The Traffic Noise Externality: Costs, Incidence and Policy Implications

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Abstract

More than 42 million Americans are exposed to medium or high traffic noise. 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. 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 buyers are willing to pay an economically meaningful amount for each decibel of reduced noise. In the five years prior to barrier construction, we observe no differential trends in property values; after construction, however, prices increase immediately and permanently. The effects are largest within 100 meters and decline with distance. We use these estimates to calculate the aggregate cost of traffic noise at $110 billion nationwide. The cost varies widely across cities, due to differences in noise levels and property values. The burden of the externality is disproportionately borne by lower income and minority households, suggesting that the externality is regressive. Using our estimates we calculate that the socially efficient Pigouvian tax amounts to $974 per vehicle. We estimate that the widespread adoption of electric vehicles could generate $77.3 billion in noise reduction benefits, concentrated among low-income families.

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1 Introduction

Traffic noise is an understudied and potentially costly negative externality. More than 42 million Americans live in census tracts with medium or high traffic noise levels, and exposure is even higher in Europe (European Environmental Agency, 2020). Low-income households are disproportionately represented in neighborhoods near major roads. 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 indicating 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 \$110 billion – an economically significant burden. In per capita terms, this burden 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 estimate that the socially efficient Pigouvian tax amounts to a one-time levy of \$974 per internal combustion engine vehicle. We also estimate that the widespread adoption of electric vehicles could generate \$77.3 billion in noise reduction benefits, concentrated among low-SES families.

Our empirical analysis is based on transaction-level housing price data from CoreLogic, location-specific estimates of traffic noise 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 traffic with changes in prices for properties located 500–1500 m from traffic. 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 nearby 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. This is probably not too surprising: Since the control group and the treatment group are geographically close, most local amenities that 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 6.8%. 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. When we focus on repeated sales of the same property to control for property fixed effects, we find slightly larger estimates.

To assess whether the impact on home prices increases in the amount of noise abatement, we use information on each barrier's efficacy. This allows us to scale the price increase by decibels of noise reduction due to the barrier. We find that the effect of a barrier increases with its noise reduction, but the relationship is concave in decibel reduction.

In principle, the construction of a sound barrier may reduce not only noise exposure but also air pollution and it may improve visual amenities by blocking views of the road. If so, our estimates could conflate the effects of noise reduction with endogenous 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. 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 or buildings. If tree cover or dense development blocks the view of the road, the additional visual benefit from a sound barrier should be limited. Empirically, we find little evidence consistent with these patterns. 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 sold 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 and property values to quantify the total economic cost of the traffic noise externality. To examine how this burden is distributed, we relate our estimates of tract-level costs to socioeconomic characteristics, including median family income, the poverty rate and the share of the population that is Black. We find that the burden of the noise externality is unevenly distributed and is larger in low-socioeconomic status (SES) tracts. For Florida, a 10% decrease in a tract's median family income is associated with 1% higher per-capita costs of traffic noise. A 10 percentage point increase in the share of the population that is Black or that live in poverty is associated with a 0.8% and 6.3% increase in the per-capita costs of traffic noise, respectively. We find similar correlations for the United States as a whole. These correlations are even stronger if the cost of traffic noise is calculated as a share of local median family incomes or property values. In sum, the externality is "regressive," meaning that its cost 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.

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 the cost of the externality amounts to \$7.0 billion and \$110 billion for Florida and the United States, respectively. 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. The cost varies widely across cities, due to differences in noise levels, property values and the interaction of the two – namely, the relative noise exposure of expensive and inexpensive neighborhoods. In absolute terms, the cost of the noise externality among the most populous counties is largest in Los Angeles county at \$8.8 billion. Harris and Orange counties follow, with total costs exceeding \$2 billion. Los Angeles also has the highest per-capita costs (\$870 per resident) followed by Orange (\$710), Dallas (\$700) and Miami-Dade (\$630) counties. At the other end of the spectrum, Cook (\$90) and Maricopa (\$50) stand out as examples of low per-capita costs.

In the final part of the paper, we discuss the policy implications of our findings. One approach to internalize the noise externality is a Pigouvian tax equal to the marginal external economic cost of noise. Our estimates imply that the cost of the noise externality produced by the average internal combustion engine (ICE) vehicle over its lifetime is \$974. A comparison with existing estimates of the local costs of air pollution and global costs of CO_2 emissions generated by the average vehicle (Allcott et al., 2024) indicates that the noise externality accounts for a large share of local externalities, and a small share of total externalities of vehicles.

We also discuss the external benefits of electric vehicles (EVs). EVs generate less traffic noise than traditional vehicles because electric engines are quieter. Estimates from the engineering literature suggest that replacing all gas vehicles with EVs would reduce traffic noise by an average of 7.1 decibels in areas adjacent to roads – a reduction similar to the 7 decibels achieved by sound barriers in our sample. Combining this estimate with our estimates of the cost of traffic noise, we calculate that universal EV adoption would generate aggregate noise reduction benefits of $5.4 billion in Florida and $77.3 billion nationwide. These benefits would be concentrated among low-SES and minority households.[1] Finally, we use data on current EV adoption by county to quantify the realized benefits of existing EVs as of 2023. Our estimates imply economically sizable realized benefits for counties with a currently high EV share. For example, we find the benefits in San Francisco, Santa Clara and Orange counties to be $276 million, $265 million and $193 million, respectively, or $315, $137 and $60 per resident. By contrast, in low adoption counties, the estimated benefits are trivial.

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 Traffic Noise on Housing Prices

The earlier literature on the link between traffic noise and property values has tended to focus on the correlation between exposure and prices, conditional on housing observables (Hughes and Sirmans, 1992, Verhoef, 1994, Espey and Lopez, 2000, Wilhelmsson, 2000, Navrud, 2002, Nelson, 2004, Theebe, 2004, Rich and Nielsen, 2004, Hofstetter and Müller-Wenk, 2005, Kim et al., 2007, Li et al., 2009, Marmolejo-Duarte and González-Tamez, 2009, Andersson et al., 2010, Blanco and Flindell, 2011, Brandt and Maennig, 2011, Franck et al., 2015, Swoboda et al., 2015, von Graevenitz, 2018). Due to the likely presence of omitted variables correlated with noise, it is unclear whether the estimates in these studies can be interpreted in causal terms. More recent work has sought to use credible research designs to isolate the causal effect of traffic noise. For example, Wang et al. (2023) use the outbreak of COVID-19 to study tenants' changing responses to road traffic noise in the rental housing market in Singapore. Most recently, Magagnoli and Tassinari (2024) use within-block variation in perceived street noise in a Barcelona district to quantify the effect of street noise and find that increasing the perceived street noise reduces rents.[2]

[1] These estimates do not include the value of other externalities of EVs relative to ICEs. Adding our estimate to Allcott et al. (2024)'s estimate indicates that a quarter of the external benefits of an EV (relative to an ICE) stems from noise reduction.

[2] Tang (2021) uses the adoption of the London Congestion Charge estimate the elasticity of housing values with respect to all traffic-related disamenities, including noise, pollution, congestion, etc.

