the coordination problem that arises when building a wall across multiple properties, which is necessary for a sound wall to be effective.

5.3 Placebos

We perform two placebo tests to help rule out alternative explanations for our findings. In Figure 6, we examine the effects of barrier construction on housing prices on the opposite side of the highway, where noise levels should not be affected. We uncover no significant effect of the new barrier on prices.

In Figure 7, we examine the effects of barrier construction on housing prices randomly permuting the year of barrier construction. We show the distribution of the coefficient on 0–100 m × $\mathbb{1}\{\tau \geq 0\}$, obtained from 100 permutations. The placebo distribution has mean (std deviation) 0.012 (0.020). For reference, the red vertical dotted line shows the estimate that we obtain using the correct year of construction (from Table 3, column 1). It is clear that the placebo sample yields estimates that are indistinguishable from random noise.

5.4 Intensity of Treatment Based on Expected Noise Reduction

We test whether the effect of a new barrier on home prices varies as a function of the expected noise reduction induced by the barrier. This question is important for two reasons. First, if our interpretation of the evidence is correct, the estimated effect should increase in the amount of expected noise reduction. Finding that noise reduction is not systematically related to the estimated price change would cast doubt on the causal interpretation of our estimates. Second, being able to scale the price increase by decibels of noise reduction will be important in the last two sections of the paper, where we quantify the total cost of the noise externality and study the potential economic benefits of quieter streets from the adoption of electric vehicles.

We reiterate that we do not have empirical data on the actual noise reduction obtained by direct acoustic measurement of the noise level at each property before and after barrier construction. As discussed in the Section 3, we rely on data from FDOT, which assigns to each barrier a predicted decibel reduction based on barrier's height, depth and construction materials combined with baseline measurements of traffic flow at the site prior to the barrier construction, topography, layout and acoustic measurements of traffic noise.[10] While the measure of expected noise reduction is an engineering estimate and may not necessarily capture all individual features of each barrier, we assume that it is correct on average.

In Table 5, we estimate a model where the effect of barriers on prices is allowed to vary by their expected effectiveness in noise reduction. For reference, column (1) is from a model with no interactions (as in Table 3, column 1). In columns (2) though (4), the effect of the barrier is allowed to vary as a linear, quadratic and cubic function of the expected noise reduction **dB** measured in decibels. We center the expected noise reduction on 7 decibels, which is the average for barriers in our sample. For parsimony, in this table we focus on properties within 100 meters of the barrier.

In column (2), the coefficient on the linear interaction is positive but statistically insignificant. In columns (3) and (4), the coefficient on the linear interaction is positive (significant at the 10%-level), while the coefficient on the quadratic interaction is negative (significant at the 5%-level), suggesting a concave relationship. The coefficient on the cubic interaction in column (4) is not significant, leading us to reject a cubic functional form.

The table suggests that the price effect of sound barriers is indeed larger for barriers with larger expected decibel reduction and the effect is a quadratic function of expected decibel reduction. Figure 8 shows more explicitly the functional form implied by the estimates in

[10] Information on FDOT methodology can be found here: `https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/environment/pubs/final-practitioners-handbook---december-2018-version.pdf?sfvrsn=95bb91d6_2`.

column (3) as well as the confidence band. To simplify interpretation, we have rescaled the x-axis so that it's measured in dB, as opposed to deviation from the mean. The figure shows that for properties in the 0–100 m range, the benefits of reducing noise less than 5.75 dB (the 5th percentile for barriers in our sample) are limited. The benefits become significant above 5.75 dB and appear to peak at a noise reduction of 10 dB (96th percentile) and then stabilize. Our estimates imply an average price depreciation of 0.9% with every decibel of noise.[11] To put the magnitude of this estimate into perspective, consider that a 10 dB decline in noise levels implies a reduction of the intensity of noise by one half. Our estimates indicate that for properties that are 0–100 m from the barrier, cutting traffic noise by half results in a 9% mean increase in property values.

5.5 Endogenous Confounders: Pollution, Views and New Constructions

In interpreting our findings, it is important to establish if the construction of new barriers results in endogenous changes in important characteristics other than noise reduction that may affect home prices. We consider three potentially important changes that represent alternative explanations of the evidence: a reduction in air pollution, an improvement in views, and the construction of new homes.

Pollution. The erection of a sound barrier may reduce not just exposure to noise but also to air pollution. In this case, our estimate of the price effect of the barriers would be biased upwards, as it would reflect not just the benefits of noise reduction but also the benefits of pollution reduction.

Sound barriers are designed to block noise and are likely less effective at blocking air pollutants. Air pollutants are spatially more diffuse and travel further than noise, and it is unclear that we should expect the same sharp drop in pollutants following a barrier construction that we see in noise. Ahangar et al. (2017) and Thiruvenkatachari et al. (2022) find reductions in air pollution immediately next to a barrier, but less is known on the spatial decay in pollution caused by barriers.[12]

The main question for our purposes is whether localized improvements in air quality are salient enough for the average home buyer to affect their willingness to pay. Unlike noise, differences in air pollution are more difficult for home-buyers to detect personally and quantify with any level of precision. Since our models compare changes near the barrier with changes further away, what matters is the ability of home buyers to detect differential

[11] This number comes from the fact that an average barrier increases property prices by 6.76% and reduces noise by 7.23 decibels. This effect is similar to effect from a 1 pp decline in tree cover (Han et al., 2024).

[12] We searched the main engineering Handbook on sound barriers used by state governments DOTs (Knauer et al., 2000) for the terms "pollution" or "air quality" and found no mention of either.

changes in air quality near the barrier and further away. It is easy to imagine that a home-buyer visiting two open houses located at 100 m and 400 m from a freeway is aware of the difference in traffic noise (as illustrated in Table 2 above). However, it is less plausible that the same home-buyer would be able to detect the difference in air quality between the two locations, if such a difference even exists.

We also note that even if a buyer was particularly focused on pollution, spatially granular information on pollution differences across properties within a neighborhood is not available in most locations, as EPA monitors are spaced too widely to provide this type of spatial detail. For example, Purple Air monitors were unavailable for most of our sample period and far too sparse. When we searched 200 randomly chosen postings of open houses in 7 Florida counties, we found no mention of the terms "air quality", "clean air" or "pollution." By contrast, we found that 18% of postings contained the terms "quiet" or "peaceful" or "noise." Zillow announced only in September 2024 that they had partnered with a firm to begin providing some air quality measures for listings.[13] But even so, they do not vary at the granularity of we consider.

Ultimately, this is an empirical question. We provide two pieces of evidence that are helpful in assessing the relevance of air pollution changes as an alternative explanation. First, we use information on wind direction and speed to test if our estimate of the effect of the barriers is different for observations downwind of traffic and in areas where wind speed is typically low. There is evidence that barriers affect air pollution, but only downwind of traffic and only when wind is low or non existent (Ran et al., 2020, Baldauf et al., 2016, Bowker et al., 2021, 2007, Heist et al., 2009). Barriers upwind from traffic or in areas where wind speed tends to be high appear to have no detectable effect on air quality. If our estimates are mainly explained by air quality improvements, as opposed to noise improvements, we should see that our estimates are larger for properties located downwind of traffic and in areas where wind speed is typically low. We should see smaller or no effect for properties located upwind from traffic or in areas where wind speed tends to be high.

In Table 6, we estimate a version of Equation 3 where the effect is allowed to vary with measures of wind speed and direction. Wind data is from NCEI (2025) and includes daily information on average wind speed, average sustained wind speed, average sustained wind direction, and share of days over the year with the wind blowing in directions of 10-degree bins. For each barrier, we construct a spatial average of the 2024 wind sensors in Florida with weights inversely proportional to distance.

Columns (1) and (2) report the estimated coefficients on the interactions of our main

[13]Source: https://investors.zillowgroup.com/investors/news-and-events/news/news-details/2024/Zillow-introduces-First-Streets-comprehensive-climate-risk-data-on-for-sale-listings-across-the-U

effect with average wind speed and average sustained wind speed, respectively. Columns (3) and (4) interact with whether wind is perpendicular from the road to barrier. In particular, column (3) uses a measure of how far the wind is from being perpendicular to the barrier. The measure is based on the angle between the wind direction and the line from the sound barrier to the focal property: $\min\{|\theta_1 - \theta_2|, 360 - |\theta_1 - \theta_2|\}$, where θ_1 is the angle from the sound barrier to each property and θ_2 is the average wind direction. In Column (4), we calculate the share of days over a year in which the wind was blowing in the direction of the barrier from the road plus or minus 45 degrees, and we interact this measure with our main effect. The entries in Table 6 indicate that none of the estimated interactions are statistically different from zero, suggesting that the estimated effect does not depend on wind direction or its typical strength.

For a second piece of empirical evidence on the role of air pollution in explaining our estimated effects, we turn to the effect of one specific type of pollutant: lead. Lead offers a good case study because it is a particularly harmful pollutant that has been banned from gasoline since 1996. In column (5), we test whether our estimate of the effect of new barriers for the period after the ban is different from the estimate for the period before the ban. The estimate for period after the ban is not significantly different from the estimate for the period prior to it, indicating that at least this specific type of air pollutant is not driving our results.

Overall, the evidence in Table 6 suggests that air quality improvements are unlikely to be an important alternative explanation of our estimated price effects.

Views. Another alternative explanation of the evidence is the possibility that the construction of a sound barrier may increase the attractiveness of nearby properties by blocking the view of the road. Our estimates of the price effect would be biased upward, as they would reflect the benefits of improved views, not just noise reduction.

To assess this possibility, we test if the estimated effect of a barrier is smaller for properties whose view of the road is blocked by trees along or near the road. The idea is that if there are many trees between a property and the road the visual impact of a new barrier is likely to be less pronounced, as the tree canopy helps shielding views of the road even in the absence of the barrier. Finding that the estimated effect does not depend on the presence of trees would cast doubt on the hypothesis that our estimated price increases are explained by improved views rather than improved noise. We also test if the estimated effect of a barrier is smaller for properties whose view of the road is blocked by other properties.

In column (1) of Table 7, we estimate a variant of Equation 3 where we interact our main 0–100 m effect with the percentage of tree canopy cover in the vicinity of the road. To

construct this measure, we use the MRLC Consortium (2025) data to calculate land cover at each property and identify barrier canopy cover near the road as that for the property closest to the road.[14] In Columns (2) and (3), we construct measures of the build environment 0–100 m from the barrier that would block the view for properties 100–200 m away. Our first measure calculates the aggregate building square footage 0–100 m from the barrier, normalizes it by the length of the barrier, and then standardizes this measure to have mean zero and standard deviation one. The second measure calculates the average number of stories for buildings 100 m away from the barrier. Columns (2) and (3) interact our 100–200 m effect with these measures of build density near the barrier.[15]

None of the interactions are statistically different from zero. We conclude that our estimated effects do not vary with tree canopy coverage or the presence of buildings, suggesting that the role of views in explaining our findings is limited.

New Construction. If the arrival of a new barrier raises prices, one may expect some supply response in the form of new construction. This could affect the interpretation of our estimates for two reasons. First, if newly built homes have higher unobserved quality and command higher prices, our estimates could be contaminated by endogenous changes in the local mix of properties. In this respect, we note that all our models condition on year built $\times$ year of sale fixed effects, and therefore directly control for all differences in typical quality that are associated with age of the buildings. We also note that new developments confound our analysis only if the arrival of a new barrier spurs construction of new homes between 0 and 500 m more than 500 to 1500 m.

Second, even in the absence of unobserved quality differences, a strong supply response would affect how to interpret of our estimates because it would mute the price effects observed in the data. In the extreme, if supply was infinitely elastic, we would observe no price increase following the barrier construction, even if buyers value quiet, are willing to pay for it and the barrier increases demand. Thus, measuring how many new units are built following the arrival of a barrier is important to understand whether to interpret our estimates as a shift in demand only or both demand and supply.

In Table 8 we present estimates that exclude newly constructed homes from our sample. Column (1) contains all transactions for properties built on or before 5 years after the barrier was built. Columns (2) through (4) restrict this further to properties built on or before the year the barrier was built, the year before, and 6 years before the barrier was built,

[14]The average and standard deviation of canopy coverage in our sample are 11.8% and 10.8%, respectively.

[15]The presence of buildings can affect the noise too. We estimated additional models where we control for noise reduction and found very similar estimates. The estimates in columns (2) and (3) are 0.00808 (0.0117) and 0.0192 (0.0263), respectively.

respectively. Our estimates appear similar to the baseline estimates in in Table 3 discussed above.

The main reason is that the number of newly constructed units is small. This is evident from the limited changes in sample size. Relative to the sample size of 594,936 used for our baseline estimate (column (1) in Table 3) the sample sizes in Table 8 drops to 588,717, 577,045, 573,234, and 541,897, depending on the column. Any supply response hinges on the availability of empty lots for sale and on clearing all regulatory barriers. It appears that in practice the supply response in treated neighborhoods is limited at least within the 5 years of our study window.

We observe virtually no differential composition changes following the construction of a new barrier in observable property characteristics (bedrooms, stories, pool, AC, garage), the types of transactions (investor, resale, new building,cash, mortgage, foreclosure), and residential types (single family home, condo, duplex, apartment) across distance bins, as shown in Appendix Tables A4, A5, and A8.[16]

In principle, it is possible that the areas affected by the barrier construction experience additional endogenous changes in local amenities. One way in which this could happen, for example, is if higher property prices attract over time a wealthier mix of residents and this inflow ultimately improves the supply of local amenities–school quality, crime, street cleanliness, etc. In practice, we do not expect these effects to be meaningful confounders in our analysis. Our study period is limited to five years and it seems unlikely that the resident stock would change dramatically to induce significant amenity changes within that period. In addition, our analysis compares changes in prices for properties 0–100 m from the barriers with changes in prices for properties 500–1500 m from the barrier, but still in the same neighborhood. We are not aware of many amenities whose supply vary systematically with distance within our narrowly defined areas.

5.6 Robustness

To assess the robustness of our findings, we conduct a series of additional sensitivity analyses. First, we explored the sensitivity of our results to the specific choice of distance bands used in our difference-in-differences specification. We re-estimated our models using alternative distance cutoffs and found that our main results were robust to these variations (Table A10). We then examine the potential impact of outliers by systematically excluding observations with extreme values for sale prices. The results remain largely unchanged, suggesting that our estimates are not driven by a small number of atypical observations (Appendix Tables

[16]To provide the most conservative form of the test possible, these three tables do not include property fixed effects.

A11 and A12). Finally, we explore the robustness of our results to an alternative estimation method: we re-estimated our models using Poisson Pseudo Maximum Likelihood (PPML) and found similar, albeit slightly larger estimates A16.

6 The Aggregate Cost of the Externality and Who Bears it

In this section, we use our estimate of the causal effect of noise on property values and spatially granular data on traffic noise exposure to quantify the economic cost of the noise externality for each census tract. We use these estimates to ask two questions. First, who bears the cost of the externality? We relate our tract-level estimates to three socioeconomic characteristics of the tract: median family income, share of the population that is black and the poverty rate. Second, we ask: how large is the aggregate cost of the noise externality? To do so, we aggregate our tract-level estimates to the state-level for Florida and, under some additional assumptions, the entire United States.

As discussed in the Section 3, data from the USDOT National Transportation Noise Map provide an estimate of exposure to traffic noise for each census tract in the U.S. We use this information combined with our intensity of treatment estimates in Table 5 and Figure 8 to assign to each property an estimated cost of traffic noise. The parameter estimates in column (3) of Table 5 indicate that the effect of decibel reductions on log prices is the following quadratic function of decibel reductions:

$$Q^*(\mathbf{dB}) = .061 + .020 \cdot (\mathbf{dB} - 7) - .004 \cdot (\mathbf{dB} - 7)^2 \quad \text{if } 4.9 \leq \mathbf{dB} \leq 10 \tag{4}$$

Figure 8 shows that the estimated effect on property values is zero when noise reductions are around 4.9 dB. This closely aligns with FDOT's Traffic Noise Modeling and Analysis Practitioners Handbook, which specifies that to justify the construction of a barrier, it must reduce noise by at least 5 dB at one benefiting location. Nearly all barriers in our data – except four – meet this threshold. The figure also indicates that the effect plateaus at 10 dB of reduction, which represents the 96th percentile in our sample. Thus, the range from 4.9 to 10 dB captures the transition from no effect to the maximum estimated impact, as well as the observed variation in noise reduction levels from barriers.

$$\hat{Q}(\mathbf{dB}) = \begin{cases} 0 & \text{if } \mathbf{dB} < 4.9 \\ Q^*(\mathbf{dB}) & \text{if } 4.9 \leq \mathbf{dB} \leq 10 \\ Q^*(10) & \text{if } \mathbf{dB} > 10 \end{cases} \tag{5}$$

Based on these estimates, we compute the cost of the noise externality for each property i as:

$$\widehat{\text{Cost}}_i = \text{Property Value}_i \times \hat{Q}(\text{noise}_i - 45) \tag{6}$$

where Property Value$_i$ is the most recent assessed value (as of 2022) of the property i from our CoreLogic assessor data measured in dollars (not logs).[17] The variable noise$_i$ is the noise level of property i from the US DOT National Transportation Noise Map measured in dBs. Traffic noise of 45 dB is the lowest level recorded in the Noise Map data, so that (noise$_i - 45$) dB is the capacity for noise reduction at property i. The $\hat{Q}(\text{noise}_i - 45)$ is the expected percent effect on prices based on our parameter estimates. We then aggregate the property-specific estimates to the 2010 census tract level by summing $\widehat{\text{Cost}}_i$ for all properties in a census tract.