The part of this literature that is most relevant for our purposes is the one that seeks to estimate the price effect of mitigating traffic noise, as through sound barriers. The two earliest attempts at studying the price effects of noise barriers are Kamerud and Von Buseck (1985) and Hall and Welland (1987), with the former finding no significant price effects, and the latter finding mixed effects. Their respective samples sizes however are too small to draw definitive conclusions. The two papers that are closest to ours are Julien and Lanoie (2007) who quantify how the price of 134 houses responds to the construction of one particular noise barrier in a Montreal neighborhood; and Lindgren (2021), who evaluates a noise mitigation program run by the Swedish Road Administration that installed facade insulation in dwellings as well as noise barriers and finds increases in property values particularly for properties with lower energy efficiency and exterior quality.

Our work is also indirectly related to papers that study the price effects of noise from airplanes (Mieszkowski and Saper, 1978, Cohen and Coughlin, 2008, Salvi, 2008, Pope, 2008, Cohen and Coughlin, 2009, Boes and Nüesch, 2011, Almer et al., 2017, Thanos and Dube, 2199, Vestman et al., 2023, Sugasawa et al., 2024), trains (Szczepańska et al., 2018, Ahlfeldt et al., 2019, Li et al., 2023), wind turbines (Hoen et al., 2015, Jensen et al., 2018) and manufacturing plants (Dubin and Zabel, 2021).[3]

3 Data

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.[4]

[3]Greenhill (2024) estimates the causal effect of noise on health of pregnant mothers and newborns. A much larger literature focuses on other environmental externalities. Examples include but are not limited to Hoek et al. (2002), Chay and Greenstone (2005), Gauderman et al. (2007), Greenstone and Gallagher (2008), Bayer et al. (2009), Currie and Walker (2011), Grainger (2012), Currie et al. (2015), Bayer et al. (2016a), Anderson (2020).

[4]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.

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 generated by aviation, rail and road traffic. For our analysis, we focus specifically on noise emanating from road traffic. Murphy and King (2014) offers a methodological discussion of noise mapping and its limitations. 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.

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 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 by each state differently.

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.[5] 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 (Murphy and King, 2014), calibrated to actual measurements of traffic flow, traffic noise and topography. FDOT also provides information on barriers that were proposed but not built, which we use as an additional way to validate our estimates.

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 barrier starting and end points are often incomplete or imprecise.[6] In

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

[6] The straight line connecting the starting and end points is a poor approximation to the actual shape of barriers that follow curves in the road. The Florida data show that many barriers have curved segments.

addition, we are not aware of states other than Florida that make available information on barriers that were proposed but not built.

In our sample, there are $N = 1143$ barriers built between 1988 and 2023 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. Column 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 characteristics. Specifically, they have the same costs, height, length, and expected noise reduction. Proposed barriers are located in tracts with higher incomes, college share and white share of the population, though these differences are economically small. For example, the median family income is \$70,000 for constructed barriers versus \$73,000 for recommended barriers. The corresponding college shares are 0.22 versus 0.23.

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 far side of the highway. This is illustrated in Figure 1 which shows an example of a barrier in Daytona Beach 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, we include properties on the relevant side of the barrier. We use properties on the "wrong side" (i.e. those that would not benefit from the noise abatement) 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.[7] We overlay properties that were ever transacted in Florida from CoreLogic using the property's centroid from the assessor files. First, we extract the end points of the barrier and construct a line segment between the points.[8] 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

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

[8]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.

a highway a noise barrier was constructed.[9]

The final dataset contains all properties within 1500 m of a built or proposed barrier, transacted within 10 years of the barrier construction, and on both the "correct" and "wrong" sides. 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 properties in our sample are not exactly identical in all distance bins. On the other hand, most variables do not display an obvious 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 property quality is an important identification concern that we discuss in our empirical analysis below.

3.2 Correlation Between Noise Exposure and Neighborhood Characteristics

To understand which type of neighborhoods are more exposed to traffic noise, we document the within-county correlation between noise in a census tract and the socioeconomic characteristics of its residents. Table 1 reports mean neighborhood characteristics by level of noise exposure, in deviation from the county mean. The unit of observation is a census tract.[10] We categorize tracts into three groups: those with a population-weighted average of greater than 50 dB of traffic noise, and those with traffic noise between 46 and 50 dB, or less than 46 dB, respectively. The top panel includes tracts in Florida. For comparison, the bottom panel includes all tracts in the U.S. Relative to the county mean, U.S. tracts in the "high" noise exposure group have 40 percentage points more of their population exposed to any traffic noise. They are also 13.9 percentage points more likely to be exposed to extreme traffic noise of greater than 90 dB - a level common for major highways.

Column (1) shows that 2.2 million individuals in Florida and 42.1 million individuals in the U.S. live in census tracts exposed to high levels of traffic noise. Tracts with average traffic

[9] 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.

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

noise above 50 dB (column 1) have lower median property values, median family incomes and share of college-educated residents compared to tracts with lower levels of noise exposure (columns 2 and 3). Tracts exposed to high traffic noise also have higher poverty rates, Black and urban shares of the population and population density.

Notably, the relationship between noise and socioeconomic characteristics appears similar between the U.S. and Florida. For example, moving from column (1) to column (3) is associated with an increase in 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 U.S. and 3.7 and -1.6 for Florida. The similarity between the U.S. and Florida in the correlation between noise and socioeconomic characteristics is helpful in assessing the external validity of our estimates based on Florida data, a point that we will discuss in detail later.[11]

4 Econometric Specifications and Identification Assumptions

Figure 2 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 4,212 census tracts in Florida. The negative correlation indicates that tracts with higher noise exposure have lower median property values. The slope is -0.007 (0.001), indicating that one additional decibel is associated with 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. 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 shown in the previous section, tracts that are exposed to noise are indeed denser, more urban and have higher poverty rates. Thus, the negative slope in Figure 2 could simply reflect the presence of omitted variables correlated with 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.

[11]For comparison, Appendix Table A3 reports similar statistics without adjusting for county mean. Here, the correlation between noise and socioeconomic characteristics is weaker. Thus, when comparing neighborhoods within a county there is a strong negative correlation between noise and socioeconomic characteristics, while when comparing neighborhoods across 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, wealthy suburban neighborhoods within each county tend to be quieter than poorer urban core neighborhoods.

Rochat (2016) estimates that the average noise reduction achieved by sound barriers in the U.S. is 7 dB 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 perceived loudness of the noise.

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.

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 the construction of a noise barrier. Since the average barrier reduces traffic noise by 7 dB, entries in column 3 are equal to the ones in column 2 minus 7 dB. The magnitudes in columns 2 and 3 are not immediately interpretable because they are measured in decibels. To make the entries easier to interpret, in columns 4 and 5 we report how loud a property can expect to be using a scale from 0 to 100, with 100 representing the unobstructed level of loudness experienced at 25 m from the barrier (row 1, column 4).

Column 6 shows the expected change in loudness caused by the construction of the barrier. 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 salient to home buyers and consequently, to affect housing demand. By contrast, the benefits for properties at distances 400 m or more appear less noticeable. For example, moving from the noise level of a refrigerator hum to that of a bird call is likely less salient for buyers and likely to have smaller impacts on housing demand.[12]

4.1 Difference-in-Differences Model

In our empirical analysis, we use two specifications to estimate the effect of noise exposure on transacted home prices. 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 construction of a barrier for properties located 0–500 m from it (and on its relevant side) with changes in prices for properties located 500–1500 away (and also on its relevant side). 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.

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.[13] 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 the traffic noise map) $\times$ year of sale fixed effects; no traffic noise indicator $\times$ year

[12] The fact that doubling the distance results in a 6 dB reduction in noise is for an environment with no obstructions. The noise decay is likely even faster in our setting where building structures are present.

[13] The barrier $\times$ event time fixed effects are identical to barrier $\times$ year fixed effects because each barrier only has one event timing.

of sale fixed effects; land use category × 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.[14]

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 homogeneously distributed over space within our comparison areas. 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 is systematically correlated with the construction of new barriers. For example, it is implausible that after the construction of a barrier, school quality or crime would change 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 five years before the barrier construction, the movement of prices of properties located 0–500 m and 500–1500 m from the barriers are indistinguishable.

4.2 Triple-Differences Model

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 from the barrier experienced by properties near constructed and proposed barriers.

Using the matched barriers, we estimate the following specification:

[14] 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: $\sum_j (\mathbb{1}\{\text{dist} = j\} \cdot \mathbb{1}\{\tau < -5\} \cdot \beta_j^0 + \mathbb{1}\{\text{dist} = j\} \cdot \mathbb{1}\{\tau > 5\} \cdot \beta_j^1)$. Transactions outside of the 5-year window help to pin down the barrier by distance bin fixed effects, as well as any price trends in building characteristics. They also ensure a greater comparability between the samples used in our main estimation with those used in our repeat-sales specification, which includes property fixed effects. The repeat-sales specification necessarily omits properties that had a single sale over the study window.

$$\log \rho_{it} = \sum_{j \leq 500\text{m}} \mathbb{1}\{\text{Barrier built}\} \cdot \mathbb{1}\{\text{dist} = j\} \cdot \mathbb{1}\{\tau \geq 0\} \cdot \beta_j$$

$$+ \sum_j \left(\mathbb{1}\{\text{Barrier built}\} \cdot \mathbb{1}\{\text{dist} = j\} \cdot \mathbb{1}\{\tau < -5\} \cdot \beta_j^0 + \mathbb{1}\{\text{Barrier built}\} \cdot \mathbb{1}\{\text{dist} = j\} \cdot \mathbb{1}\{\tau > 5\} \cdot \beta_j^1 \right)$$

$$+ \eta_{b(i)\tau} + \xi_{mj\tau} + \gamma_{b(i)d(i)} + x_{it}'\zeta + \varepsilon_{it} \quad (2)$$

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 $\times$ distance bin $\times$ 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.

5 The Effect of Noise on Property Values

5.1 Graphical Evidence

We start with an event study that allows us to both assess the validity of our identification assumption, as well as study the timing of the effect. We begin with a single distance group $d^* =$ 0–100 m. The omitted category is the 500–1500 m group and the controls are the same as those used 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 3 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 6.8%.

Figure 4 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 bin 100–200 m, although smaller than the one for the 0–100 m bin in Figure 3. The effect for other distance bins appears even smaller and not statistically different form zero in many event times. Overall, a comparison of this figure with the previous one confirms that the price effects become smaller and less clearly detectable as we move away from the barrier, consistent with the spatial decay of noise.

One possible concern is that our control group is indirectly treated through demand spillovers. This could happen if the construction of the barrier shifts demand from properties in the 500 to 1500 m range to properties in the 0 to 500 m range. In Appendix Figure A1, we use transactions 500–1500 m way from barriers that have yet to be constructed as the control group. 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. Since this design is subject to concerns over two-way fixed effects models with variation in treatment timing, we use the estimator of de Chaisemartin and D'Haultfœuille (2024). We find no evidence of a change in transacted home prices beyond 500 m from the barrier. The average effect over the 5-year window is -0.0075 (0.021).[15]

[15] An alternative test is to consider whether there is any evidence of price effects beyond 500 m using properties farthest from the barriers as a control group. We implement this test within the same difference-

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.

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 the mean effect observed in Figure 3. 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. 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. The effect on properties 300–400 m from the barrier is marginally statistically significant. The fact that the estimated effects are larger than those in column 1 indicates that if anything, unobserved heterogeneity in time-invariant property characteristics biases estimates in column 1 downward.

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 here, we have yet to match barriers that were proposed but not built to barriers that were actually built. For now, we simply include properties near recommended barriers to the control group.[16] 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.

in-differences design of Equation 3, but using 1200–1500 m as the control group. The difference-in-differences estimates for all distance bins from 0–100 m through 1100–1200 m are depicted in Appendix Figure A2. The figure shows the same clear decay pattern with increasing distance from the barrier. We find no evidence for significant effects 500–1200 m away relative to sales 1200–1500 m away from the barrier.

[16]Since later we match the two types of barriers, the estimates in column (3) demonstrate that the inclusion of barriers not built do not greatly affect the difference-in-differences estimates.

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. However, these models do not account for the possibility that house quality may differentially change 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 shocks to the unobserved determinants of house prices.[17] The coefficients in column (5) and (6) are larger than those in column (3) and (4), respectively. 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.

In Table 4, we estimate an alternative triple-differences model (Equation 2) to further strengthen our identification strategy. We match each of the barriers that were proposed but not built to a barrier that was built. 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 $\eta_{b(i)\tau}$. This is a DD model in the style of those presented in Table 3, and consequently, the estimated impacts are quite similar. Column (2) controls for match m $\times$ distance bin $\times$ event time fixed effects $\xi_{mj\tau}$. Identification relies on 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.

Finally, in column (3) we estimate the full DDD specification that includes both barrier by event time ($\eta_{b(i)\tau}$) and match $\times$ distance bin $\times$ 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. For houses situated within 100 m of the barrier, we find a 9.67% increase in sale prices. The estimated effect declines to 5.69% for houses 100–200 m away, 5.89% for houses 200–300 m away, and is statistically indistinguishable from zero for houses located 300–400 m or more from the barrier.

Overall, Tables 3 and 4 indicate that within 100 m of the barrier, the construction of a new barrier raises property values by 6.8%–10.3% and 7.0%–9.7%, respectively, and by a smaller amount 100–300 m from the barrier. We conclude that the estimates appear generally

[17]The proposed barriers help pin down these distance bin by year fixed effects.

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). The average MVPF for barriers that were built amounts to 1.7, while the MVPF for barriers proposed but not built is 1.4.[18] 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).

Most barriers in the U.S. are built by state governments. Since barriers raise property values, it is reasonable to ask why homeowners and developers do not build private barriers everywhere there is a noisy road. In the case of urban roads with sidewalks and retail establishments, this is often practically infeasible. In the case of freeways, one limiting factor is that the land next to the freeway where barriers can be built is often state-owned and barriers are most effective when placed directly next to the sound source. An additional 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 5, we examine the effects of barrier construction on housing prices on the opposite side of the highway where noise levels should not be affected. For this analysis, we ignore properties that are on the correct side of another constructed barrier. Since there are often few properties on the "wrong" side of the barrier within 100 m due to the existence of the highway, we pool distance bins to study the effect within 0–200 m. We uncover no significant effect of the new barrier on prices.

In Figure 6, we examine the effect of barrier construction on housing prices after randomly permuting the year of barrier construction. We show the distribution of the coefficient on 0–100 m $\times$ $\mathbb{1}\{\tau \geq 0\}$, obtained from 100 permutations. The placebo distribution has mean and standard deviation of 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.

For completeness, in Appendix Figure A3 we also show estimates of the effect on transacted home prices for proposed (but not built) barriers. As expected, no effect is detectable.

[18]We calculate the benefits within 300 meters since that is the range we find significant price effects.