Incidence. To understand who bear the cost of the noise externality we plot the properly-scaled estimates of the cost of the externality for each tract in Florida against the tract median family income, share of the population that is black and poverty rate. There are two ways to scale the tract-specific cost of the externality: we can use the per-capita cost, obtained by dividing the tract-level aggregate cost by the number of its residents; or we can scale those costs as a percentage of income, obtained by dividing the tract-level nosie cost by the median family income.

In Figure 9, we focus on the cost of the externality in per capita terms. Throughout, we residualize on county fixed effects. The sample includes all tracts in Florida. The figure shows that the per-capita cost is larger for tracts in counties that have higher median incomes, lower poverty rates and a lower share of black individuals. This result may appear counterintuitive, since in Figure 2, we have shown that noise exposure is higher in tracts with lower socioeconomic status (SES). Despite being less exposed to noise, tracts with higher median incomes, lower poverty rates and lower black resident shares have a higher per-capita cost of the noise externality because they have a higher baseline level of property values. Based on this measure, the externality appears "progressive", meaning that its incidence is larger on high-SES families.

The picture that emerges is different if we measure the cost of the externality in a tract as a share of tract-level income. Figure 10 shows a negative correlation between the cost of the externality relative to income and tract median income. The correlations with the share of residents who are Black and the poverty rate are positive. The reason is that low-income families and black families are overrepresented in tracts that are more exposed to traffic noise. Based on this measure, the externality is "regressive", meaning that its incidence is

[17] We use assessed values as opposed to sale price in order to be able to include all properties, not just those that have been sold.

larger on low-SES families.

Aggregate Cost. To quantify the total economic cost of the noise externality for Florida, we aggregate tract-level estimates by summing across all tracts in the state. Table 9 reports our estimates. The entry in the top row of column 1 shows that the aggregate cost of the traffic noise externality in Florida amounts to $7.92 billion. This measure is to be interpreted as a stock, not an annual flow, since it is based on the effect of traffic noise capitalized in property values (not annual rents). The next four rows show that the costs for tracts in the bottom and top quartile of median family income are respectively, $1.91 and $2.89 billion; while the costs for tracts in the bottom and top quartile of the black share of the tract are respectively, $2.23 and $1.76 billion.

Columns 2, 3 and 4 report the cost as a percentage of income, as a percentage of property values and in per capita terms, respectively. This calculation is perforemd for tracts in the top and bottom quartile of median family income and percent Blacks. They confirm what we illustrated in Figure 10: the per-capita costs are larger in more affluent and white areas while the per-dollar (of property value or local income) costs are larger in areas that are poorer and have a higher percentage of Black residents.

The lower panel of the Table 9 extends our estimates to the entire U.S. We present three set of estimates. We begin by simply applying our Florida estimates in equation 4 to tracts in other states. This extrapolation is based on the assumption that the effect of noise on property values estimated using Florida data is externally valid for other states. This assumption is violated if the effect of noise on property values outside Florida is different from the one that we estimated for Florida. This could be the case if the effect of noise on property values varies by income and demographics, and Florida has a different mix of income and demographics than the U.S. as a whole. Recall that Table 1 and Appendix Table A3 above suggest that Florida's observables are not too different from those of the U.S., and their correlation with noise is also comparable. However, they also indicate that Florida is not identical to the U.S.

Therefore, we present two additional set of national estimates. First, we re-estimate equation 4 weighting each Florida census tract to make the mix of tracts more representative of the U.S. and use these weighted estimates to assign the cost of noise to tracts outside Florida. As weights, we use the propensity score from a model that includes the following tract characteristics: population, Gini coefficient, median household and family incomes, shares of the population by race and education, home value quartiles, average contract rents, and housing unit counts.

Second, we re-estimate equation 4 both weighting (for the propensity score) and allowing

the effect of noise on property values to be heterogeneous as a function of median income. These results are contained in Table A18. This extrapolation is valid if the effect of noise on property values varies by observable tract characteristics.

Entries in Table 9 indicate that using the first approach, the aggregate cost of noise for the U.S. is estimated to be $120.71 billion. Using the second and third approach, the aggregate cost for the US is estimated to be significantly smaller: $100.39 billions and $90.59 billions, respectively. The difference between the first and second estimates reflects the difference between Florida and U.S. tract characteristics. While Florida tract characteristics look generally similar to U.S. tract characteristics, the propensity score model shows that Florida's tracts tend to have somewhat lower SES. Median family income for U.S. is $80,000 and for Florida is $71,000. Since higher SES neighborhoods in Florida get weighted more and higher income tracts are exposed to less noise, this leads to the lower aggregate cost of noise.

The difference between the second and third estimate reflects both the heterogeneity in the estimated effects and the weights. Higher income neighborhoods are found to have lower estimated price effects, and this heterogeneity only affects the level of the estimates, not the shape of the effects in terms of noise reduction. Allowing for heterogeneous effects yields lower aggregate costs because we put higher weight on neighborhoods with lower effects.

We conclude that differences in demographics between Florida and the US and heterogeneity in the noise effects are important in estimating the aggregate costs. Our most robust estimate – which is the one that both weights the aggregation and allows the effect of noise to vary by observable characteristics – points to an estimate in excess of $90 billions, arguably a large aggregate cost of noise for the U.S. as a whole. We caution that our extrapolation takes into account a limited set of tract-level observables. In the presence of tract-level unobservables, the external validity of our estimates is unknown.

7 Policy Implications: Pigouvian Taxes and Electric Vehicles

Taxes. The textbook solution to an activity that generates a negative externality is a Pigouvian tax equal to the external economic cost of the activity. To obtain a back-of-the-envelop estimate of the cost of the noise externality produced by the average vehicle (car or truck) in Florida, we divide our estimate of the total costs of traffic noise in Florida (from column 1 of Table 9) by the number of vehicles registered in the state in 2006 (the mid-point in our sample period). The ratio is equal to $984 per car, arguably a large amount. Recall that this is a measure of a stock, not an annual flow, since it is based on the negative effect that the average car creates on property values.[18] Thus, the socially efficient corrective tax

[18]Our estimates include housing transactions in a period where most vehicles in Florida had an internal

that internalizes the externality is a one-time levy of $984 per car, or an annual levy set equal to the corresponding annualized flow. For comparison, an estimate of the economic cost of air pollution created by cars is ... XX

Of course this estimate is an average across vehicle models with vastly different external costs. A more efficient corrective tax is model-specific and is proportional to the external cost of noise emissions of each model. In principle, with engineering data on the noise generated by each model in the average hour of operation and each model's share of traffic in Florida, the efficient corrective tax on the number of decibels emitted in an hour of operation can be computed as the term C in the following expression:

$$\sum_m S_m \cdot C \cdot N_m = \$984 \tag{7}$$

where S_m is model m's share of vehicles in Florida during our sample period; and $N_m = D_m \cdot H_m$ is the lifetime number of decibels generated by model m calculated as the product of the mean number of decibels produced in an hour of typical operation $D_m \times$ the model's expected lifespan measured in hours H_m. Thus, the efficient corrective tax on model m is a function of observable variables and can be calculated as:

$$T_m = C \cdot N_m = \left(\frac{\$984}{\sum_m S_m \cdot N_m} \right) \cdot N_m \tag{8}$$

Electric Vehicles. Besides taxes, there is a limited set of policy levers that can be adopted to reduce traffic noise in U.S. cities.[19] In principle, Pigouvian subsidies to incentivize the adoption of electric vehicles (EVs) are an alternative policy tool. EVs generate a smaller noise externality than traditional cars vehicles because electric engines tend to be significantly quieter than Internal Combustion Engines (ICEs).

Here we provide an estimate of the potential external benefits of the widespread adoption of EVs in terms of noise abatement. To do so, we use our estimates of the cost of the noise externality from the previous section combined with engineering estimates on the average noise difference between EVs and ICEs.[20]

A nascent literature in the field of noise engineering seeks to quantify the effect of EV diffusion on traffic noise. In one of the most recent papers, (Lan et al., 2018) conduct a noise

combustion engine. Electric vehicles were a trivial number of the vehicles in circulation in Florida.

[19] Changing the materials used to pave roads has been shown to be effective at reducing noise.

[20] We cannot directly estimate the effect of EVs on property values in the U.S. for two reasons. First, estimates would necessarily need to be at the MSA or Commuting Zone level. At this time, the number of EVs in the U.S. is still too small to detect anything meaningful at such a level of aggregation. Second, we are not aware of a credible design to measure home price effects.

measurement experiment to compare the noise emissions from traffic flow with different proportions of EVs. They collect data from 1,434 acoustic records, with observed speeds ranging from 22km/h to 67 km/h. They find that an increase in the proportion of EVs causes a decrease in measured noise. They estimate that a scenario where 100% of vehicles are EVs implies a reduction in noise near the road between 7.1 dB(A) and 7.3 dB(A), depending on the exact mix of vehicles. This amounts to a 9.6-11.1% reduction in noise. Walker et al. (2016) and Pallas et al. (2014) find significant noise reduction from EVs.[21] Another finding in the literature is that the magnitude of noise reduction is larger at lower speeds and smaller at higher speeds because at higher speeds the contribution of rolling noise becomes more important. Pallas et al. (2016) find that the overall noise reduction is around 5 dB(A) at 20 km/h and decreases and becomes insignificant beyond 50 km/h.[22]

To compute the external benefits of EVs we make a number of assumptions. First, based on the existing engineering literature, we assume that if all internal combustion engine vehicles are replaced by EVs, traffic noise in the immediate vicinity would decline by 7.1 dB on average. We note that the average reduction achieved by sound barriers in our sample is similar – about 7 dB. Thus, our estimates of the costs of noise are based on variation that is consistent with the expected noise reduction from the adoption of EVs. Second, we base our calculations on the average noise decline induced by EVs and ignore possible heterogeneities experienced by properties near urban roads–where speed is lower and an EV's noise reduction is larger–and freeways–where speed is higher and an EV's noise reduction is limited or zero. Third, we focus on changes in noise intensity—arguably the main effect of EV adoption—and ignore any possible changes in noise quality due to changes in wave frequency, which is likely a second-order effect. For a given decibel level, wave frequency affects how noise is perceived. There is evidence that EVs affect the wave length, but we have no way to evaluate the impact of changes in wave frequency on property prices.[23] Fourth, we keep the total number of vehicles on the road constant, by assuming that adoption of EVs does not affect the total number of vehicles.

Table 10 reports the estimated aggregate benefits of 100% EV adoption in terms of forgone noise. As we did in the previous section, we rely on the extrapolation procedure in Equation 4 to produce a dollar benefit of noise reduction for each census tract. For Florida, we estimate that 100% EV adoption would generate $6.23 billion in benefits (column 1).

[21] See also Pallas et al. (2016), King (2017).

[22] See also Iversen and Holck (2015) and Marbjerg (2013).

[23] Lan et al. (2018) find that EV adoption changes the frequency content. Specifically, the noise energy of EVs is more concentrated than that of ICEs. The noise energy of light EVs is concentrated within the range of 500 Hz to 1,600 Hz. The equivalent frequency for traffic flow increases with an increasing proportion of EVs.

The next two columns are informative of the distributional impacts of policies that aim to increase EV diffusion. In per-capita terms, the benefits of EV adoption are larger for high-income tracts and tracts with a lower share of Black residents (column 4). By contrast, in per-dollar terms, the benefits are larger for low-income tracts and tracts with a higher share of Black residents (columns 2 and 3).

The three rows at the bottom of the table report estimates for the U.S. as a whole. They indicate that 100% EV adoption would generate aggregate benefits in terms of noise reduction between $77.92 billion and $94.96 billion, depending on the specification. Our preferred estimate is $77.92 billion because it comes from a model that allows for heterogeneity in the effect of noise on prices and weights Florida tracts to make them comparable to the average U.S. tract.

To obtain an estimate of the benefit generated by the average EV in Florida, we divide our estimate of the total benefit in Florida (from column 1 of Table 10) by the number of vehicles registered in the state in 2006 (the mid-point of our sample period). The ratio is equal to $774. As a point of reference, consider that the Inflation Reduction Act (IRA) of 2021 provided a $7500 tax credit for EV buyers. Our estimates indicate that more than one tenth of the IRA's subsidy can be justified simply based on the external benefits of noise reduction. Of course, the total external benefits of EV (relative to ICEs) are likely to be significantly larger than $774 because they include a reduction in local air pollution and global CO2.

8 Conclusion

This paper investigates the economic costs of traffic noise – an environmental externality that, despite being widespread in urban areas, has received relatively little attention in the economics literature. We use quasi-experimental variation from the construction of noise barriers along major roadways to estimate how reductions in traffic noise affect nearby property values. Our analysis suggests that homebuyers are willing to pay a substantial premium for quieter living environments: we find that housing prices increase by 9.7% within 100 m of a new barrier.

Building on these estimates, we combine spatially detailed data on noise exposure with housing data to provide an aggregate estimate of the social cost of traffic noise. Our results point to a nationwide external cost of approximately $90.6 billion. Notably, the burden of traffic noise is not evenly distributed. Lower-income households tend to live near and bear the burden of noisier areas, meaning that noise pollution acts as a regressive externality.

These findings have several implications for policy. A Pigouvian tax aimed at internalizing the costs of traffic noise would translate to a one-time fee of roughly $984 per ICE vehicle. In

addition, we estimate that a broader shift to EVs – which are significantly quieter than ICE vehicles – could yield noise reduction benefits on the order of $77.9 billion. Importantly, much of this benefit would accrue to low-income households, suggesting that policies promoting EV adoption could help advance both efficiency and equity goals.

More broadly, our findings contribute to the growing body of research on the distributional consequences of environmental harms. They underscore the importance of integrating noise pollution considerations into urban planning and transportation policy. Future research could explore potential links between chronic noise exposure and health outcomes or examine how noise interacts with other forms of environmental stress to shape life in urban areas.

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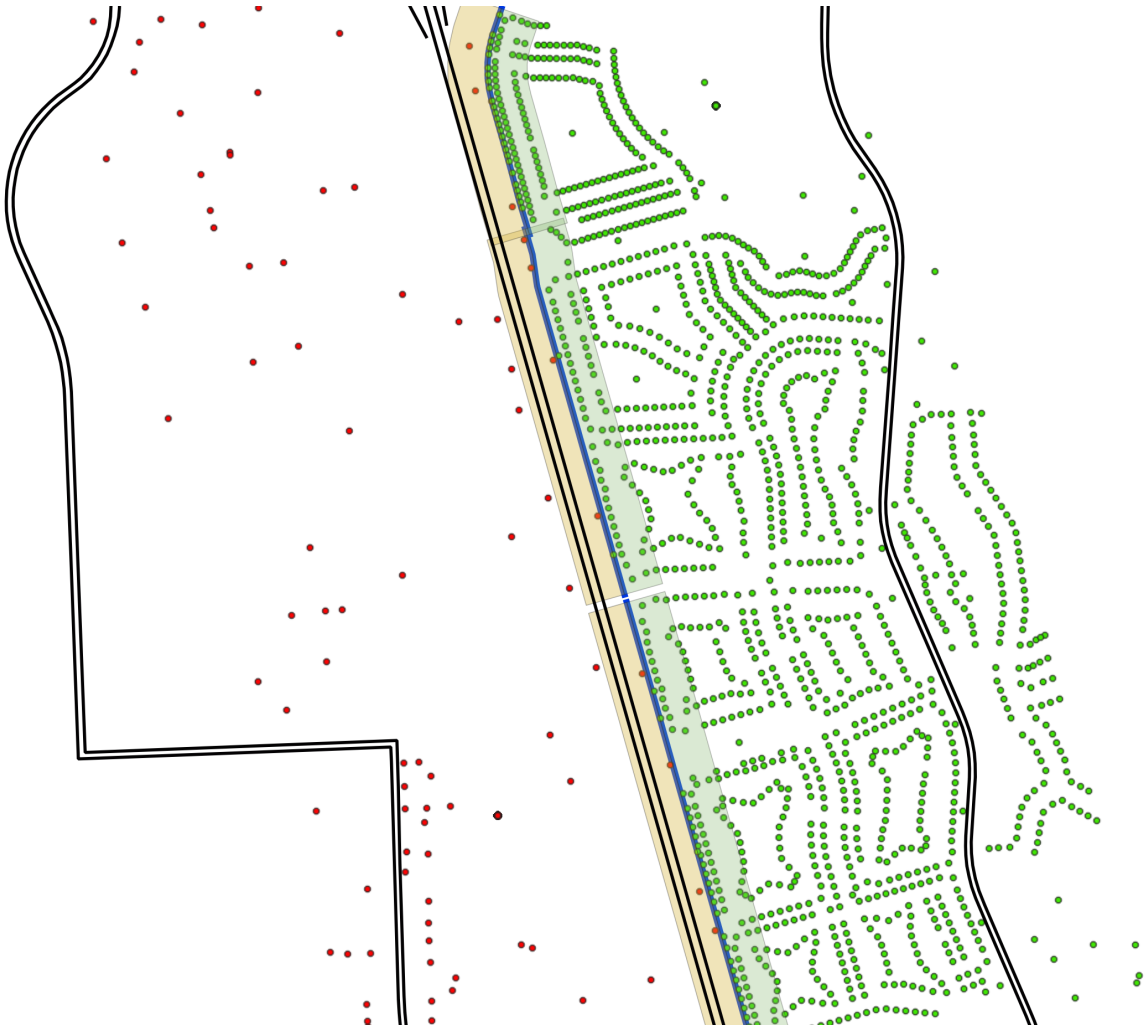
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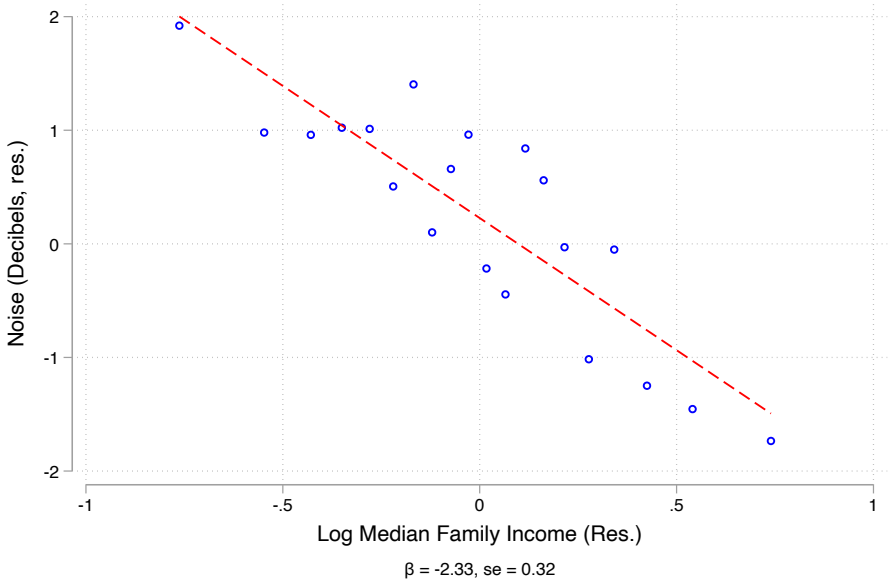
Figure 1: Spatial sampling of home value transactions