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, it is an additional way to probe the validity of our identification. 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 changes in sales prices would cast doubt on the causal interpretation of our estimates. Second, it allows us to scale the price increase by decibels of noise reduction. This feature is particularly important to the last two sections of the paper, where we quantify the total cost ofthe noise externality and study the potential economic benefits of policies that foster quieter streets.

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 Section 3, we rely on data from FDOT, which assigns to each barrier a predicted decibel reduction based on a barrier's height, depth and construction materials combined with baseline measurements at the site prior to the barrier construction of traffic flow, traffic noise and topography.[19] 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. Prior studies comparing predicted with actual (measured) reductions in traffic noise from sound barriers found an average discrepancy of just 1 dB (Rochat and Fleming, 2002).

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 dB, which is the average for barriers in our sample. For parsimony, we focus on properties within 100 m 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, while the coefficient on the quadratic interaction is negative (significant at the 10%-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.[20]

[19] 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`.

[20] To investigate robustness, Appendix Table A4 shows estimates under an alternative set of controls and finds that the estimates tend to be generally stable and the coefficient on the quadratic term becomes statistically significant at the 5% level.

Thus, the table confirms that the price effect of sound barriers is indeed larger for barriers with larger expected noise reduction. Figure 7 shows more explicitly the functional form implied by the estimates in 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. Three features are worth highlighting. First and most importantly, the effect is a quadratic function of expected decibel reduction. Second, 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. Third, the figure also indicates that the effect plateaus at 10 dB of reduction, which represents the 96th percentile in our sample.

Our estimates imply an average price depreciation of 0.9% with every decibel of noise.[21] 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) do find reductions in air pollution immediately next to a barrier, but less is known on the

[21] 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 the effect from a 1 pp decline in tree cover (Han et al., 2024).

spatial decay in pollution caused by barriers.

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 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 clear 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 and 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."[22]

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 speeds are 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

[22]Zillow announced only in September 2024 that they had partnered with a firm to begin providing some air quality measures for listings. But even so, they do not vary at the granularity of we consider. 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-US`.

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 in meters.

Columns (1) and (2) report the estimated coefficients on the interactions of our main 0–100 m 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 increases 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 first 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 shields 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. In addition, 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 that is closest to the barrier.[23] 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.[24]

None of the interactions in the table 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 differences in typical quality that are associated with age of the buildings.

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 neighborhoods, are willing to pay for it and the barrier increases demand. Thus, measuring the extent of sales for newly constructed homes 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 Appendix Table A5 we present estimates that exclude newly constructed homes from our sample. Column (1) contains all transactions for properties built within 5 years of the

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

[24]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.

date of barrier construction. 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. Our estimates do not vary much and appear similar to the baseline estimates in Table 3. The main reason is that the number of newly constructed units is small. This is evident from the limited change in sample size. The number of properties that exist at $t = 0$ is 577,045 (column 2 of Appendix Table A5), not too different from the sample size of 594,936 used for our baseline estimates (column (1) in Table 3). 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.

In addition, we observe virtually no differential composition changes following the construction of a new barrier in property characteristics (bedrooms, stories, pool, AC, garage), the types of transactions (investor, resale, new building, cash purchases, mortgage, foreclosures), and residential types (single family home, condo, duplex, apartment) across distance bins, as shown in Appendix Table A6.[25]

In principle, it is possible that the areas affected by the barrier construction experience endogenous changes in the type of residents, if quieter and more expensive homes attract over time a wealthier mix of residents. While we show that the number of new constructions in itself is too small to induce a profound change in the character of the neighborhood, we cannot rule out that some churning takes place within the existing housing stock. This change would be problematic for the validity of our findings if it results in improvements to 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. We compare changes in prices for properties 0–500 m from the barriers with changes in prices for properties 500–1500 m from the barrier, but still in the same neighborhood. The set of local amenities whose supply varies across space within this narrowly defined geography is limited.

5.6 Robustness

To assess the robustness of our findings, we conduct a series of additional sensitivity analyses. First, we explore 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. Second, we find that our estimates are stable to including additional or fewer years around the timing of the barrier construction. Third, we examine the potential impact of outliers by systematically excluding observations with extreme values for sale prices. The results remain

[25]To provide the most conservative form of the test possible, this table does not include property fixed effects.

largely unchanged, suggesting that our estimates are not driven by a small number of atypical observations. These analyses are contained in Appendix Table A7. 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 (available on request).

6 The Aggregate Cost of the Externality and Its Distribution

In this section, we use our estimate of the causal effect of noise on property values and spatially granular data on traffic noise exposure and property values to estimate the economic cost of the noise externality for each census tract. We use these estimates to ask two questions. First, is the cost of the externality experienced by economically disadvantaged families higher or lower than the cost experienced by wealthier families? 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. It is s a priori unclear whether we should expect positive or negative correlations. On the one hand, we have shown that noise exposure is higher in tracts with lower socioeconomic status and higher minority shares, suggesting that the cost of the externality borne by more disadvantaged families could be larger than the cost borne by wealthier families. On the other hand, tracts with higher SES and lower minority shares tend to have higher baseline levels of property values. Despite being less exposed to noise, they could in principle experience a higher per-capita cost of the noise externality. 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.

The objective of the first question is not to measure how traffic noise affects welfare of different SES groups or welfare inequality. Our goal is simply to document whether the cost is positively or negatively correlated with socioeconomic and minority status. We caution that we do not aim to measure welfare or utility. Housing units in noisier tracts are more affordable so residents who choose to live near traffic also experience lower costs to housing (in the form of lower rents and prices, for renters and owners respectively).

Incidence depends on preferences and ownership status. The price of noise – defined as the equilibrium price per dB – is set by the marginal resident, who is the one indifferent between living in a noisy tract with a lower cost of hosing and a quiet tract with a higher cost of housing. In the case of homogeneous preferences, the disutility from noise is the same across individuals, and the equilibrium price of noise is such that everyone is indifferent between noisy and quiet tracts. In the case of idiosyncratic preferences over noise – namely, each individual utility function includes an idiosyncratic draw that determines their disutility from noise – there will be inframarginal residents in noisy and quiet tracts. For example, quiet tracts will have inframarginal residents with a stronger disutility from noise than the one of the marginal individual. For owners, there is the additional consideration that properties in noisy tracts are an asset that is made cheaper by noise. If noise is stable over time, then buyers of properties in noisy tracts buy and re-sell an asset for the same, lower price. When noise levels change unexpectedly, the gains or losses fall on incumbent owners – windfalls if noise declines, losses if it rises.

Whether preferences are homogeneous or heterogeneous, and whether an individual owns or rents, in equilibrium some individuals are exposed to more noise than others. Since noise has been linked to significant physical and mental health conditions, it seems important to quantify differences in the cost of noise experienced by different SES groups, which is what we do next.