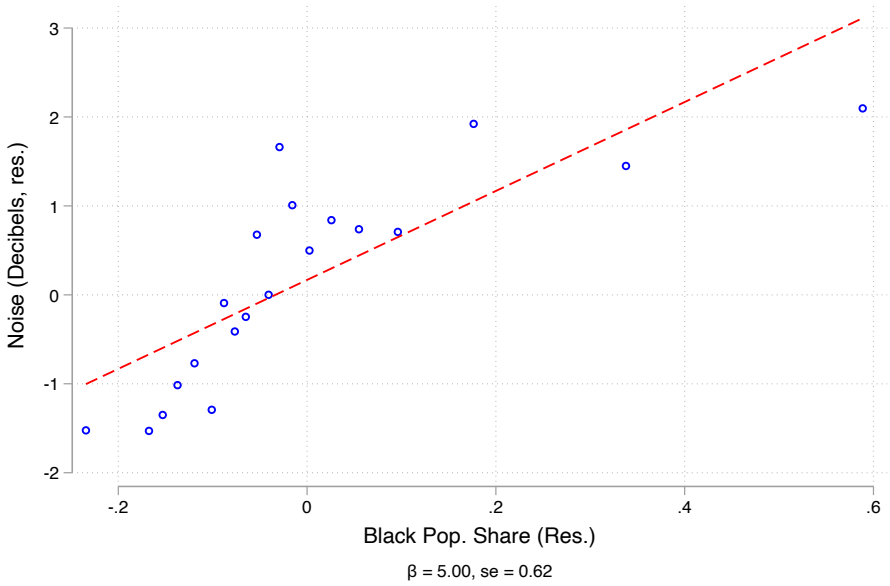
Notes: This figure contains details of the spatial sampling algorithm discussed in Section 3. The black lines is a layer of roads from the Florida Department of Transportation. The blue lines are a series of noise barriers built to the east of the road. Dots correspond to home sales and their locations from Corelogic. The green and yellow shaded areas depict 100 meter buffers on the right and left side of the barrier, respectively. 100 meters from the barrier often contains the first one to two rows of homes. We use these buffers to determine which side of the highway has homes affected by the barrier. In particular, we aggregate the length of road contained in either 100 meter buffer. The "wrong" side contains more road on it (here, the left side indicated by the yellow buffer). The "correct" side has less road on it (here, the right side indicated by the green buffer).

Figure 2: Correlation of noise with neighborhood characteristics

Median family income

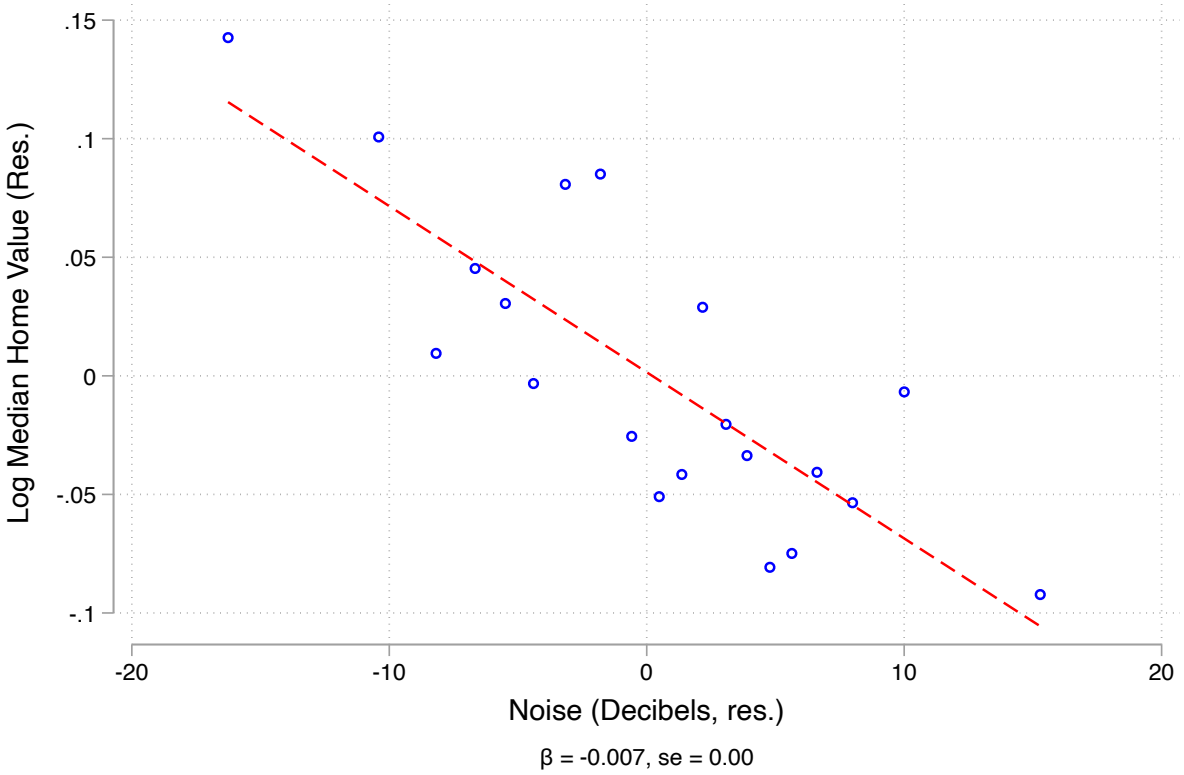


Black share of the neighborhood



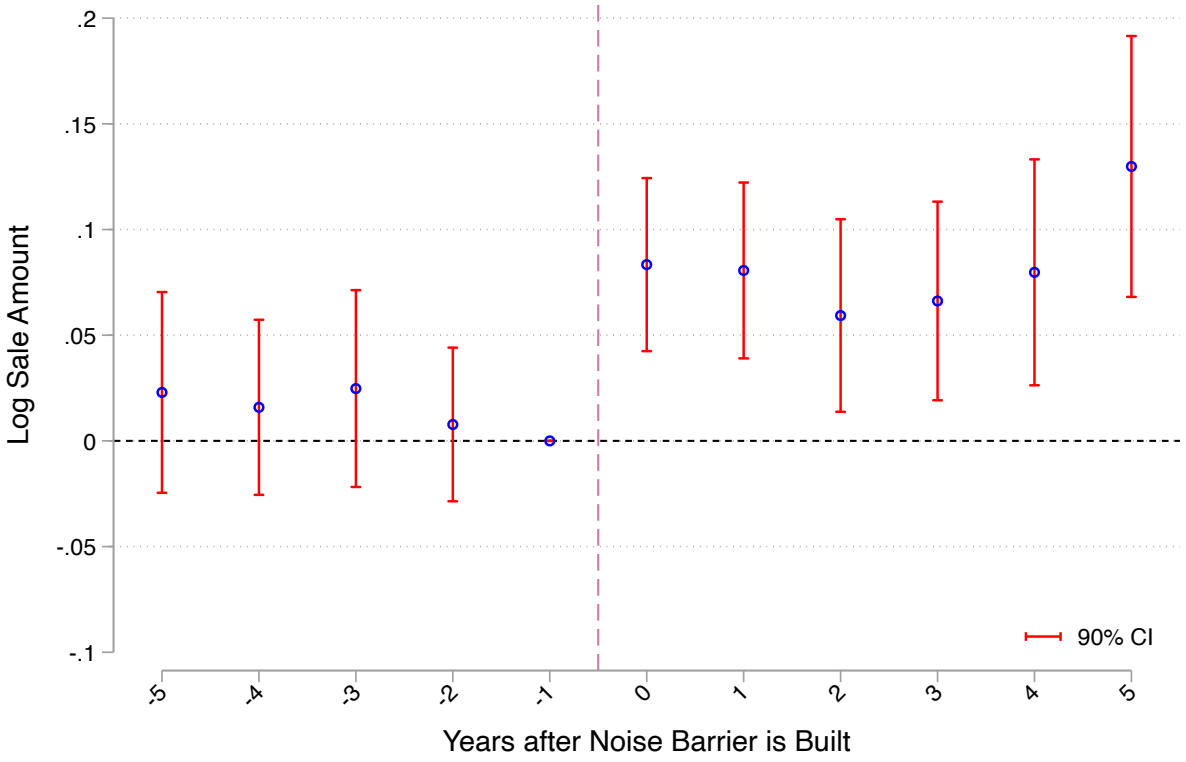
Notes: These figures contain binscatter plots of neighborhood noise exposure with socioeconomic characteristics. Our measure of noise is the maximum decibel level, as modeled by the National Transportation Map (2020), across parcels in a 2010 census tract. Median family incomes come from the 2015-2019 5-year American Community Survey. We residualize both local incomes and noise on county fixed effects. Our sample consists of 4,212 census tracts in Florida. The line of best fit is plotted in red.

Figure 3: Home values and noise



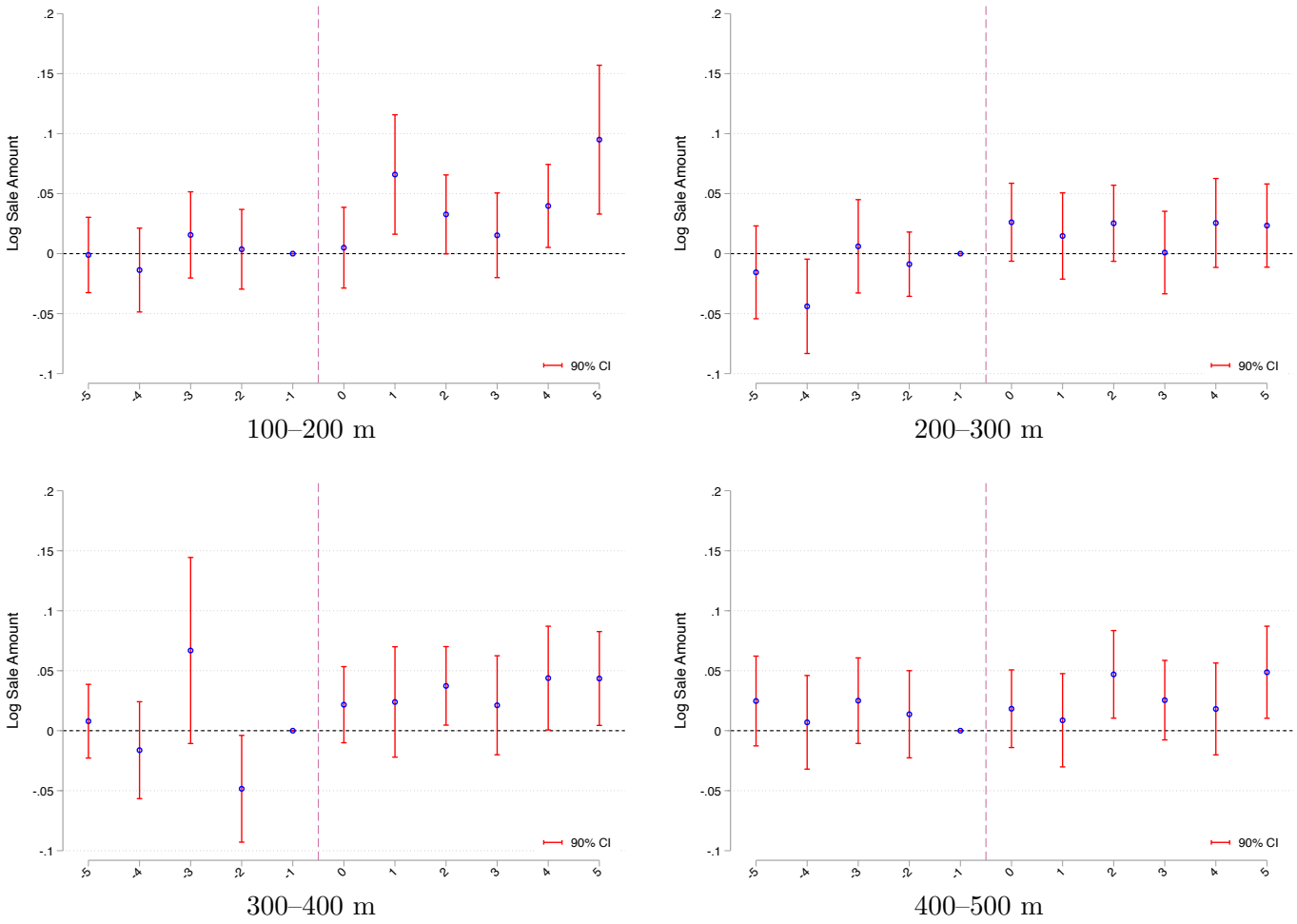
Notes: These figures contain binscatter plots of neighborhood median home values with noise exposure. Our measure of noise is the maximum decibel level, as modeled by the National Transportation Map (2020), across parcels in a 2010 census tract. Median home values come from the 2015-2019 5-year American Community Survey. We residualize both local home values and noise on county fixed effects. Our sample consists of 4,212 census tracts in Florida. The line of best fit is plotted in red.

Figure 4: Effects for 0-100m by event time



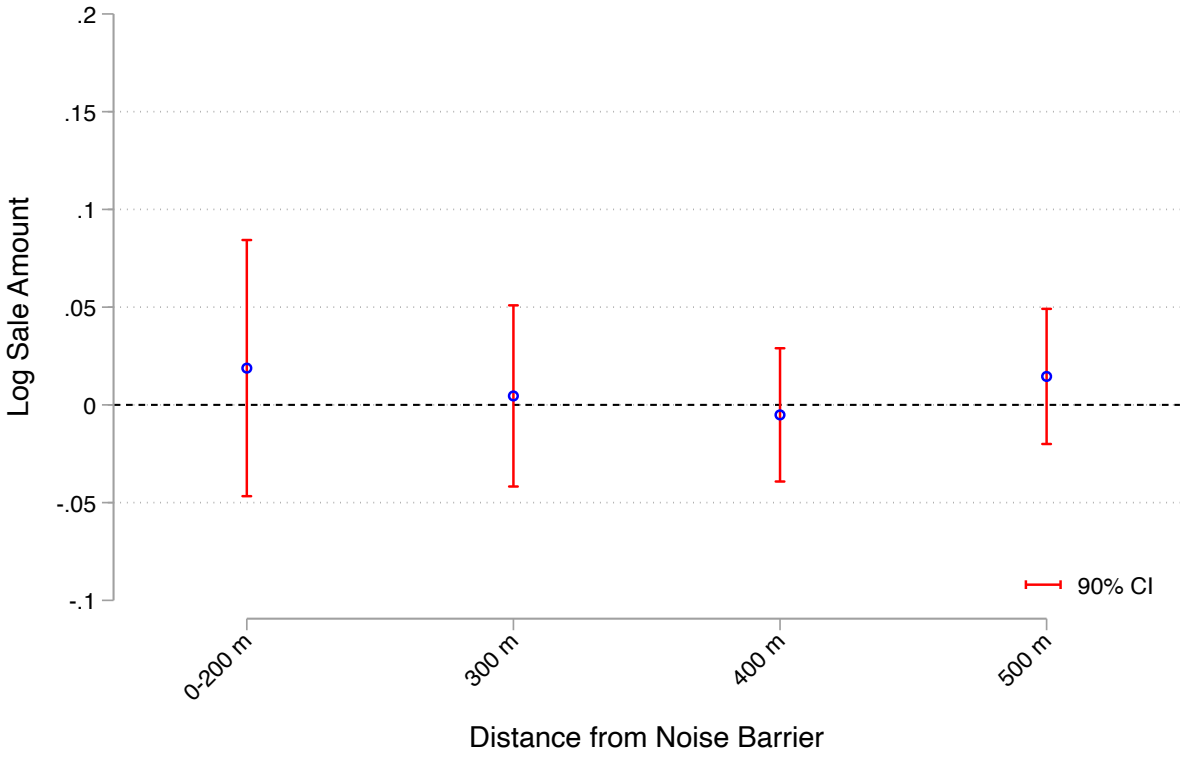
Notes: This figure contains estimates from Equation 2 of the effect on transacted home prices within 100 m of the noise barrier in each year leading up to after the barrier was built. Estimates are in blue and standard errors at the 90% level are in red. Coefficients are plotted for each of the 5 years leading up to the barrier construction and each of the five years after. The estimates use transactions that were 500–1500 m away as the control group. The average effect is 6.8%. All errors are clustered at the barrier-level.