We also note that conceptually our empirical estimates of the price effects cannot necessarily be interpreted as willingness to pay. Kuminoff and Pope (2014), for example, show that trading between heterogeneous buyers and sellers drives a wedge between the "capitalization effects" and welfare changes. In their context, capitalization effects of the type identified in our Equations 1 and 2 understate the willingness to pay for a non-market amenity, suggesting that our estimates may be a lower bound for willingness to pay.[26]

As discussed in the Section 3, the USDOT National Transportation Noise Map provides an estimate of exposure to traffic noise for each location in the U.S. We use this information combined with our "intensity of treatment" estimates to assign to each property an estimated dollar cost of traffic noise. In particular, we estimate the cost of the noise externality for property i as:

$$\widehat{\text{Cost}}_i = \text{Property Value}_i \times \hat{Q}(\text{noise}_i - 45) \tag{4}$$

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;[27] $\hat{Q}(\text{noise}_i - 45)$ is the predicted percent effect of decibel changes on prices based on our intensity of treatment parameter estimates; and noise_i is the property's noise level from the Noise Map measured in dB. Traffic noise of 45 dB is the lowest level recorded in the Noise Map data, so that $(\text{noise}_i - 45)$ dB is the

[26]Banzhaf (2021) argues that quasi-experimental evidence of the type identified in Equations 1 and 2 identifies movement along the ex-post price function and this effect is a lower bound on general equilibrium welfare. See Kuminoff et al. (2013) for a review of the literature and Bayer et al. (2016b) for a prominent example of estimating the marginal willingness to pay for non-marketed amenities in a dynamic framework.

[27]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.

noise level in a tract relative to the minimum level observed.

To predict $\hat{Q}(\text{noise}_i - 45)$ for each property, we could use the quadratic function estimated in column (3) of Table 5, which, for a given decibel level, gives us the predicted percent effect on prices.[28] However, since we are interested in estimating $\widehat{\text{Cost}}_i$ not just in Florida but also in the rest of the US, our preferred specification is based on a richer model. We are concerned that the relationship between noise and house prices that we estimate in Table 5 using Florida data may not necessarily extend to the rest of the U.S. The extrapolation is invalid if the effect of noise changes on property values outside Florida is different from the one that we estimate with our Florida data. This could be the case, for example, if the effect of noise on prices is heterogeneous across SES strata. If the effect of noise on prices is different in poor and wealthy neighborhoods, and Florida has a different mix of poor and wealthy neighborhoods, then our parameter estimates for Florida should not be used to predict $\hat{Q}(\text{noise}_i - 45)$ outside Florida.[29] To increase the external validity of our Florida estimate, we re-estimate the regression including the interactions between all terms and tract median home values from the 2015–2019 American Community Survey and use this richer specification to predict $\hat{Q}$. The estimates, reported in Appendix Table A8, suggest that the effect of noise is indeed heterogeneous across tracts. In what follows we focus on this specification and report the estimates based on the more restrictive model in the Appendix.

6.1 Distribution of the Cost of the Externality by Income and Race

With a predicted $\widehat{\text{Cost}}_i$ for each property in hand, we aggregate the property-specific estimates to the 2010 census tract-level for all properties in each census tract in Florida and the U.S., yielding an estimate of the total economic cost of the noise externality for each tract. We then divide the tract-specific cost by the tract population to obtain the per-capita cost.

We relate our tract-level estimate of the cost of the externality to measures of the tract's socioeconomic status and minority share. Figure 8 plots the estimated per-capita cost of the externality for each tract in Florida against the tract log median family income, share of the population that is black and poverty rate. We log-transform the per-capita costs to interpret the slope in percentage terms. The level of observation is a tract and the sample includes all tracts in Florida. Throughout, we residualize on county fixed effects. The figure shows a negative correlation between the cost of the externality and median family incomes.

[28] The percent effect of decibel on prices is predicted to be: $\hat{Q}(\text{noise}_i - 45) = .061 + .0204 \cdot (\text{noise}_i - 45) - .00401 \cdot (\text{noise}_i - 45)^2$. This relationship applies above 4.9 dB and below 10 dB. Figure 7 shows that the estimated effect is zero when noise reductions are below 4.9 dB and it plateaus above 10 dB. In these ranges, which include only a handful of observations, $\hat{Q}$ is set accordingly.

[29] Recall that in practice Florida's observables are not too different from those of the U.S., and their correlation with noise is also comparable (Table 1 and Appendix Table A3). However, there are some differences, indicating that this may be a valid concern.

The slope is -0.10 (0.01), indicating that a 10% lower income is associated with a 1% higher per capita cost. The correlations with the share of residents who are Black and the poverty rate are positive. The slopes are 0.08 (0.01) and 0.63 (0.05), respectively, indicating that a 10 percentage point higher share of blacks or a 10 percentage point higher poverty rate are associated with 0.8% and 6.3% higher per-capita costs.[30]

Therefore, the noise externality appears "regressive," meaning that its cost is larger for low-income and black families. The reason is that low-income families and black families are overrepresented in tracts that are more exposed to traffic noise and that this sorting dominates the level differences in prices. In Appendix Figure A4 we show that the same conclusion applies when we use two alternative measures of costs: the per-capita cost as a share of the tract median family income (obtained by dividing the per capita cost by the tract MFI) and the cost as a share of local property values (obtained by dividing the tract total cost by the total assessed value of properties).

6.2 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 8 reports our estimates based on the preferred specification, namely the model that allows for heterogeneity. The entry in the top row of column 1 in Table 8 shows that the aggregate cost of the traffic noise externality in Florida amounts to $7.0 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, $2.31 and $1.56 billion, while the costs for tracts in the bottom and top quartile of the black share of the tract are respectively, $1.50 and $2.06 billion.

Columns 2, 3 and 4 report the cost in per capita terms, and as a percentage of income and property values, respectively. The results confirm those illustrated in Figure A4: the costs are smaller in more affluent and White areas and larger in low-income areas and areas with a higher share of Black residents. For example, the per-capita costs in tracts in the bottom income quartile are $470 compared to $300 in tracts in the top income quartile. The per-capita costs for tracts in the bottom quartile by Black population share are $360 compared to $380 for tracts in the top quartile. The differences are more pronounced when costs are scaled as a share of median family incomes or local property values: 0.40% versus 0.74% of incomes (column 3), and 0.17% versus 0.46% of property values (column 4).

[30] The figures is essentially the same if we use the more restrictive model that does not allow for heterogeneity in the effect of noise across tracts with different baseline price.

The lower panel of Table 8 extends our estimates to the entire U.S. Entries indicate that the aggregate cost of traffic noise for the nation as a whole is \$109.75 billion, arguably a large amount. Unlike for Florida, the per-capita costs for tracts in the bottom income quartile are now slightly smaller than those for tracts in the top income quartile. However, the pattern of a higher burden of noise borne by lower SES tracts is confirmed in columns 3 and 4 when costs are scaled in dollars of median family incomes or local property values. The per-capita costs for tracts in the bottom quartile of the Black population share are \$270 compared to \$300 for tracts in the top quartile. The differences are larger when costs are scaled by income and property values: 0.31% vs 0.52% of incomes (column 3), and 0.22% vs 0.44% of property values (column 4).[31]

To give a sense of the geographical differences in the cost of the noise externality, Table 9 shows our estimates for the ten most populous counties. In absolute terms, the cost of the noise externality is largest in Los Angeles county: \$8.8 billion. Harris and Orange counties follow, with total costs exceeding \$2 billion. In per-capita terms, Los Angeles county has the highest costs (\$870 per resident) followed by Orange (\$710), Dallas (\$700) and Miami-Dade (\$630) counties. At the other end of the spectrum, Cook (\$90) and Maricopa (\$50) counties stand out as examples of low per-capita costs. The heterogeneity in per-capita costs reflects geographical differences in the level of noise, the overall value of properties and the interaction of the two—namely the relative noise exposure of expensive and inexpensive neighborhoods. Geographical differences in the level of noise reflect differences in the degree of proximity of residents to major roads and freeways.

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 marginal external economic cost of the activity. We can use our estimates from the previous section to obtain a back-of-the-envelope estimate of the cost of the noise externality produced by the average vehicle (car or truck) in Florida.[32] To do so, we divide our estimate of the total costs of traffic noise in Florida from column 1 of Table 8 by the number of vehicles registered in the state in 2006 (the mid-point in our sample period).[33] The ratio is equal to \$974 per car.

[31] The alternative estimates based on the model that does not allow for heterogeneous effects are similar for Florida, suggesting that the more parsimonious model is well specified in this case (Appendix Table A9). The alternative estimates for the U.S. are much larger, indicating that heterogeneity in the noise effects are important in extrapolating the costs outside Florida.

[32] See Bento et al. (2009), Fowlie et al. (2012) for broader discussion of environmental regulation of the car market. See also Kahn (1996).

[33] Our estimates include housing transactions in a period where most vehicles in Florida had an internal combustion engine and electric vehicles were a negligible share of the vehicles in circulation.

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. Thus, it needs to be interpreted as the lifetime external cost of the average vehicle. The efficient annual levy would be set equal to the corresponding annualized flow. For comparison, Allcott et al. (2024) estimate that the lifetime economic cost of air pollution created locally by driving the average vehicle is only \$378 – reflecting the fact that emissions have fallen spectacularly in recent years (Jacobsen et al., 2022) – while the lifetime global externality from CO2 emissions is much higher: \$13,833. Taken literally, this comparison would suggest that noise accounts for the majority of the average vehicle's local external costs, but a trivial share of its global external costs.

Of course, our 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 measured in decibels (D_m) and each model's share of traffic (S_m), the lifetime corrective tax on model m can be calculated as a function of observable variables:

$$T_m = 974\left(\frac{D_m}{\sum_m S_m \cdot D_m}\right) \tag{5}$$

where the term in parenthesis ($\frac{D_m}{\sum_m S_m \cdot D_m}$) reflects how noisy model m is relative to the weighted average of all models in circulation.[34]

Electric Vehicles. Besides taxes, there is a limited set of policy levers that can be adopted to reduce traffic noise in U.S. cities. In principle, policies that incentivize the adoption of electric vehicles (EVs) lower traffic noise because electric engines tend to be significantly quieter than Internal Combustion Engines (ICEs). To provide a back-of-the-envelope estimate of the potential external benefits of the widespread adoption of EVs in terms of noise abatement, we combine our estimates of the cost of the noise externality in each Census tract with engineering estimates of the noise difference between EVs and ICEs. We report estimates for a scenario of universal EV adoption, although our methodology can be used to provide estimates for any share of EV adoption of interest.[35]

We make three assumptions. First, based on Lan et al. (2018), we assume that if all internal combustion engine vehicles are replaced by EVs, traffic noise in the immediate vicinity of traffic would decline by 7.1 dB on average.[36] For each tract i, we use Equation

[34]Knittel and Sandler (2018) and Jacobsen et al. (2020) estimate welfare losses from imperfectly pricing heterogeneous externalities from cars. See also (Jacobsen et al., 2022).

[35]We do not attempt to directly estimate the effect of EVs on property values because we lack an exogenous source of variation in local EV adoption.

[36]Lan et al. (2018) conduct a noise measurement experiment where they randomly vary the proportions

4 as before, setting the counterfactual level of noise equal to $\text{noise}_i - 7.1$. Since the average reduction achieved by sound barriers in our sample is about 7 dB, 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 ignore the possible heterogeneity in the effect of EVs experienced by properties near fast and slow traffic. We stress that this a strong assumption and an important limitation of our methodology, because the EV noise reduction has been found to be smaller at high speeds, since the contribution of rolling noise becomes relatively more important (Pallas et al., 2016, Iversen and Holck, 2015, Marbjerg, 2013). Thus, our estimates almost certainly overstate the relative benefits of EV near fast roads, like freeways. We note that in practice the number of properties exposed to noise from urban roads – where average speed tends to be lower – is likely to be much larger than the number of properties exposed to noise from freeways – where average speed tends to be higher. In principle, with speed data on each road one could relax this assumption.

Third, we focus on changes in noise intensity – arguably the main effect of EV adoption – and ignore possible second-order effects through changes in noise quality due to changes in wave frequency. There is evidence that EVs may affect the wave length (Lan et al., 2018), but we have no way to evaluate the impact of changes in wave frequency on property prices. Given the limitations of our three assumptions, our estimates need to be interpreted more as a back-of-the-envelope illustration of the potential order of magnitude involved, rather than an exact calculation. On the other hand, the *relative* magnitudes of the benefits for low-SES and high-SES groups are likely to be more informative, as any bias in our estimates is likely to be at least partially shared across SES groups.[37]

Table 10 reports the estimated aggregate benefits of 100% EV adoption in terms of forgone noise. For Florida, we estimate that 100% EV adoption would generate $5.39 billion in benefits (column 1). Of particular interest are the distributional impacts (Holland et al., 2019). In per-capita terms, the benefits of EV adoption are larger for low-income tracts and tracts with a higher share of Black residents (column 2). The progressivity of EV benefits is more pronounced when costs are measured as a share of local incomes and property values

of EVs that drive by and compare the noise emissions from traffic flows with different proportions of EVs. Their data include 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). Walker et al. (2016) and Pallas et al. (2014) also find significant noise reduction from EVs. See also Pallas et al. (2016), King (2017).

[37] Our focus is squarely on noise reduction, while previous studies have focused on other externalities of EVs (Allcott et al., 2024). Holland et al. (2016) estimate differences in EV externalities across localities due to different fuels used in the electric grid. See also Graff Zivin et al. (2014), Delmas et al. (2017).

(columns 3 and 4). For example, the EV benefits for the bottom and top income quartiles are 0.99% and 0.16% of income, respectively. The EV benefits for the bottom and top quartiles of the Black population share are 0.28% and 0.62% of income, respectively. The bottom panel reports estimates for the U.S. as a whole based on the model that allows for heterogeneity in the effect of noise on prices. They suggest aggregate benefits of $77.28 billion.[38] Like for Florida, the benefits are larger for low-income neighborhoods and neighborhoods with more Black residents.

Of course, a 100% EV adoption is just a hypothetical benchmark. Another way to illustrate the potential benefits of EVs is to use our estimates to quantify the realized benefits from foregone noise that already exist given the current rate of EV adoption. Table 11 reports the realized benefits for the 7 counties with the highest EV adoption and the 7 counties with the lowest EV adoption in 2023.[39] Entries indicate that among high adoption counties, the three counties with the highest aggregate benefits are San Francisco, Santa Clara and Orange. Our estimates imply that in these counties, the benefits of EVs amount to $276 million, $265 million and $193 million, respectively. These are arguably sizable benefits. In per-capita terms, the realized benefits of EVs are the largest in San Francisco ($315 per resident), Santa Clara ($137) and King ($77) counties. Per-capita benefits in Alameda, Orange, Contra Costa and San Diego counties are $75, $61, $38 and $31, respectively. At the other side of the spectrum, the per-capita benefits in low adoption counties are trivial. For example, in St. Louis county they amount to 25 cents, reflecting both the small share of EVs and the low property values.[40]

Finally, to obtain a back-of-the-envelope estimate of the benefit generated by the average EV relative to the average ICE, 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

[38]Estimates based on the model without heterogeneity are much larger: $128.81 billion (available on request).