Figure 5: Event studies for further out distances



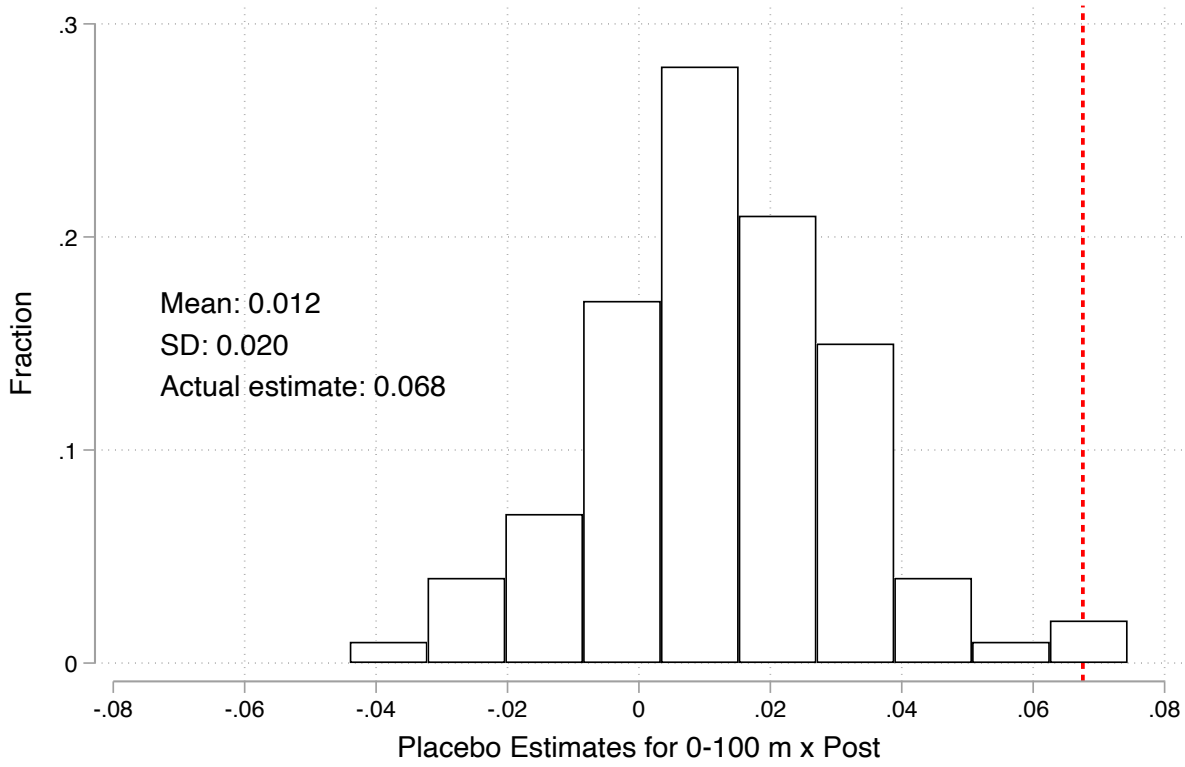
Notes: These figures contains estimates from Equation 2 of the effect on transacted home prices within 100 meter bins of the noise barrier in each year leading up to after the barrier was built. Estimates are in blue and standard errors at the 90% level are in red. Figures are shown for 100–200, 200–300, 300–400, and 400–500 m from the barrier. Coefficients are plotted for each of the 5 years leading up to the barrier construction and each of the five years after. The estimates use transactions that were 500–1500 m away as the control group. All errors are clustered at the barrier-level.

Figure 6: Placebo using "wrong" side of highway difference-in-differences



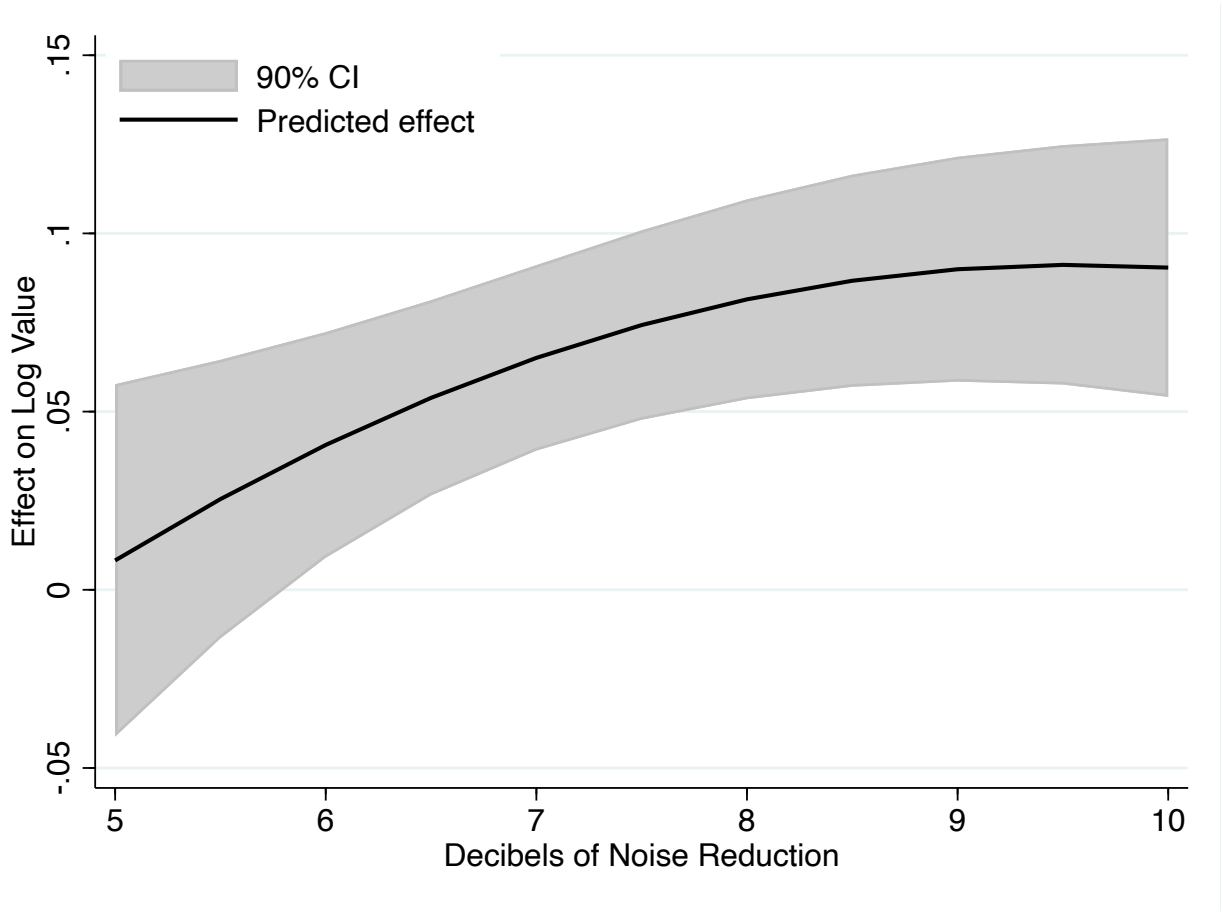
Notes: These figures contains estimates from Equation 3 of the effect on transacted home prices on the "wrong" side of the barrier, within 100 m bins of the noise barrier. The "wrong" side is the one opposite the highway. Details of how we identified it can be found in Section 3. Estimates are in blue and standard errors at the 90% level are in red. Figures are shown for 0–200, 200–300, 300–400, and 400–500 meters from the barrier. We combine the 0–100 m and 100–200 m bins for this analysis because, on the wrong-side of the highway, there tend to be few properties within 100 meters due to the highway. The difference-in-differences design considers changes in transaction values five years after the barrier was built with five years before and uses transactions that were 500–1500 m away as the control group. All errors are clustered at the barrier-level.

Figure 7: Placebos by permuting the year each barrier was built



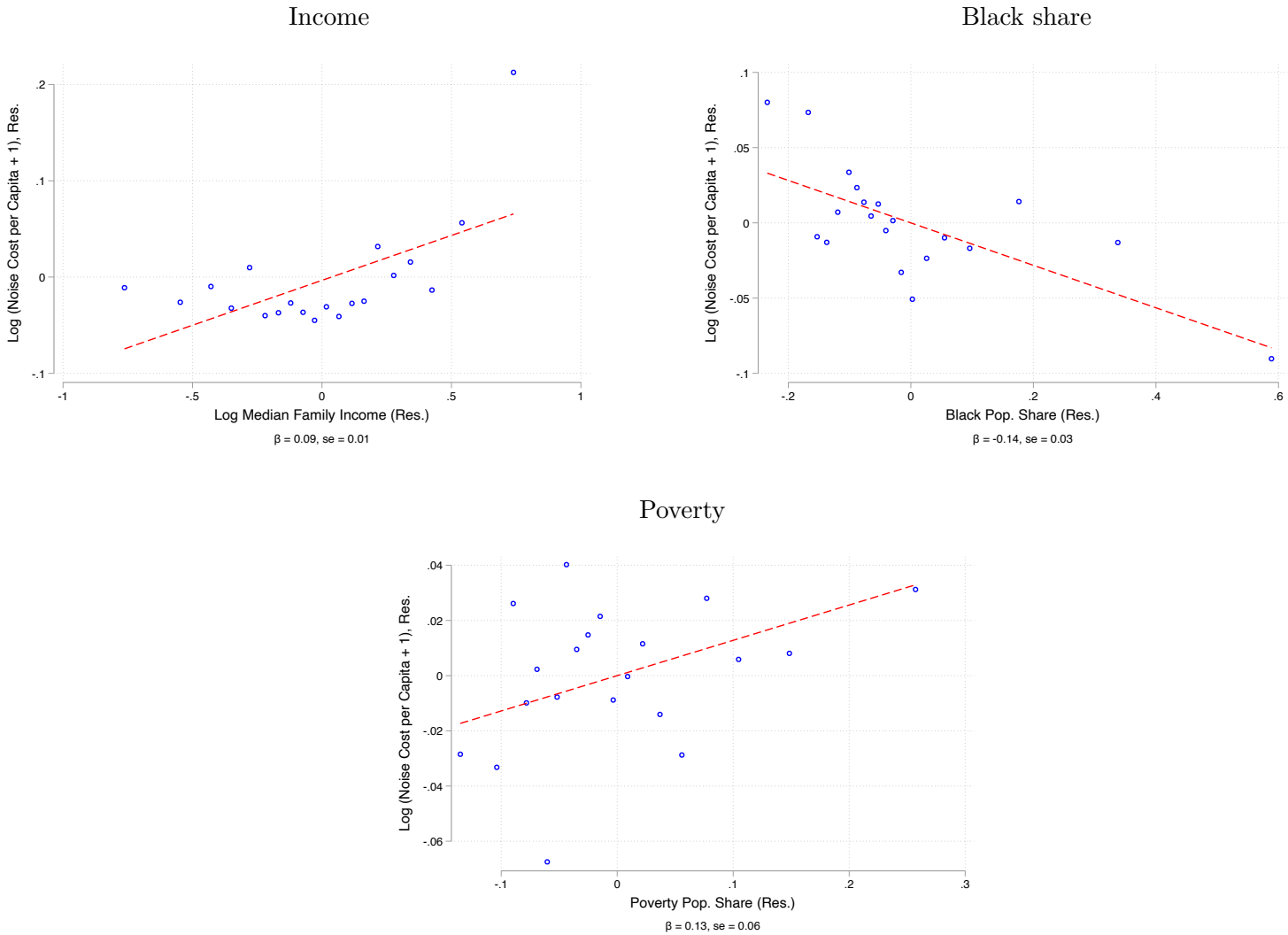
Notes: These figures contains estimates from Equation 3 of the effect on transacted home prices within 100 m of the noise barrier. We randomize each barriers built year using the empirical distribution of actual years barriers were built. For each randomization, we estimate the main difference-in-differences model. The difference-in-differences design considers changes in transaction values five years after the barrier was built with five years before and uses transactions that were 500–1500 m away as the control group. We repeat this randomization 100 times and plot the distribution of estimates. The y-axis is the fraction of simulations with a certain estimate value. The red dashed line shows our true estimate of 6.8%. All errors are clustered at the barrier-level.

Figure 8: Quadratic effect in noise reduction of barriers on home values



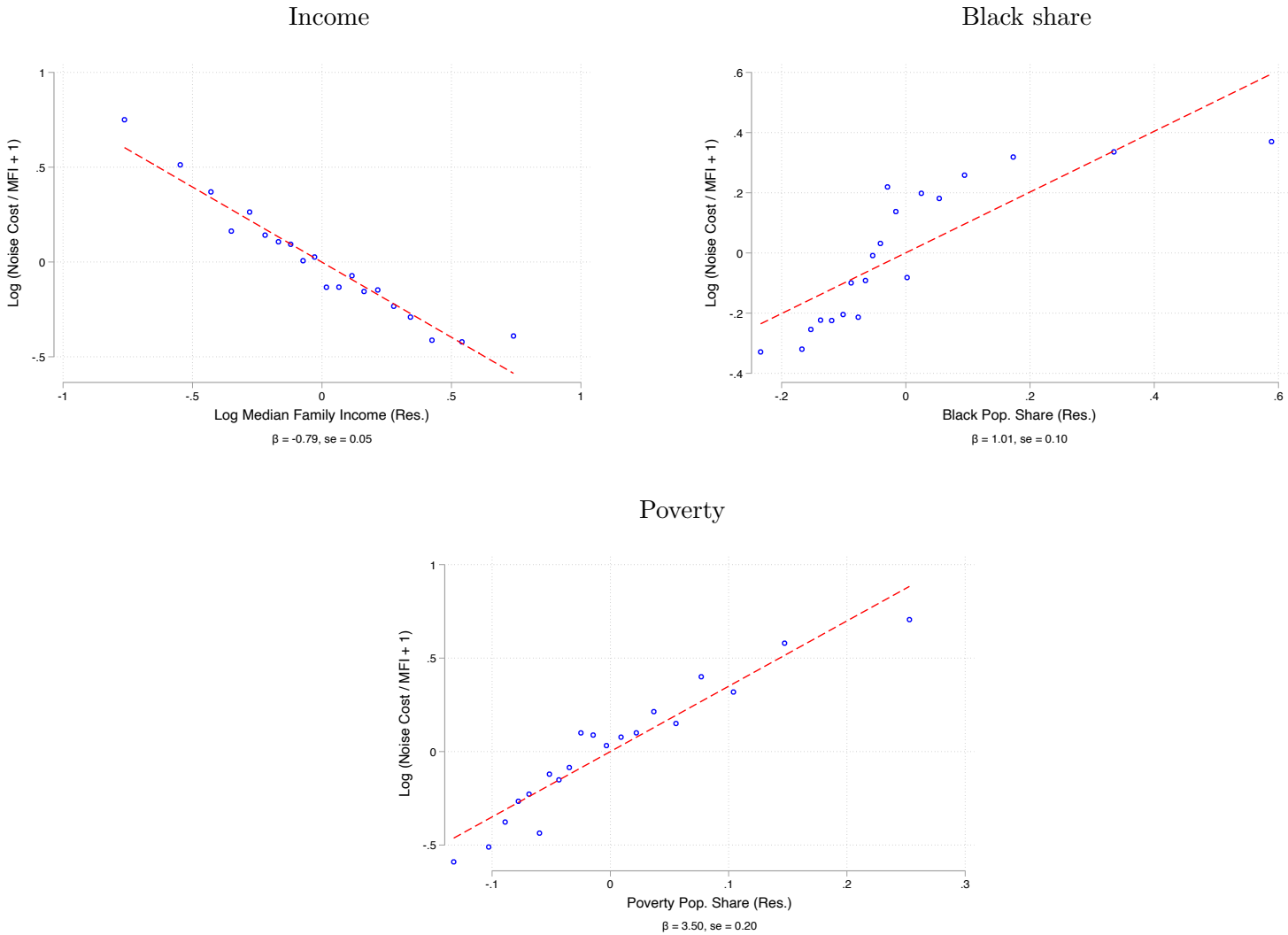
Notes: This figure contains a plot of the quadratic effects estimate from Table 5 in expected noise reduction of the barrier. We use these estimates in our extrapolation exercise (Equation 5) for the cost of the noise externality and expected benefits from the diffusion of electric vehicles. The plot was constructed using the Stata command `marginsplot`. Confidence intervals are at the 90% level. All errors are clustered at the barrier-level.

Figure 9: Noise externality costs (per capita) across neighborhoods



Notes: These figures contain binscatter plots of estimates of the dollar value of the noise externality with neighborhood socioeconomic characteristics. Our externality estimates extrapolates our findings on home value appreciation for each decibel of noise reduction to all properties in Florida. We divide this number by the total population in the 2010 census tract, and then log-transform it. Median family incomes, the share of the population that is black, and the poverty rate come from the 2015-2019 5-year American Community Survey. We residualize both our logged per capita externality measure and tract characteristics by county fixed effects. Our sample consists of 4,212 census tracts in Florida. The line of best fit is plotted in red.

Figure 10: Noise externality costs (per capita as a fraction of income) across neighborhoods



Notes: These figures contain binscatter plots of estimates of the dollar value of the noise externality with neighborhood socioeconomic characteristics. Our externality estimates extrapolates our findings on home value appreciation for each decibel of noise reduction to all properties in Florida. We divide this number by the population and then the median family income in the 2010 census tract, and then log-transform it. Median family incomes, the share of the population that is black, and the poverty rate come from the 2015-2019 5-year American Community Survey. We residualize both our logged per capita externality measure and tract characteristics by county fixed effects. Our sample consists of 4,212 census tracts in Florida. The line of best fit is plotted in red.

Table 1: Noise and neighborhoods in the U.S. relative to county means

	dB > 50	*[46,50]*	*dB < 46*
Florida			
Median Fam. Income ($1k)	-12.5	-3.4	6.7
College Educated (%)	-2.7	-0.8	1.5
Poverty (%)	3.7	0.6	-1.6
Black (%)	4.8	1.3	-2.5
Median Home Val. ($1k)	-48.4	-15.1	27.6
Urban (%)	3.1	3.6	-4.5
Density (#/sq. km)	699	32	-213
Any Exp. to >90 dB (%)	15.7	-0.3	-3.7
N	537	2124	2090
United States			
Median Fam. Income ($1k)	-13.2	-2.2	6.4
College Educated (%)	-2.7	-0.2	1.1
Poverty (%)	4.0	0.6	-1.9
Black (%)	3.1	0.9	-1.9
Median Home Val. ($1k)	-42.5	-5.6	18.7
Urban (%)	4.8	8.2	-9.5
Density (#/sq. km)	564	102	-290
Any Exp. to >90 dB (%)	13.9	-1.0	-3.8
N	11,644	33,020	34,336

Notes: This table contains summary statistics for neighborhoods across the U.S. and Florida by noise exposure. We use (Seto and Huang, 2023)'s publicly available dataset contain estimates of the share of a 2020 census tract's population exposed to different 10-decibel bins of traffic noise (rail, aviation, or car). We use these shares to an extrapolate an average noise exposure for each tract. We then bin tracts into three groups: high exposure (greater than 50 dB of average exposure), medium (between 46 and 50 dB of average exposure), and low (less than 46 dB of average exposure). We then calculate average neighborhood characteristics for each of these three groups. We use 2016-2020 American Community Survey data and 2020 census tract boundaries to do so. Each characteristic is residualized on county fixed effects. The interpretation of the average median home value, for example, is how many thousands of dollars is the median home value less or more than the county average for each group. Row (1) contains the share of the population exposed to any noise. Row (2) contains the share of the population exposed to extreme noise (greater than 90 dB). Row (3) through (9) contain averages for median home values, median family income, the poverty rate, the percentage of the population that is black, the percentage of the population that is college educated, the percentage of the population that lives in an urban area, and the density as measured by persons per square kilometer. The area of 2020 census tracts was calculated directly from the 2020 U.S. Census TIGER/Line Shapefiles. The final row contains the number of census tracts in each group.

Table 2: Expected effect of sound barriers on noise, by distance

Distance	Noise (Db scale)		How Loud (0-100 scale)		Change in How Loud	What It Sounds Like	
	Before	After	Before	After		Before	After
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
25 m	76 dB	69 dB	100	61.5	-38.5	food mixer	dishwasher
50 m	70 dB	63 dB	65.9	40.2	-25.7	dishwasher	normal conversation
100 m	64 dB	57 dB	43.5	26.5	-17.0	normal conversation	electric toothbrush
200 m	58 dB	51 dB	28.7	17.6	-11.1	electric toothbrush	refrigerator
400 m	52 dB	45 dB	18.9	11.5	- 7.4	refrigerator	bird calls
800 m	46 dB	39 dB	12.5	7.6	-4.9	bird calls	library

Notes: This table contains the expected reduction in decibels and perceived loudness at every distance from the sound barrier. Column (1) contains the distance from the sound barrier. Column (2) contains the level of noise without the sound barrier. Column (3) contains the level of noise with a sound barrier that reduces noise by 7 dB - about the average barrier for our sample. We use 76 dB as the highway sound without the barrier, following median estimates from Corbisier (2003). According to the "inverse square law," the decibel of a noise is reduced by 6 with every doubling of the distance. Hence, we reduce the decibel level by 6 in both Columns (2) and (3) with each additional row. Column (3) and (4) convert decibels to a perception of loudness, indexed to 100 for the sound of a highway 25 meters away without a sound barrier. It is commonly accepted that a reduction of 10 dB corresponds to a reduction of half in the perceived loudness; thus, a reduction of x decibels changes perceived loudness by $(1/2)^{(x/10)}$. Columns (7) and (8) give everyday sounds that are of a similar decibel level to Columns (2) and (3).

Table 3: Effect of sound barriers on prices

	(1) Log. Value	(2) Log. Value	(3) Log. Value	(4) Log. Value	(5) Log. Value	(6) Log. Value
100 meters x post	0.0676***	0.0859***	0.0669***	0.0884***	0.0777***	0.103***
	(0.0139)	(0.0228)	(0.0163)	(0.0264)	(0.0172)	(0.0266)
200 meters x post	0.0399***	0.0578***	0.0421***	0.0633***	0.0582***	0.0814***
	(0.0141)	(0.0195)	(0.0161)	(0.0228)	(0.0168)	(0.0234)
300 meters x post	0.0319**	0.0441**	0.0320**	0.0439*	0.0431***	0.0546**
	(0.0131)	(0.0207)	(0.0150)	(0.0236)	(0.0156)	(0.0231)
400 meters x post	0.0285	0.0445*	0.0303	0.0458*	0.0318	0.0492*
	(0.0196)	(0.0231)	(0.0219)	(0.0246)	(0.0226)	(0.0254)
500 meters x post	0.0132	0.0160	0.0146	0.0194	0.0232*	0.0304
	(0.0111)	(0.0169)	(0.0122)	(0.0177)	(0.0131)	(0.0187)
Observations	594,936	474,033	1,093,205	933,301	1,093,205	933,301
R^2	0.677	0.806	0.659	0.785	0.659	0.785
Not Built BIDs			✓	✓	✓	✓
Main FE	✓	✓	✓	✓	✓	✓
Parcel FE		✓		✓		✓
Dist x Yr FE					✓	✓

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains versions of our main estimation given in Equation 3, with additional fixed effects and also by including properties near proposed (but not built) barriers. The coefficients correspond to the β_j in Equation 3, and capture the effect of the barrier construction on transacted home value prices. The design compares transactions in the five years after barrier construction with the five years prior, and for properties near to the barrier with those that were between 500–1500 m away. All specifications include barrier by date, and barrier by distance bin fixed effects. Column (1) is our main specification. Columns (2), (4), and (6) include parcel (the tax unit for a property) fixed effects, and consequently, rely on repeat-sales. Columns (3) through (6) add barriers that were proposed for construction, but have yet to be built, to the sample. Columns (5) and (6) add distance from the barrier by year fixed effects. All errors are clustered at the barrier-level.

Table 4: Effect of sound barriers on prices
Difference-in-differences and DDD using proposed barriers

	(1) Log. Value	(2) Log. Value	(3) Log. Value
100 meters x post	0.0705***	0.0817**	0.0967***
	(0.0172)	(0.0361)	(0.0370)
200 meters x post	0.0421***	0.0336	0.0569**
	(0.0151)	(0.0230)	(0.0273)
300 meters x post	0.0361***	0.0131	0.0589*
	(0.0137)	(0.0293)	(0.0329)
400 meters x post	0.0392**	0.00816	0.0391
	(0.0165)	(0.0240)	(0.0244)
500 meters x post	0.0158	0.0281	0.0333
	(0.0126)	(0.0227)	(0.0216)
Observations	1,183,327	1,143,946	1,142,992
R^2	0.694	0.743	0.751
Specification	DD (by dist.)	DD (by match)	DDD
Base FE	✓	✓	✓
BID x E. Time FE	✓		✓
Match x Dist x E. Time FE		✓	✓

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains alternative difference-in-differences designs of our main specification given in Equation 3. The coefficients correspond to the β_j in Equation 3, and capture the effect of the barrier construction on transacted home value prices. Throughout, the sample includes all built *and* proposed barriers, and their associated transactions. The design compares transactions in the five years after barrier construction with the five years prior. Barriers that were built are "matched" to their closest proposed (but not built) barrier that was at least 1000 meters away. Using these matched barriers, Columns (1) through (3) vary in which control group is used. Column (1) relies on barrier by event time fixed effects, and is our main specification. Thus, the control group are transactions near the same barrier but 500–1500 m away. Column (2) relies on match by distance bin by event time fixed effects. Thus, the control group for, say 0–100 m, are transactions that were 0–100 meters away from the matched proposed barrier. Column (3) relies on both barrier by event time and match by distance bin by event time fixed effects. This is the difference-in-difference-in-differences (DDD) specification. All errors are clustered at the barrier-level.

Table 5: Price effect by expected noise reduction

	(1) Log. Value	(2) Log. Value	(3) Log. Value	(4) Log. Value
100 meters x post	0.0676***	0.0581***	0.0610***	0.0640***
	(0.0139)	(0.0147)	(0.0150)	(0.0160)
$\mathbb{1}(d \leq 100\mathbf{m}) * \mathbf{post} \times (\mathbf{dB}s - 7)$		0.0111	0.0204**	0.0213**
		(0.00727)	(0.00986)	(0.00984)
$\mathbb{1}(d \leq 100\mathbf{m}) * \mathbf{post} \times (\mathbf{dB}s - 7)^2$			-0.00401*	-0.00716*
			(0.00231)	(0.00420)
$\mathbb{1}(d \leq 100\mathbf{m}) * \mathbf{post} \times (\mathbf{dB}s - 7)^3$				0.000523
				(0.000539)
Observations	594,936	588,003	588,003	588,003
R^2	0.677	0.677	0.677	0.677
Main Controls	✓	✓	✓	✓
DBA effects	Const.	Linear	Quad.	Cubic

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains a version of our main specification given in Equation 3 where the effects are allowed to vary with how much noise the barriers reduce. The design compares transactions in the five years after barrier construction with the five years prior, and for properties near to the barrier with those that were between 500–1500 m away. All specifications include barrier by date, and barrier by distance bin fixed effects. Column (1) is our main specification. Column (2) interacts our effect with the number of decibels a barrier was expected to reduce traffic noise. We center the expected noise reducted on 7 decibels - near the average for barriers in our sample. Columns (2) and (3) add in quadratic and cubic terms, respectively. All errors are clustered at the barrier-level.

Table 6: Testing the role of air pollution

	(1) Log. Value	(2) Log. Value	(3) Log. Value	(4) Log. Value	(5) Log. Value
$\mathbb{1}(d \leq 100\mathbf{m}) * \mathbf{post} \times$ **Average Wind (m/s)**	0.0384				
	(0.0544)				
$\mathbb{1}(d \leq 100\mathbf{m}) * \mathbf{post} \times$ **Avg. Sustained Wind (m/s)**		0.0592			
		(0.0592)			
$\mathbb{1}(d \leq 100\mathbf{m}) * \mathbf{post} \times$ **Perpendicular to Barrier (deg.)**			-0.000161		
			(0.000236)		
$\mathbb{1}(d \leq 100\mathbf{m}) * \mathbf{post} \times$ **Perp. to Barrier (shr.)**				0.0408	
				(0.0887)	
$\mathbb{1}(d \leq 100\mathbf{m}) * \mathbf{post} \times$ **Sale in 1997-2003**					0.0315
					(0.0500)
Observations	594,936	594,936	594,936	594,936	594,936
R^2	0.677	0.677	0.677	0.677	0.677
Main Controls	✓	✓	✓	✓	✓

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains a version of our main specification given in Equation 3 where the effects are allowed to vary with measures of wind speed and direction. The design compares transactions in the five years after barrier construction with the five years prior, and for properties near to the barrier with those that were between 500–1500 meters away. All specifications include barrier by date, and barrier by distance bin fixed effects. Wind data is from NCEI (2025) for 45 sensors in Florida in 2024. From this data, we collect daily information on average wind speed, average sustained wind speed, average sustained wind direction, and share of days over the year with the wind blowing in directions of 10-degree bins. For each barrier, we construct a spatial average of the sensors with weights inversely proportional to distance. The interactions of our main effect with each of these wind speed measures is contained in Columns (1) and (2). To assess whether the wind is blowing at the barriers, we calculate the angle θ_1 from the sound barrier to each property. For θ_2 the average wind direction, $\min\{|\theta_1 - \theta_2|, 360 - |\theta_1 - \theta_2|\}$ is a measure of how far the wind is from being perpendicular to the barrier. We interact our main effect with this measure in Column (3). Finally, we calculate the share of days over 2024 in which the wind was blowing in the direction of the barrier from the road, plus or minus 45 degrees. We interact this measure with our main effect in Column (4). In Column (5), we interact our main 0—100 m effect with whether the sale happened in 1997–2003 relative to 1996 or before. In this specification, we separately estimate the effect on sales after 2003. All errors are clustered at the barrier-level.

Table 7: Testing the role of blocking the view of the road

	(1) Log. Value	(2) Log. Value	(3) Log. Value
$\mathbb{1}(d \leq 100\mathbf{m}) * \mathbf{post} \times \mathbf{BID\ Canopy\ \%}$	0.000227		
	(0.000830)		
$\mathbb{1}(d \leq 200\mathbf{m}) * \mathbf{post} \times 100\mathbf{m\ B.\ Area\ (std.)}$		0.00734	
		(0.0113)	
$\mathbb{1}(d \leq 200\mathbf{m}) * \mathbf{post} \times 100\mathbf{m\ Avg.\ \#\ Stories}$			0.0193
			(0.0258)
Observations	594,936	594,936	594,936
R^2	0.677	0.677	0.677
Main Controls	✓	✓	✓

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains a version of our main specification given in Equation 3 where the effects are allowed to vary with a suite of barrier and neighborhood measures. The design compares transactions in the five years after barrier construction with the five years prior, and for properties near to the barrier with those that were between 500–1500 meters away. All specifications include barrier by date, and barrier by distance bin fixed effects. In Column (1), we interact our main 0–100 m effect with tree canopy cover (as a percentage) close to the barrier. To do this, we use the MRLC Consortium (2025) data to calculate land cover at each property. We identify barrier canopy cover as that for the property closest to the barrier. In Columns (2) and (3), we construct measures of the build environment 0–100 m from the barrier that would block the view for properties 100–200 m away. Our first measure calculate the aggregate building square footage 0–100 m from the barrier, normalizes it by the length of the barrier, and then standardizes this measure to have mean zero and standard deviation one. The second measure calculates the average number of stories for buildings 100 m away from the barrier. Columns (2) and (3) interact our 100–200 m effect with these measures of build density nearer to the barrier. All errors are clustered at the barrier-level.

Table 8: Robustness to excluding new developments

	(1) Log. Value	(2) Log. Value	(3) Log. Value	(4) Log. Value
100 meters x post	0.0661***	0.0668***	0.0631***	0.0486***
	(0.0137)	(0.0136)	(0.0131)	(0.0122)
200 meters x post	0.0385***	0.0369***	0.0345**	0.0220*
	(0.0139)	(0.0136)	(0.0135)	(0.0126)
300 meters x post	0.0303**	0.0327***	0.0305**	0.0143
	(0.0128)	(0.0121)	(0.0121)	(0.0106)
400 meters x post	0.0255	0.0265	0.0250	0.000463
	(0.0195)	(0.0192)	(0.0192)	(0.0180)
500 meters x post	0.0106	0.0133	0.0130	0.000145
	(0.0109)	(0.0106)	(0.0106)	(0.0104)
Observations	588,717	577,045	573,234	541,897
R^2	0.678	0.679	0.680	0.679
Main Controls	✓	✓	✓	✓
Built on/before event time?	t=5	t=0	t=-1	t=-6

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains our main specification given in Equation 3 for alternative sample restrictions based on property build year. The coefficients correspond to the β_j in Equation 3, and capture the effect of the barrier construction on transacted home value prices at different distances from the barrier. The design compares transactions in the five years after barrier construction with the five years prior. All specifications include barrier by date, and barrier by distance bin fixed effects. Column (1) contains all transactions for properties built on or before 5 years after the barrier was built. Columns (2) through (4) restrict this further to properties built on or before the year the barrier was built, the year before, and 6 years before the barrier was built, respectively. All errors are clustered at the barrier-level.

Table 9: Aggregate costs of the noise externality

	Noise Costs			
	Total ($1b)	Costs pc per MFI (%)	Costs per Prop. Val. (%)	Cost ($1k) per Capita
Florida	7.92	0.602	0.293	0.378
Q1 (MFI)	1.91	1.083	0.497	0.390
Q4 (MFI)	2.89	0.485	0.243	0.561
Q1 (% Black)	2.23	0.628	0.258	0.529
Q4 (% Black)	1.76	0.784	0.397	0.329
United States	120.71			
U.S. (weighted)	100.39			
U.S. (wgts + het.)	90.59			

Notes: This table contains estimates of the dollar value of the noise externality. We rely on our extrapolation procedure in Equation 3 to produce a dollar cost of noise at every property in Florida. Column (1) contains the aggregate of those costs in billions of 2022 U.S. dollars. Column (2) contains estimates of the cost per capita as a percentage of local median income. Column (3) contains estimates of those costs as a percentage of total assessed property values. Column (4) contains estimates of those costs in thousands of 2022 U.S. dollars per capita. Row (1) performs this analysis for all of Florida. Rows (2) through (5) disaggregate them by neighborhoods in the lower and upper quartiles by local median family incomes and the share of the population that is black, respectively. These measures are at the 2010 census tract level and come from the 2015-2019 American Community Survey. Row (6) extrapolates the cost to the entire U.S. using Florida's population share of the U.S. Row (7) re-weights Florida's census tracts by a propensity score. The resulting re-weighted Florida matches the U.S. in aggregate demographics. Row (8) allows the estimates of the cost of noise to vary by tract income.