[39]We focus on the top and bottom 7 counties in Appendix 2 in Davis et al. (2025). Since they measure of adoption over the period 2012 to 2023, while we are interested in the most up-to-date figures, we collect the 2023 number of EVs for those 14 counties and divide it by the corresponding total number of registered vehicles. We follow Davis et al. (2025) and define EVs as including both zero emission EVs (ZEV, like Tesla models) as well as plug-in hybrid EVs (PHEVs, like the Toyota RAV4 Prime). We do not include traditional hybrid vehicles (like the Toyota Prius) because their noise is not very different from the traditional ICE vehicles. We couldn't find data on PHEV for all counties, so we use data from `https://afdc.energy.gov/vehicle-registration` and the estimates in Davis et al. (2025) to impute the number of PHEV when missing.

[40]The map in Appendix Figure A5 shows the distribution of the realized benefits of current EV adoption. We lack systematic data on the number of EVs for all U.S. counties, but we have the total numbers by state in 2023 from the U.S. Department of Energy. To make this map, we assume that within each state the share of each county EVs is proportional to the number of chargers in the county. Data on the location of chargers as of March 2025 are from the Joint Office of Energy and Transportation. Total personal vehicles in the county come from the 2019–2023 American Community Survey.

of our sample period). The ratio is equal to \$765. As a point of reference, consider that the Inflation Reduction Act (IRA) of 2021 provided a \$7,500 tax credit for EV buyers. Of course, the externalities of EVs are not limited to noise. Allcott et al. (2024) find that including all the externalities (air pollution, CO2, accidents, manufacturing externalities, etc), EVs generate \$3,237 lower negative externalties relative to ICEs over their lifetime. Adding our estimate of the external benefits of EVs in terms of noise reduction to Allcott et al. (2024)'s estimate implies that the total external benefit of EVs (relative to ICEs) increases from \$3,237 to \$4,002. Taken literally, this indicates that about one fifth of the total external benefits of EVs (relative to ICEs) stem from noise reduction.

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 6.8% 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 \$110 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 \$974 per ICE vehicle. In addition, we estimate that a broader shift to EVs – which are quieter than ICE vehicles – could yield noise reduction benefits on the order of \$77.3 billion. While policies to incentivize EV adoption are typically thought of as a way to reduce CO2 – a global externality – our findings indicate that EVs may also have potentially important localized benefits in the form of lower traffic noise – a local externality. 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.

References

Ahangar, F. E., D. Heist, S. Perry, and A. Venkatram (2017) "Reduction of air pollution levels downwind of a road with an upwind sound barrier," *Atmospheric Environment*, 155, 137–10, 10.1016/j.atmosenv.2017.02.001.

Ahlfeldt, Gabriel M., Volker Nitsch, and Nicolai Wendland (2019) "Ease vs. noise: Long-run changes in the value of transport (dis)amenities," *Journal of Environmental Economics and Management*, 98, 102268, https://doi.org/10.1016/j.jeem.2019.102268.

Allcott, Hunt, Reigner Kane, Maximilian S Maydanchik, Joseph S Shapiro, and Felix Tintelnot (2024) "The Effects of "Buy American": Electric Vehicles and the Inflation Reduction Act," Working Paper 33032, National Bureau of Economic Research, 10.3386/w33032.

Almer, Christian, Stefan Boes, and Stephan Nüesch (2017) "Adjustment in housing markets after an environmental shock: Evidence from a large-scale change in aircraft noise exposure," *Oxford Economic Papers*, 69 (4), 918–938, 10.1093/oep/gpw066.

Anderson, Michael L. (2020) "As the Wind Blows: The Effects of Long-Term Exposure to Air Pollution on Mortality," *Journal of the European Economic Association*, 18 (4), 1886–1927, 10.1093/jeea/jvz051.

Andersson, Hans, Lars Jonsson, and Magnus Ögren (2010) "Property prices and exposure to multiple noise sources: Hedonic regression with road and railway noise," *Environmental and Resource Economics*, 45 (1), 73–89, 10.1007/s10640-009-9300-1.

Baldauf, Richard, Vlad Isakov, Akula Venkatram, Gregory Mcpherson, and David Heist (2016) "Influence of Noise Barriers on Near-Road and On-Road Air Quality,"Technical report, U.S. Environmental Protection Agency (EPA), `https://cfpub.epa.gov/si/si_public_record_report.cfm?Lab=NERL&dirEntryId=317291`.

Banzhaf, H. Spencer (2021) "Difference-in-Differences Hedonics," *Journal of Political Economy*, 129 (8), 2385–2422.

Bayer, Patrick, Nathaniel Keohane, and Christopher Timmins (2009) "Migration and Hedonic Valuation: The Case of Air Quality," *Journal of Environmental Economics and Management*, 58, 1–14, 10.1016/j.jeem.2008.08.004.

Bayer, Patrick, Robert McMillan, Alvin Murphy, and Christopher Timmins (2016a) "A Dynamic Model of Demand for Houses and Neighborhoods," *Econometrica*, 84 (3), 893–942, 10.3982/ECTA10170.

——— (2016b) "A Dynamic Model of Demand for Houses and Neighborhoods," *Econometrica*, 84 (3), 893–942.

Bento, Antonio M., Lawrence H. Goulder, Mark R. Jacobsen, and Roger H. von Haefen (2009) "Distributional and Efficiency Impacts of Increased US Gasoline Taxes," *American Economic Review*, 99 (3), 667–699.

Blanco, Joan C. and Ian Flindell (2011) "Property prices in urban areas affected by road traffic noise," *Applied Acoustics*, 72, 133–141, 10.1016/j.apacoust.2010.11.004.

Boes, Stefan and Stephan Nüesch (2011) "Quasi-experimental evidence on the effect of aircraft noise on apartment rents," *Journal of Urban Economics*, 69 (2), 196–204, 10.1016/j.jue.2010.09.005.

Bowker, Gary E., Richard W. Baldauf, David K. Heist, Scott G. Perry, and Alan F. Vette (2021) "A Field Study to Estimate the Impact of Noise Barriers on Mitigation of Near-Road Air Pollution," *Air Quality, Atmosphere Health*, 14, 1175–1187, 10.1007/s11869-021-01104-9.

Bowker, G.E., R. Baldauf, V. Isakov, A. Khlystov, and W. Petersen (2007) "The Effect of Roadside Structures on the Transport and Dispersion of Ultrafine Particles from Highways," *Journal of the Air Waste Management Association*, 57 (5), 586–595, 10.3155/1047-3289.57.5.586.

Brandt, Sandra and Wolfgang Maennig (2011) "Road noise exposure and residential property prices: Evidence from Hamburg," *Transportation Research Part D: Transport and Environment*, 16 (1), 23–30, 10.1016/j.trd.2010.07.004.

de Chaisemartin, Clément and Xavier D'Haultfœuille (2024) "Difference-in-Differences Estimators of Intertemporal Treatment Effects," *The Review of Economics and Statistics*, 10.1162/rest_a_01414.

Chay, Kenneth Y. and Michael Greenstone (2005) "Does Air Quality Matter? Evidence from the Housing Market," *Journal of Political Economy*, 113 (2), 376–424, 10.1086/427462.

Cohen, Jeffrey P. and Cletus C. Coughlin (2008) "Spatial hedonic models of airport noise, proximity, and housing prices," *Journal of Regional Science*, 48 (5), 859–878, 10.1111/j.1467-9787.2008.00576.x.

——— (2009) "Changing noise levels and housing prices near the Atlanta airport," *Growth and Change*, 40 (2), 287–313, 10.1111/j.1468-2257.2009.00473.x.