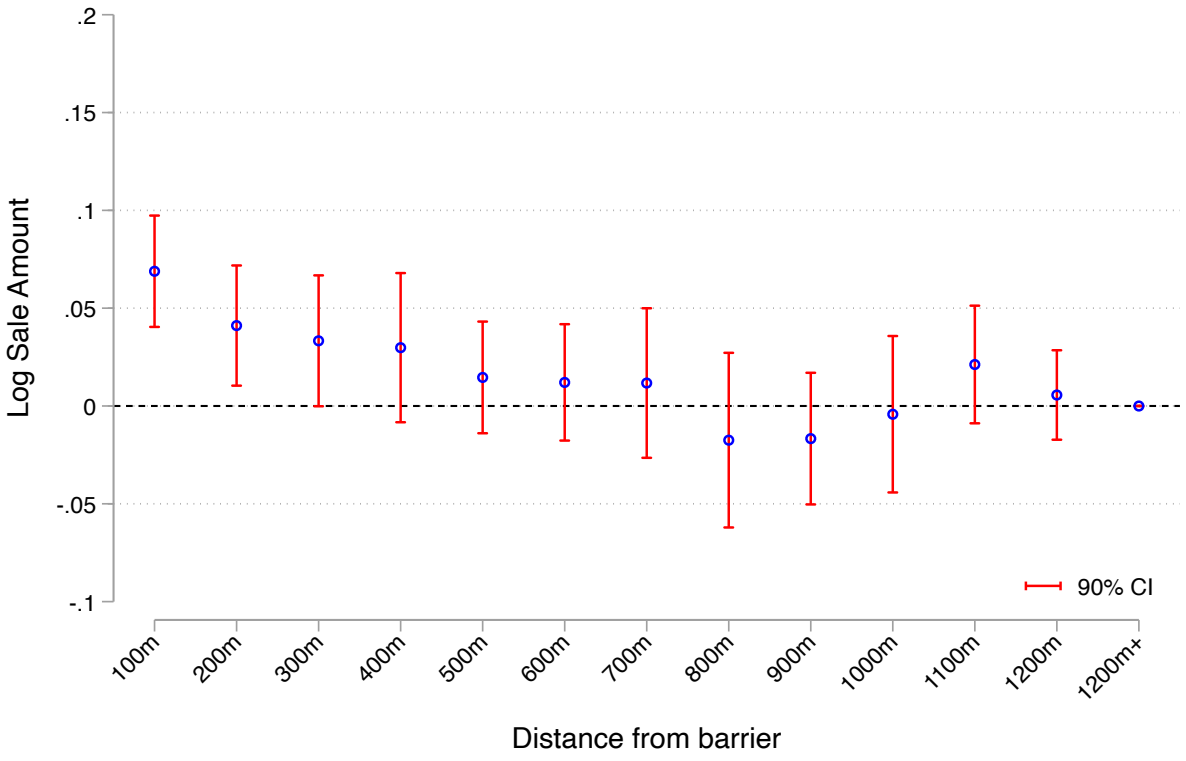
Table 10: Electric vehicle benefits

	100% EV Benefits			
	Total ($1b)	Costs pc per MFI (%)	Costs per Prop. Val. (%)	Cost ($1k) per Capita
Florida	6.23	0.473	0.230	0.298
Q1 (MFI)	1.50	0.846	0.389	0.305
Q4 (MFI)	2.29	0.384	0.192	0.444
Q1 (% Black)	1.76	0.495	0.204	0.418
Q4 (% Black)	1.38	0.613	0.311	0.258
United States	94.96			
U.S. (weighted)	78.96			
U.S. (wgts + het.)	77.92			

Notes: This table contains estimates of the dollar value of 100% diffusion of electric vehicles (EVs). We use 7.1 dBs as the anticipated reduction in sound from EVs. We rely on our extrapolation procedure in Equation 3 to produce a dollar cost of noise at every property in Florida. We use this to calculate an expected benefit from the diffusion of EVs. Column (1) contains the aggregate of those benefits in billions of 2022 U.S. dollars. Column (2) contains estimates of the benefit per capita as a percentage of local median income. Column (3) contains estimates of those benefits as a percentage of total assessed property values. Column (4) contains estimates of those benefits in thousands of 2022 U.S. dollars per capita. Row (1) performs this analysis for all of Florida. Rows (2) through (5) disaggregate them by neighborhoods in the lower and upper quartiles by local median family incomes and the share of the population that is black, respectively. These measures are at the 2010 census tract level and come from the 2015-2019 American Community Survey. Row (6) extrapolates the benefits to the entire U.S. using Florida's population share of the U.S. Row (7) re-weights Florida's census tracts by a propensity score. The resulting re-weighted Florida matches the U.S. in aggregate demographics. Row (8) allows the estimates of the benefits of EVs to vary by tract income.

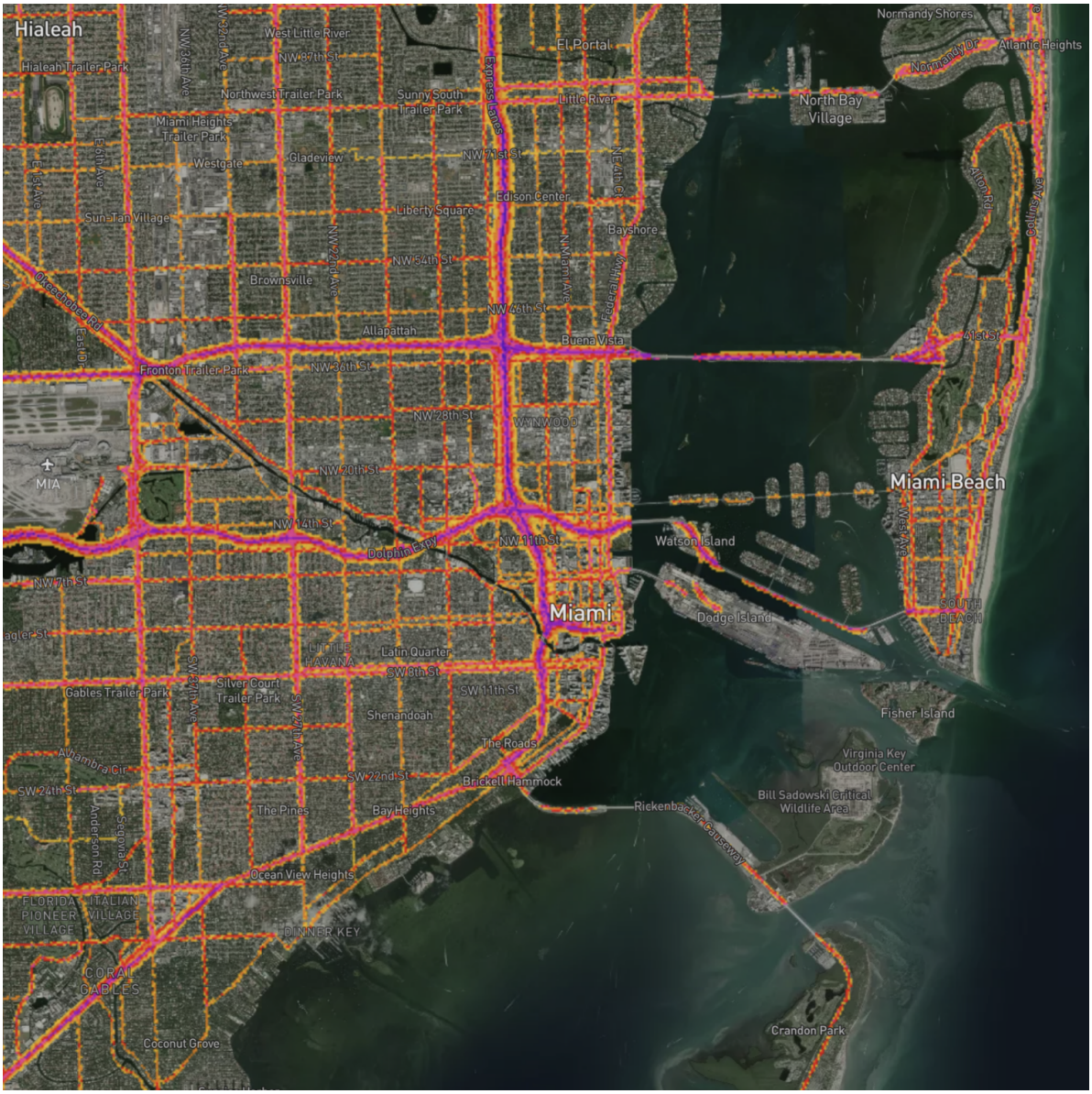
Appendix

Appendix Figure A1: Difference-in-differences estimates by distance



Notes: This figure contains estimates from Equation 3 of the average effect on transacted home prices in 100 meter bins from the noise barrier. Estimates are in blue and standard errors at the 90% level are in red. The difference-in-differences design considers changes in transaction values five years after the barrier was built with five years before and uses transactions that were 1200–1500 m away as the control group. All errors are clustered at the barrier-level.

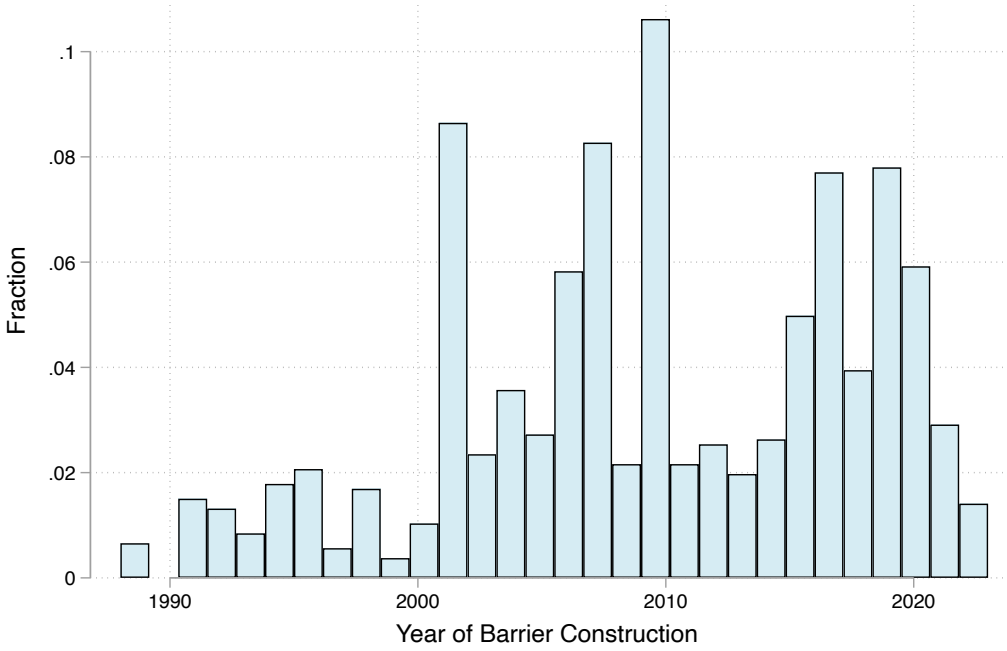
Appendix Figure A2: Road noise in Miami, Florida



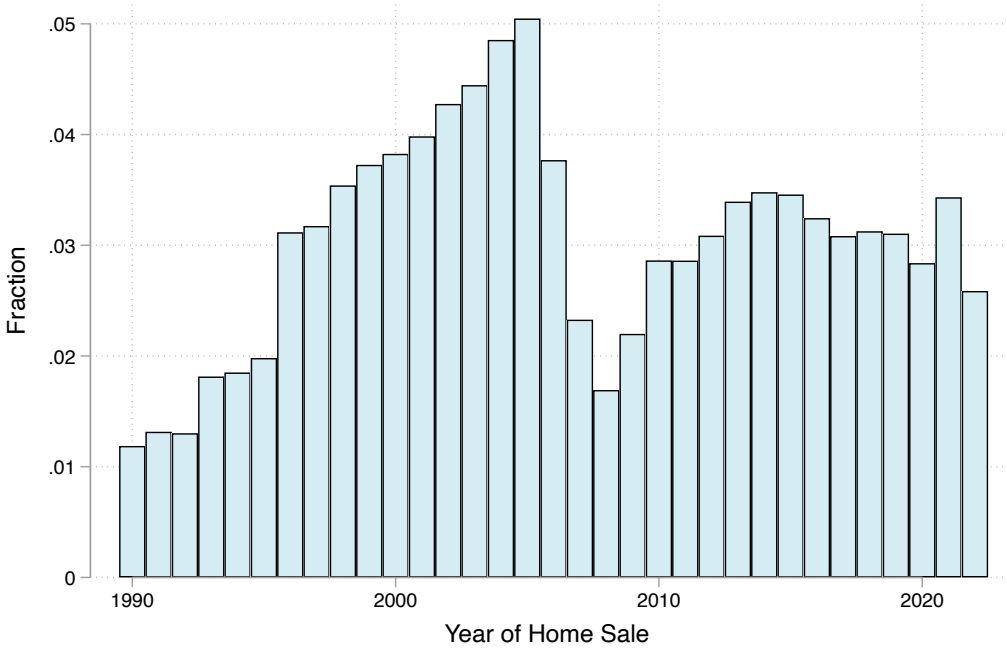
Notes: This map for transportation noise in Miami comes from U.S. Department of Transportation, Bureau of Transportation Statistics (BTS). Darker purple areas have higher levels of road noise.

Appendix Figure A3: Distribution of Barrier Construction Years and Transaction Years

Panel A: Barriers

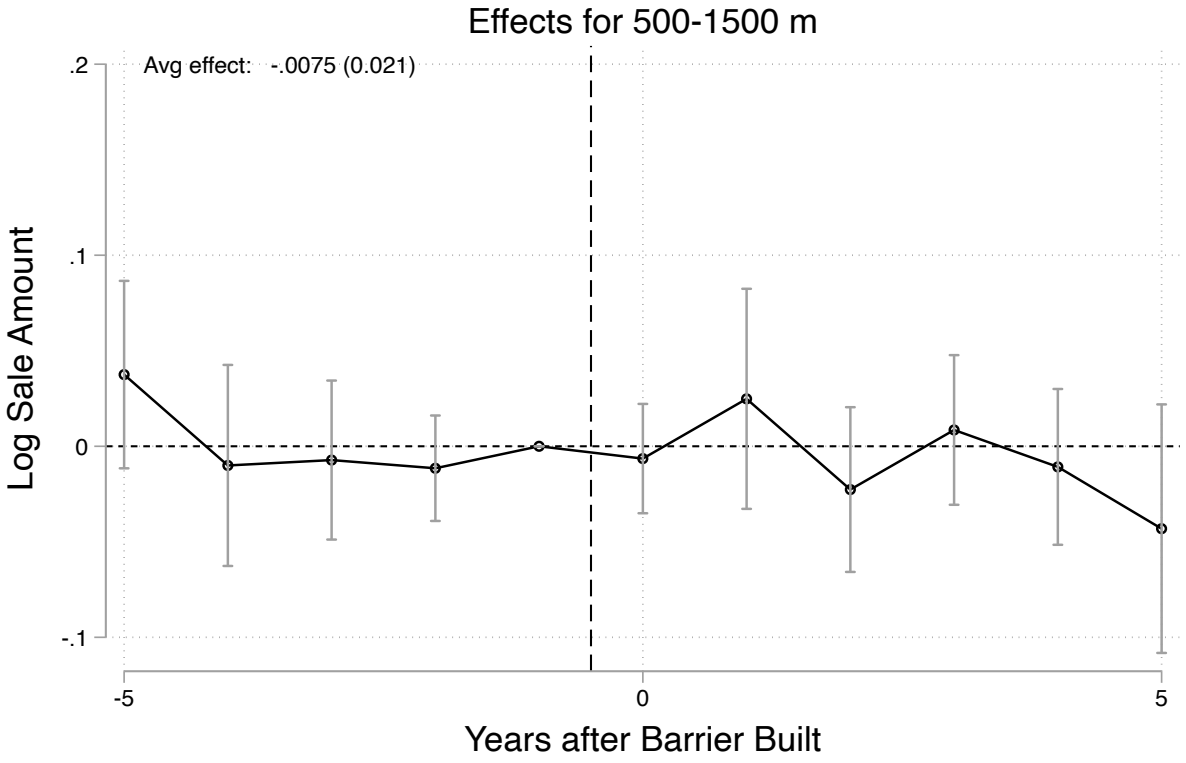


Panel B: Transactions



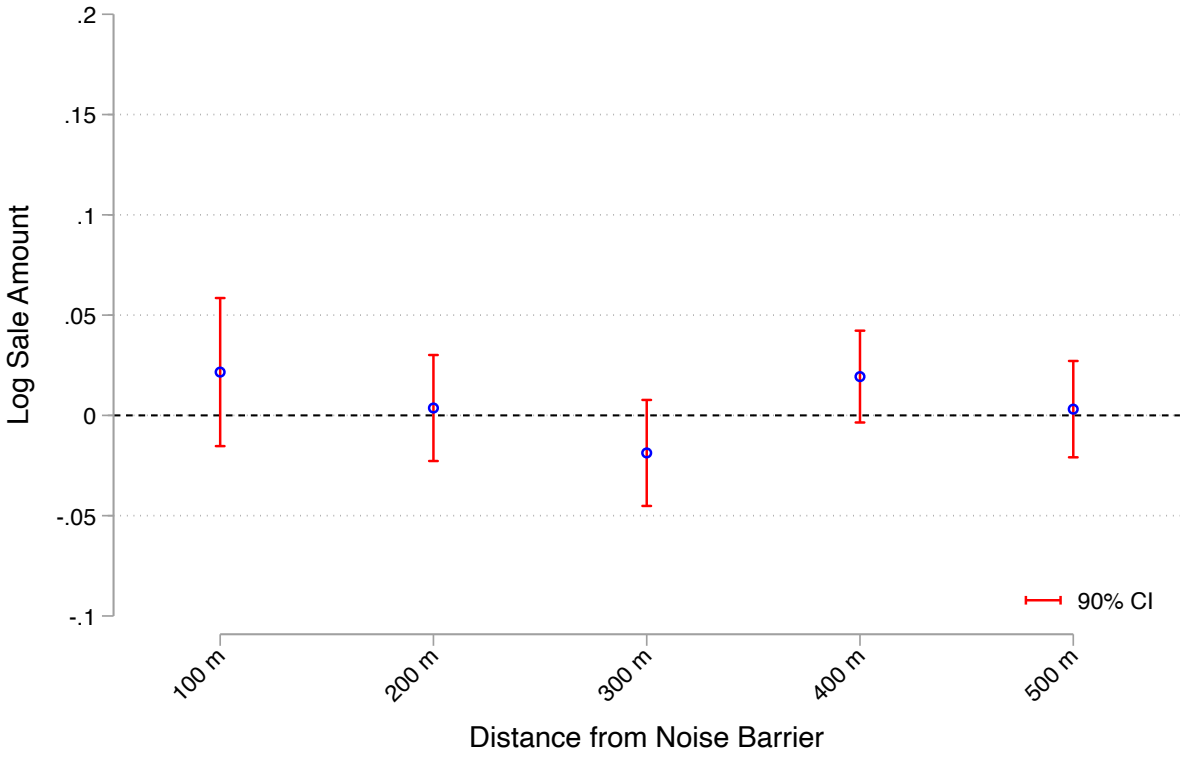
Notes: These figures plot the distribution of barrier and home sale years for our sample. Panel A is the histogram of barrier built years. Panel B is the histogram of transaction years.

Appendix Figure A4: Event study effects for 500–1500 m from the noise barrier



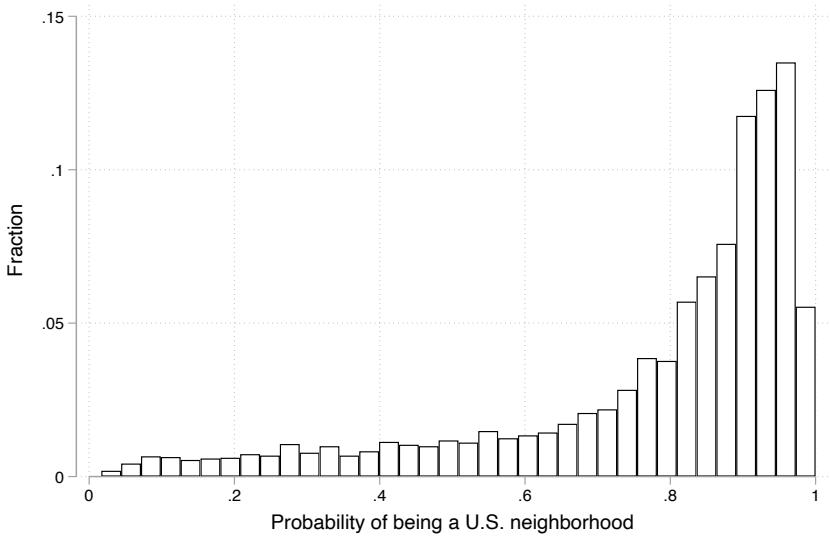
Notes: This figure plots event study estimates of the effect of the barrier on transacted home value prices 500–1500 m away from the barrier. To do this, we use transactions 500–1500 m way from barriers that have yet to be constructed as the control group. This design is subject to concerns over two-way fixed effects models with variation in treatment timing. Thus, we use the estimator of de Chaisemartin and D'Haultfœuille (2024) to address these concerns. The specification includes barrier, event time, and year fixed effects. Each coefficient corresponds to the effect of the barrier on transacted home values in the years before and after the barrier was built, relative to the year prior to barrier construction. The average effect over the 5-year window was −0.0075. Coefficients are plotted with their 90% confidence interval. All errors are clustered at the barrier-level.

Appendix Figure A5: Placebo estimates using proposed barriers

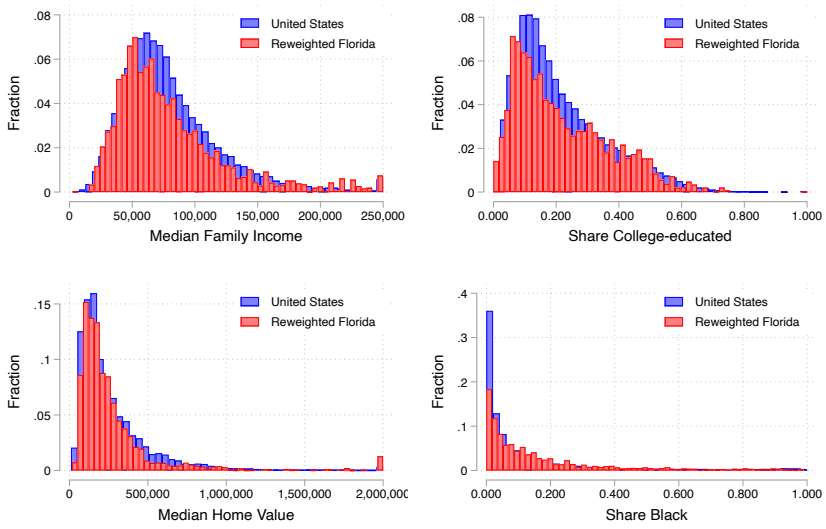


Notes: This figures contains estimates from Equation 3 of the effect on transacted home prices for proposed (but not built) barriers within 100 meter bins of the proposed barrier. Estimates are in blue and standard errors at the 90% level are in red. Figures are shown for 0–100, 100–200, 200–300, 300–400, and 400–500 m from the barrier. As in Table 4, we match proposed barriers to their nearest constructed barrier that was at least 1000 m away. The difference-in-differences design considers changes in transaction values five years after the matched barrier was built with five years before and uses transactions that were 500–1500 m away as the control group. All errors are clustered at the barrier-level.

Appendix Figure A6: Propensity scores for Florida neighborhoods



(a) Florida census tract propensity scores



(b) Re-weighted distribution of demographics

Notes: This figures contains estimates of a propensity score model that estimates the probability a 2010 census tract in Florida is a 2010 cenus tract in the U.S. at large, given its demographics. The propensity score model includes population, Gini coefficient, median household and family incomes, shares of the population by race and education, home value quartiles, average contract rents, and housing unit counts. Panel (a) shows the estimated propensity scores for each Florida census tract. Panel (b) shows the distribution of median family income, college educated share, median home values, and share of the population that is black for the U.S. at large and for a reweighted version of Florida using the estimated propensity scores. We trim the inverse propensity scores at the bottom and top 1%. All data is from the 2015–2019 American Community Survey.

Appendix Table A1: Sound barrier summary statistics

Summary Statistics					
	Constructed		*Recommended*		*Diff.*
Barrier Attribute	mean	s.d.	mean	s.d.	p-val
Year Built	2009	8			
Length (m)	496	456	499	519	0.90
Height (m)	4.46	1.59	4.50	1.62	0.63
Cost ($1k)	741	846	799	1,007	0.23
Decibels	7.15	2.02	7.28	1.10	0.18
Home Val. ($1k)	240	115	230	110	0.11
MFI ($1k)	70	29	73	30	0.02
Poverty Shr	0.15	0.09	0.14	0.11	0.12
College Shr	0.22	0.11	0.23	0.12	0.01
White Shr	0.66	0.24	0.69	0.20	0.06
N	1143		497		

Notes: This table contains summary statistics for all noise barriers. The first two columns contain summary statistics for constructed barriers. The second two columns contain summary statistics for recommended barriers, which we make use of in various alternative specifications and robustness exercises. Columns (1) and (3) contain averages. Columns (2) and (4) contain standard deviations. Column (5) contains the p-value on the difference between columns (1) and (3). Rows (1) through (5) contain the year built, the length, the height, the cost, and the expected noise reduction, respectively. Rows (6) through (10) contain median home values, median family income, poverty rates, college-educated share, and white population shares for the 2010 census tracts of the barriers. This data comes from the 2015–2019 American Community Survey. The last row contains counts of the total number of barriers.

Appendix Table A2: Property and transactions summary statistics

Summary Statistics					
	Full Sample	*0-100m*	*400-500m*	*900-1000m*	*1400-1500m*
Sale Characteristics	mean	mean	mean	mean	mean
Year of Sale	2007	2008	2007	2007	2007
Year Built	1980	1983	1978	1978	1980
Price ($1k, 2022)	298	320	280	321	306
Area (sq ft)	1,868	1,763	1,844	1,918	1,917
SFR	0.72	0.71	0.75	0.76	0.66
Condo	0.26	0.26	0.23	0.21	0.30
Duplex	0.01	0.02	0.01	0.02	0.02
Apt.	0.01	0.01	0.01	0.02	0.03
Cash	0.35	0.35	0.34	0.33	0.35
New	0.09	0.10	0.07	0.07	0.11
N	596,419	48,166	41,761	34,390	31,427

Notes: This table contains summary statistics for all transactions in our sample. Each column contains averages of different property and transaction characteristics. The first column contains these estimates for the entire sample. Columns (2) through (5) consider averages for 0–100, 400–500, 900–1000, and 1400–1500 m from the barrier, respectively. Rows (1) through (4) contains the year of the transaction, the year the property was built, the price in 2022 U.S. Dollars, and the building area in square feet. Rows (5) through (8) contain the share of properties that were single family residences, condominiums, duplexes, or apartments. Rows (9) and (10) contain shares of transactions that were bought with cash, and the share of properties that were newly built. Row (11) contains total counts of transactions in each distance bin.

Appendix Table A3: Noise and neighborhoods, unadjusted

	dB > 50	*[46,50]*	*dB < 46*
Florida			
Median Fam. Income ($1k)	64	72	79
College Educated (%)	21	23	23
Poverty (%)	17	14	11
Black (%)	23	17	10
Median Home Val. ($1k)	239	251	260
Urban (%)	99	98	80
Density (#/sq. km)	3,212	1,902	930
Any Exp. to >90 dB (%)	26	10	7
N	537	2124	2090
United States			
Median Fam. Income ($1k)	80	86	85
College Educated (%)	23	24	21
Poverty (%)	18	13	11
Black (%)	20	15	9
Urban (%)	99	96	52
Median Home Val. ($1k)	368	312	247
Density (#/sq. km)	5,272	2,479	589
Any Exp. to >90 dB (%)	31	17	20
N	11,644	33,020	34,336

Notes: This table contains summary statistics for neighborhoods across the U.S. by noise exposure. We use (Seto and Huang, 2023)'s publicly available dataset contain estimates of the share of a 2020 census tract's population exposed to different 10-decibel bins of noise (rail, aviation, or car). We use these shares to extrapolate an average noise exposure for each tract. We then bin tracts into three groups: high exposure (greater than 50 dB of average exposure), medium (between 46 and 50 dB of average exposure), and low (less than 46 dB of average exposure). We then calculate average neighborhood characteristics for each of these three groups. We use 2016-2020 American Community Survey data and 2020 census tract boundaries to do so. Unlike Table 1, here, we do not residualize each characteristic on county fixed effects. Row (1) contains the share of the population exposed to any noise. Row (2) contains the share of the population exposed to extreme noise (greater than 90 dB). Row (3) through (9) contain averages for median home values, median family income, the poverty rate, the percentage of the population that is black, the percentage of the population that is college educated, the percentage of the population that lives in an urban area, and the density as measured by persons per square kilometer. The area of 2020 census tracts was calculated directly from the 2020 U.S. Census TIGER/Line Shapefiles. The final row contains the number of census tracts in each group.

Appendix Table A4: Effect of barrier construction on property characteristics

	(1) Bedrooms	(2) Stories	(3) Pool (0/1)	(4) Central AC (0/1)	(5) Fin. Garage (0/1)
100 meters x post	-0.0105	-0.00873	0.00527	-0.00382	0.00134
	(0.0204)	(0.00835)	(0.00520)	(0.00290)	(0.00470)
200 meters x post	-0.0236	-0.0184	0.00329	-0.000875	0.00524
	(0.0171)	(0.0129)	(0.00405)	(0.00256)	(0.00421)
300 meters x post	-0.0104	0.00315	0.0120**	0.000471	0.00275
	(0.0166)	(0.00737)	(0.00493)	(0.00265)	(0.00428)
400 meters x post	-0.0283	-0.000326	0.000247	-0.00651	0.00143
	(0.0217)	(0.00893)	(0.00502)	(0.00470)	(0.00520)
500 meters x post	0.00518	-0.000496	0.00859	-0.00235	-0.000290
	(0.0154)	(0.00653)	(0.00531)	(0.00316)	(0.00422)
Observations	594,936	594,936	594,936	594,936	594,936
R^2	0.550	0.718	0.467	0.907	0.792
Outcome Mean	2.84	1.23	0.18	0.30	0.22
Barrier x Dist FE	✓	✓	✓	✓	✓
Barrier x E. Time FE	✓	✓	✓	✓	✓
Built Yr x Yr FE	✓	✓	✓	✓	✓
Noise x Yr FE	✓	✓	✓	✓	✓

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains estimates of Equation 3 using 500–1500 m as the control group. Outcomes are given in the column headers, and contain property characteristics. Thus, the table assesses whether the construction of the barrier induces any change in the types of properties that are sold at various distances from the barrier. Columns (1) through (5) consider whether there is a change in the number of bedrooms, the number of stories, whether the property has a pool, a central AC, or a finished garage, respectively. All specifications include our main set of fixed effects and controls. All errors are clustered at the barrier-level.

Appendix Table A5: Effect of barrier construction on transaction type

	(1) Investor (0/1)	(2) Resale (0/1)	(3) New Bldg (0/1)	(4) Cash (0/1)	(5) Mortg. (0/1)	(6) Forecl. (0/1)
100 meters x post	-0.000361	-0.0108	0.0107	-0.00494	-0.00209	-0.00253
	(0.00233)	(0.00769)	(0.00769)	(0.00737)	(0.00748)	(0.00685)
200 meters x post	-0.000176	-0.00375	0.00377	0.00345	-0.00911	0.00448
	(0.00216)	(0.00656)	(0.00656)	(0.00753)	(0.00780)	(0.00669)
300 meters x post	-0.00458*	-0.00951**	0.00973**	-0.000259	-0.00256	-0.00139
	(0.00239)	(0.00432)	(0.00432)	(0.00778)	(0.00788)	(0.00694)
400 meters x post	-0.00167	-0.00827	0.00836*	0.00630	-0.00851	-0.00483
	(0.00249)	(0.00506)	(0.00506)	(0.00942)	(0.00954)	(0.00716)
500 meters x post	-0.00102	-0.00751*	0.00748*	-0.0157*	0.0128	-0.000159
	(0.00223)	(0.00418)	(0.00418)	(0.00905)	(0.00891)	(0.00621)
Observations	594,936	594,936	594,936	594,936	594,936	594,936
R^2	0.103	0.669	0.669	0.372	0.328	0.315
Outcome Mean	0.02	0.91	0.09	0.35	0.62	0.14
Barrier x Dist FE	✓	✓	✓	✓	✓	✓
Barrier x E. Time FE	✓	✓	✓	✓	✓	✓
Built Yr x Yr FE	✓	✓	✓	✓	✓	✓
Noise x Yr FE	✓	✓	✓	✓	✓	✓

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains estimates of Equation 3 using 500–1500 m as the control group. Outcomes are given in the column headers, and contain transaction characteristics. Thus, the table assesses whether the construction of the barrier induces any change in the types of transactions that occur at various distances from the barrier. Columns (1) through (5) consider whether there is a change in whether the transaction was an investor purchase, a resale, a new building, a cash purchase, a mortgage purchase, or a foreclosure purchase, respectively. All specifications include our main set of fixed effects and controls. All errors are clustered at the barrier-level.

Appendix Table A6: Effect of barrier construction on residence type

	(1) SFR (0/1)	(2) Condo (0/1)	(3) Duplex (0/1)	(4) Apt. (0/1)
100 meters x post	0.00720	-0.00477	-0.000745	-0.00168
	(0.00670)	(0.00619)	(0.00231)	(0.00195)
200 meters x post	-0.00723	0.00522	0.000965	0.00105
	(0.00763)	(0.00730)	(0.00182)	(0.00182)
300 meters x post	-0.00252	0.00238	-0.000307	0.000453
	(0.00503)	(0.00446)	(0.00186)	(0.00184)
400 meters x post	-0.00419	0.00103	0.00414**	-0.000976
	(0.00680)	(0.00624)	(0.00195)	(0.00176)
500 meters x post	-9.95e-05	-0.00386	0.00467**	-0.000706
	(0.00491)	(0.00417)	(0.00208)	(0.00169)
Observations	594,936	594,936	594,936	594,936
R^2	0.796	0.841	0.490	0.297
Outcome Mean	0.72	0.26	0.01	0.01
Barrier x Dist FE	✓	✓	✓	✓
Barrier x E. Time FE	✓	✓	✓	✓
Built Yr x Yr FE	✓	✓	✓	✓
Noise x Yr FE	✓	✓	✓	✓

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains estimates of Equation 3 using 500–1500 m as the control group. Outcomes are given in the column headers, and contain residence characteristics. Thus, the table assesses whether the construction of the barrier induces any change in the types of residences sold at various distances from the barrier. Columns (1) through (5) consider whether there is a change in whether the property is a single family residence, a condominium, a duplex, or an apartment, respectively. All specifications include our main set of fixed effects and controls. All errors are clustered at the barrier-level.

Appendix Table A7: Sensitivity of difference-in-differences estimates to fixed effects

	(1) Log. Value	(2) Log. Value	(3) Log. Value
100 meters x post	0.0688***	0.0634***	0.0689***
	(0.0236)	(0.0174)	(0.0173)
200 meters x post	0.0451*	0.0404**	0.0411**
	(0.0243)	(0.0187)	(0.0187)
300 meters x post	0.0262	0.0332	0.0333
	(0.0240)	(0.0203)	(0.0203)
400 meters x post	0.0318	0.0297	0.0298
	(0.0272)	(0.0232)	(0.0232)
500 meters x post	0.0253	0.0145	0.0146
	(0.0205)	(0.0173)	(0.0173)
600 meters x post	0.0200	0.0119	0.0121
	(0.0208)	(0.0181)	(0.0181)
700 meters x post	0.0255	0.0115	0.0117
	(0.0287)	(0.0232)	(0.0232)
800 meters x post	-0.0110	-0.0175	-0.0175
	(0.0340)	(0.0271)	(0.0271)
900 meters x post	-0.0109	-0.0167	-0.0167
	(0.0220)	(0.0204)	(0.0204)
1000 meters x post	0.0144	-0.00411	-0.00421
	(0.0283)	(0.0243)	(0.0243)
1100 meters x post	0.0226	0.0212	0.0212
	(0.0207)	(0.0183)	(0.0183)
1200 meters x post	0.000178	0.00574	0.00562
	(0.0169)	(0.0139)	(0.0139)
Observations	595,124	594,936	594,936
R^2	0.629	0.677	0.677
BID x Dist FE	✓	✓	✓
BID x E. Time FE	✓	✓	✓
Bldg Cov x Yr FE		✓	✓
Noise x Yr FE			✓

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains estimates of Equation 3 using 1200–1500 meters as the control group and varying the fixed effects and controls used. All specifications include barrier by distance bin and barrier by event time fixed effects. Column (1) contains only this core set of fixed effects. Column (2) adds in trends in building characteristics. Column (3) adds in trends in baseline noise level, and is our main specification. All errors are clustered at the barrier-level.

Appendix Table A8: Main estimate by sample restrictions

	(1) Log. Value	(2) Log. Value	(3) Log. Value	(4) Log. Value	(5) Log. Value
100 meters x post	0.0759***	0.0743***	0.0737***	0.0751***	0.0676***
	(0.0273)	(0.0274)	(0.0156)	(0.0157)	(0.0139)
200 meters x post	0.0716***	0.0741***	0.0490***	0.0526***	0.0399***
	(0.0228)	(0.0228)	(0.0163)	(0.0163)	(0.0141)
300 meters x post	0.0253	0.0275	0.0224	0.0240	0.0319**
	(0.0220)	(0.0221)	(0.0156)	(0.0157)	(0.0131)
400 meters x post	0.0373	0.0363	0.0249	0.0176	0.0285
	(0.0300)	(0.0305)	(0.0191)	(0.0197)	(0.0196)
500 meters x post	0.0197	0.0196	0.00239	0.00456	0.0132
	(0.0193)	(0.0194)	(0.0122)	(0.0120)	(0.0111)
Observations	699,902	688,904	669,709	642,243	594,936
R^2	0.447	0.448	0.619	0.655	0.677
Small bldgs	No	Yes	Yes	Yes	Yes
No outliers	No	No	Yes	Yes	Yes
Arm's length	No	No	No	Yes	Yes
Residential	No	No	No	No	Yes
Main controls	✓	✓	✓	✓	✓

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains estimates of Equation 3 using 500–1500 m as the control group under different sample restrictions. All specifications include our main set of fixed effects and controls. Column (1) contains no additional sample restrictions. Column (2) eliminates buildings that are greater than 4 stories high or more than 2 units. Column (3) eliminates transactions that are less than $1,000 or more than $7,500,000 dollars. Column (4) keeps on arm's length transactions. Column (5) keeps only single family residences, condominiums, duplexes, or apartments. Column (5) is our main sample and specification. All errors are clustered at the barrier-level.

Appendix Table A9: Robustness to different time horizons

	(1) Log. Value	(2) Log. Value	(3) Log. Value	(4) Log. Value
100 meters x post	0.0676***	0.0603***	0.0684***	0.0674***
	(0.0139)	(0.0133)	(0.0136)	(0.0143)
200 meters x post	0.0399***	0.0347***	0.0403***	0.0396***
	(0.0141)	(0.0134)	(0.0141)	(0.0146)
300 meters x post	0.0319**	0.0302**	0.0327**	0.0306**
	(0.0131)	(0.0123)	(0.0128)	(0.0134)
400 meters x post	0.0285	0.0265	0.0282	0.0275
	(0.0196)	(0.0177)	(0.0194)	(0.0200)
500 meters x post	0.0132	0.0158	0.0162	0.0133
	(0.0111)	(0.0107)	(0.0109)	(0.0113)
Observations	594,936	332,028	492,594	690,711
R^2	0.677	0.678	0.678	0.669
Main Controls	✓	✓	✓	✓
Time window for sales	-10 to 10	-5 to 5	-8 to 8	-12 to 12

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains estimates of Equation 3 using 500–1500 m as the control group under different time horizon restrictions. All specifications include our main set of fixed effects and controls. Column (1) limits our sample to transactions that occurred 10 years prior to 10 years after the barrier was constructed and is our main sample and specification. Column (2) limits our sample to transactions within five years of barrier construction. Column (3) extends the window to eight years around the barrier construction. Column (4) further extends the window to 12 years around the barrier construction. All errors are clustered at the barrier-level.

Appendix Table A10: Robustness to different definitions of distance groups

	(1) Log. Value	(2) Log. Value	(3) Log. Value	(4) Log. Value
100 meters x post	0.0676***	0.0459***	0.0637***	0.0664***
	(0.0139)	(0.0152)	(0.0155)	(0.0146)
200 meters x post	0.0399***	0.0239*	0.0364***	0.0367***
	(0.0141)	(0.0144)	(0.0138)	(0.0141)
300 meters x post	0.0319**	0.0187*	0.0291***	0.0280**
	(0.0131)	(0.0109)	(0.0106)	(0.0114)
400 meters x post	0.0285	0.00648	0.0188	0.0243
	(0.0196)	(0.0186)	(0.0180)	(0.0190)
500 meters x post	0.0132	0.00545	0.0133	0.0124
	(0.0111)	(0.0120)	(0.0112)	(0.0109)
Observations	594,936	356,580	426,386	495,117
R^2	0.677	0.694	0.688	0.683
Main Controls	✓	✓	✓	✓
Sales within distance	$\leq$ 1500m	$\leq$ 800m	$\leq$ 1000m	$\leq$ 1200m

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains estimates of Equation 3 using 500–1500 m as the control group under different distance restrictions for the control group. All specifications include our main set of fixed effects and controls. Column (1) limits our sample to transactions that occurred within 1500 m of the barriers and is our main sample and specification. Column (2) limits our sample to transactions within 800 m of the barrier. Column (3) limits our sample to 1000 m from the barrier. Column (4) limits our sample to 1200 m from the barrier. All errors are clustered at the barrier-level.

Appendix Table A11: Small outliers sensitivity

	(1) Log. Value	(2) Log. Value	(3) Log. Value	(4) Log. Value
100 meters x post	0.0676***	0.0608***	0.0586***	0.0575***
	(0.0139)	(0.0126)	(0.0122)	(0.0118)
200 meters x post	0.0399***	0.0372***	0.0357***	0.0369***
	(0.0141)	(0.0131)	(0.0129)	(0.0128)
300 meters x post	0.0319**	0.0297**	0.0249**	0.0281**
	(0.0131)	(0.0127)	(0.0123)	(0.0114)
400 meters x post	0.0285	0.0265	0.0266	0.0291
	(0.0196)	(0.0189)	(0.0186)	(0.0181)
500 meters x post	0.0132	0.00559	0.00757	0.00676
	(0.0111)	(0.0102)	(0.00995)	(0.00941)
Observations	594,936	591,606	589,302	583,305
R^2	0.677	0.735	0.751	0.769
Main Controls	✓	✓	✓	✓
Value > Cutoff	$1k	$5k	$10k	$20k

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains estimates of Equation 3 using 500–1500 m as the control group under different restrictions on outliers. All specifications include our main set of fixed effects and controls. Column (1) does not include transactions below $1,000 and is our main sample and specification. Column (2) excludes transactions below $5,000. Column (3) excludes transactions below $10,000. Column (4) excludes transactions below $20,000. All errors are clustered at the barrier-level.

Appendix Table A12: Large outliers sensitivity

	(1) Log. Value	(2) Log. Value	(3) Log. Value	(4) Log. Value
100 meters x post	0.0676***	0.0604***	0.0416***	0.0387***
	(0.0139)	(0.0133)	(0.0112)	(0.0109)
200 meters x post	0.0399***	0.0299**	0.0144	0.0159
	(0.0141)	(0.0129)	(0.0106)	(0.0105)
300 meters x post	0.0319**	0.0253**	0.0142	0.0158
	(0.0131)	(0.0123)	(0.0107)	(0.0100)
400 meters x post	0.0285	0.0156	0.0118	0.00188
	(0.0196)	(0.0178)	(0.0121)	(0.0108)
500 meters x post	0.0132	0.00938	0.00125	0.00183
	(0.0111)	(0.0107)	(0.0103)	(0.0108)
Observations	594,936	592,541	589,921	581,004
R^2	0.677	0.678	0.684	0.684
Main Controls	✓	✓	✓	✓
Value<	$7.5m	$5m	$2.5m	$1m

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains estimates of Equation 3 using 500–1500 m as the control group under different restrictions on outliers. All specifications include our main set of fixed effects and controls. Column (1) does not include transactions above $7.5m and is our main sample and specification. Column (2) excludes transactions above $5m. Column (3) excludes transactions above $2.5m. Column (4) excludes transactions above $1m. All errors are clustered at the barrier-level.

Appendix Table A13: PPML estimation

	(1) Value	(2) Value	(3) Value	(4) Value	(5) Value	(6) Value
100 meters x post	0.0912***	0.0929***	0.103***	0.0932***	0.123***	0.114***
	(0.0177)	(0.0188)	(0.0221)	(0.0249)	(0.0257)	(0.0270)
200 meters x post	0.0698***	0.0777***	0.0822***	0.0849***	0.117***	0.114***
	(0.0179)	(0.0201)	(0.0227)	(0.0252)	(0.0249)	(0.0265)
300 meters x post	0.0524***	0.0489**	0.0544**	0.0510**	0.0721***	0.0613**
	(0.0174)	(0.0201)	(0.0227)	(0.0256)	(0.0228)	(0.0244)
400 meters x post	0.0736***	0.0490***	0.0786**	0.0506**	0.0790***	0.0581**
	(0.0261)	(0.0186)	(0.0316)	(0.0225)	(0.0304)	(0.0228)
500 meters x post	0.0388***	0.0470***	0.0465***	0.0482***	0.0545***	0.0577***
	(0.0135)	(0.0164)	(0.0160)	(0.0179)	(0.0166)	(0.0188)
Observations	594,936	474,033	1,093,205	933,301	1,093,205	933,301
Not Built BIDs			✓	✓	✓	✓
Main FE	✓	✓	✓	✓	✓	✓
Parcel FE		✓		✓		✓
Dist x Yr FE					✓	✓

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains estimates of Equation 3 using 500–1500 m as the control group and estimating the model via Poisson Pseudo Maximum Likelihood (PPML). The table recreates estimates from **??** using the PPML estimator. All specifications include barrier by date, and barrier by distance bin fixed effects. Columns (2), (4), and (6) include parcel (the tax unit for a property) fixed effects, and consequently, rely on repeat-sales. Columns (3) through (6) add barriers that were proposed for construction, but have yet to be built, to the sample. Columns (5) and (6) add distance from the barrier by year fixed effects. All errors are clustered at the barrier-level.

Appendix Table A14: Pooling 0 - 200 m effects in expected noise reduction

	(1) Log. Value	(2) Log. Value	(3) Log. Value	(4) Log. Value
200 meters x post	0.0513***	0.0433***	0.0476***	0.0536***
	(0.0126)	(0.0131)	(0.0136)	(0.0149)
$\mathbb{1}(d \leq 200\mathbf{m}) * \mathbf{post} \times (\mathbf{dB}s - 7)$		0.00995	0.0262**	0.0275**
		(0.00823)	(0.0108)	(0.0107)
$\mathbb{1}(d \leq 200\mathbf{m}) * \mathbf{post} \times (\mathbf{dB}s - 7)^2$			-0.00660***	-0.0131***
			(0.00249)	(0.00411)
$\mathbb{1}(d \leq 200\mathbf{m}) * \mathbf{post} \times (\mathbf{dB}s - 7)^3$				0.00120**
				(0.000553)
Observations	594,936	588,003	588,003	588,003
R^2	0.677	0.677	0.677	0.677
Main Controls	✓	✓	✓	✓
DBA effects	Const.	Linear	Quad.	Cubic

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains a version of our main specification given in Equation 3 where the effects are allowed to vary with how much noise the barriers reduce. The design compares transactions in the five years after barrier construction with the five years prior, and for properties near to the barrier with those that were between 500–1500 m away. All specifications include barrier by date, and barrier by distance bin fixed effects. Unlike the version of this table in the main text, we have pooled 0–100 m with 100–200 m. Column (1) is the baseline specification. Column (2) interacts our effect with the number of decibels a barrier was expected to reduce traffic noise. We center the expected noise reduction on 7 decibels - near the average for barriers in our sample. Columns (2) and (3) add in quadratic and cubic terms, respectively. All errors are clustered at the barrier-level.

Appendix Table A15: Intensity of treatment under alternative controls

	(1) Log. Value	(2) Log. Value	(3) Log. Value
100 meters x post	0.0610***	0.0825***	0.103***
	(0.0150)	(0.0230)	(0.0268)
$\mathbb{1}(d \leq 100\mathbf{m}) * \mathbf{post} \times (\mathbf{dB}s - 7)$	0.0204**	0.0430**	0.0420**
	(0.00986)	(0.0183)	(0.0185)
$\mathbb{1}(d \leq 100\mathbf{m}) * \mathbf{post} \times (\mathbf{dB}s - 7)^2$	-0.00401*	-0.0110***	-0.0106**
	(0.00231)	(0.00418)	(0.00416)
Observations	588,003	468,708	898,648
R^2	0.677	0.806	0.789
Main Controls	✓	✓	✓
Parcel FE		✓	✓
Proposed barriers?			✓
Dist x Yr FE			✓

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains a version of our main specification given in Equation 3 where the effects are allowed to vary quadratically with how much noise the barriers reduce. The design compares transactions in the five years after barrier construction with the five years prior, and for properties near to the barrier with those that were between 500–1500 m away. All specifications include barrier by date, and barrier by distance bin fixed effects. Column (1) is the baseline specification. Column (2) adds in parcel fixed effects. Column (3) adds in proposed barriers and distance bin by year fixed effects. All errors are clustered at the barrier-level.

Appendix Table A16: Heterogeneity in Price Effects by Noise Level

	(1) Log. Value	(2) Log. Value	(3) Log. Value	(4) Log. Value
100 meters x post	0.0676***	0.0732***	0.0687***	0.0731***
	(0.0139)	(0.0182)	(0.0221)	(0.0258)
T*post × No Noise		0.00175	0.00236	-0.0105
		(0.0204)	(0.0232)	(0.0260)
T*post × (Noise − 45dB)		-0.00123	0.000971	0.00306
		(0.00146)	(0.00379)	(0.00761)
T*post × (Noise − 45dB)^2			-0.000122	-0.000428
			(0.000133)	(0.000614)
T*post × (Noise − 45dB)^3				7.52e-06
				(1.33e-05)
Observations	594,936	594,936	594,936	594,936
R^2	0.677	0.677	0.677	0.677
Main Controls	✓	✓	✓	✓
Noise effects	Const.	Linear	Quad.	Cubic

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains a version of our main specification given in Equation 3 where the effects are allowed to vary with the baseline noise exposure. The design compares transactions in the five years after barrier construction with the five years prior, and for properties near to the barrier with those that were between 500–1500 m away. All specifications include barrier by date, and barrier by distance bin fixed effects. Column (1) is the main specification. Columns (2) through (4) add in linear, quadratic, and cubic terms in noise exposure from the 2020 Transportation Noise Map (U.S. Department of Transportation, Bureau of Transportation Statistics , BTS). All errors are clustered at the barrier-level.

Appendix Table A17: Heterogeneity in price effects by neighborhood demographics

	(1) Log. Value	(2) Log. Value	(3) Log. Value	(4) Log. Value	(5) Log. Value
T*post × Log Home Val.	-0.0678***				
	(0.0260)				
T*post × Log MFI		-0.0839***			
		(0.0312)			
T*post × Pov. Shr			0.404***		
			(0.132)		
T*post × College Shr				-0.159	
				(0.117)	
T*post × White Shr					-0.0667
					(0.0573)
Observations	592,016	594,914	594,936	594,936	594,936
R^2	0.677	0.677	0.677	0.677	0.677
Main Controls	✓	✓	✓	✓	✓

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains a version of our main specification given in Equation 3 where the effects are allowed to vary with neighborhood characteristics. The design compares transactions in the five years after barrier construction with the five years prior, and for properties near to the barrier with those that were between 500–1500 m away. All specifications include barrier by date, and barrier by distance bin fixed effects. Columns (1) through (4) interact our main 0–100 meter effect with log median home values, log median family income, the poverty rate, the college-educated share, and the white share. Neighborhood demographics come from the 2015–2019 American Community Survey. All errors are clustered at the barrier-level.

Appendix Table A18: Heterogeneity in price effects for counterfactual

Interaction with dB reduction			
	Base	Linear	Squared
Base	0.0602***	0.0194**	-0.0044**
	(0.0144)	(0.0092)	(0.0022)
Log MFI	-0.0810**	0.0071	-0.0033
	(0.0342)	(0.0208)	(0.0053)
Observations = 587981			

Notes: This table contains a version of our main specification given in Equation 3 where the effects are allowed to vary with neighborhood characteristics and barrier noise reduction. The design compares transactions in the five years after barrier construction with the five years prior, and for properties near to the barrier with those that were between 500–1500 m away. All specifications include barrier by date, and barrier by distance bin fixed effects. We interact our main 0–100 meter effect with log median home values and with a quadratic in the amount of decibels of traffic noise the barrier is expected to reduce. Log median incomes are demeaned, and decibels of reduction are relative to 7. Neighborhood demographics come from the 2015-2019 American Community Survey. All errors are clustered at the barrier-level.