Corbisier, Chris (2003) "Living With Noise," *Federal Highway Administration, U.S. Department of Transportation – Public Roads*, 67 (1).

Currie, Janet, Lucas Davis, Michael Greenstone, and Reed Walker (2015) "Environmental Health Risks and Housing Values: Evidence from 1,600 Toxic Plant Openings and Closings," *The American Economic Review*, 105 (2), 678–709, 10.1257/aer.20121656.

Currie, Janet and Reed Walker (2011) "Traffic Congestion and Infant Health: Evidence from E-ZPass," *American Economic Journal: Applied Economics*, 3 (1), 65–90, https://www.jstor.org/stable/25760246.

Davis, Lucas W., Jing Li, and Katalin Springel (2025) "Political Ideology and U.S. Electric Vehicle Adoption," NBER Working Paper 33591, National Bureau of Economic Research, http://www.nber.org/papers/w33591, NBER Working Paper No. 33591.

Delmas, Magali A., Matthew E. Kahn, and Stephen L. Locke (2017) "The private and social consequences of purchasing an electric vehicle and solar panels: Evidence from California," *Research in Economics*, 71 (2), 225–235, https://doi.org/10.1016/j.rie.2016.12.002.

Dubin, Robin and Jeffrey E. Zabel (2021) "Spatial implications of noise externalities: Evidence from housing prices in multiple cities," *Regional Science and Urban Economics*, 89, 103699, 10.1016/j.regsciurbeco.2021.103699.

Espey, Molly and Hilary Lopez (2000) "The Impact of Airport Noise and Proximity on Residential Property Values," *Growth and Change*, 31 (3), 408–419.

European Environmental Agency (2020) "Environmental noise in europe."

Fowlie, Meredith, Christopher R. Knittel, and Catherine Wolfram (2012) "Sacred Cars? Cost-Effective Regulation of Stationary and Nonstationary Pollution Sources," *American Economic Journal: Economic Policy*, 4 (1), 98–126.

Franck, Marieke, Johan Eyckmans, Simon De Jaeger, and Sandra Rousseau (2015) "Comparing the impact of road noise on property prices in two separated markets," *Journal of Environmental Economics and Policy*, 4 (1), 15–44, 10.1080/21606544.2014.951399.

Gauderman, W. James, Hita Vora, Rob McConnell et al. (2007) "Effect of exposure to traffic on lung development from 10 to 18 years of age: a cohort study," *The Lancet*, 369, 571–577.

von Graevenitz, Katharina (2018) "The amenity cost of road noise," *Journal of Environmental Economics and Management*, 90, 1–22, https://doi.org/10.1016/j.jeem.2018.02.002.

Graff Zivin, Joshua S., Matthew J. Kotchen, and Erin T. Mansur (2014) "Spatial and temporal heterogeneity of marginal emissions: Implications for electric cars and other electricity-shifting policies," *Journal of Economic Behavior Organization*, 107, 248–268, https://doi.org/10.1016/j.jebo.2014.03.010.

Grainger, Corbett A. (2012) "The Distributional Effects of Pollution Regulations: Do Renters Fully Pay for Cleaner Air?" *Journal of Public Economics*, 96, 840–852, 10.1016/j.jpubeco.2012.06.006.

Greenhill, Simon (2024) "Not So Silent Threat: Noise Pollution and Infant Health.," *Working paper*.

Greenstone, Michael and Justin Gallagher (2008) "Does Hazardous Waste Matter? Evidence from the Housing Market and the Superfund Program," *The Quarterly Journal of Economics*, 123 (3), 951–1003, 10.2307/25098922.

Hall, Fred L. and John D. Welland (1987) "The effect of noise barriers on the market value of adjacent residential properties," *Transportation Research Record* (1141), 1–11, Environmental Issues: Noise, Rail Noise, and High-Speed Rail.

Han, Lu, Stephan Heblich, Christopher Timmins, and Yanos Zylberberg (2024) "Cool Cities: The Value of Urban Trees,"Technical Report 32063, National Bureau of Economic Research, `https://www.nber.org/system/files/working_papers/w32063/w32063.pdf`.

Heist, David K., Steven G. Perry, and Lisa A. Brixey (2009) "Atmospheric Dispersion Modeling of Roadside Barriers," *Atmospheric Environment*, 43 (32), 5443–5454, 10.1016/j.atmosenv.2009.02.039.

Hendren, Nathaniel and Ben Sprung-Keyser (2020) "A Unified Welfare Analysis of Government Policies," *The Quarterly Journal of Economics*, 135 (3), 1209–1318.

Hoek, Gerard, Bert Brunekreef, Sandra Goldbohm, Paul Fischer, and Piet A. van den Brandt (2002) "Association between mortality and indicators of traffic-related air pollution in the Netherlands: a cohort study," *The Lancet*, 360, 1203–1209.

Hoen, Ben, Joseph P. Brown, Thomas Jackson, Mark A. Thayer, Ryan Wiser, and Peter Cappers (2015) "Spatial hedonic analysis of the effects of US wind energy facilities on surrounding property values," *Journal of Real Estate Finance and Economics*, 51 (1), 22–51, 10.1007/s11146-013-9446-z.

Hofstetter, Patrick and Ruedi Müller-Wenk (2005) "Monetization of health damages from road noise with implications for monetizing health impacts in life cycle assessment," *Journal of Cleaner Production*, 13, 1235–1245, 10.1016/j.jclepro.2005.05.011.

Holland, Stephen P., Erin T. Mansur, Nicholas Z. Muller, and Andrew J. Yates (2016) "Are There Environmental Benefits from Driving Electric Vehicles? The Importance of Local Factors," *American Economic Review*, 106 (12), 3700–3729.

——— (2019) "Distributional Effects of Air Pollution from Electric Vehicle Adoption," *Journal of the Association of Environmental and Resource Economists*, 6 (S1), S65–S94.

Hughes, William and C. F. Sirmans (1992) "Traffic Externalities and Single-Family House Prices," *Journal of Regional Science*, 32 (4), 487–500.

Iversen, L. M. and R. S. Holck (2015) "Measurement of noise from electrical vehicles and internal combustion engine vehicles under urban driving conditions," in *Euronoise*.

Jacobsen, Mark R., Christopher R. Knittel, James M. Sallee, and Arthur A. van Benthem (2020) "The Use of Regression Statistics to Analyze Imperfect Pricing Policies," *Journal of Political Economy*, 128 (5), 1826–1876.

Jacobsen, Mark R., James M. Sallee, Joseph S. Shapiro, and Arthur A. van Benthem (2022) "Regulating Untaxable Externalities: Are Vehicle Air Pollution Standards Effective and Efficient?".

Jensen, Christian U., Thomas E. Panduro, and Thomas H. Lundhede (2018) "The vindication of Don Quixote: The impact of noise and visual pollution from wind turbines," *Land Economics*, 94 (4), 496–516, 10.3368/le.94.4.496.

Julien, Benoît and Paul Lanoie (2007) "The effect of noise barriers on the market value of adjacent residential properties," *International Real Estate Review*, 10 (2), 113–130.

Kahn, Matthew E. (1996) "New Evidence on Trends in Vehicle Emissions," *RAND Journal of Economics*, 27 (1), 183–196, `https://ideas.repec.org/a/rje/randje/v27y1996ispringp183-196.html`.

Kamerud, Dana B. and Craig R. Von Buseck (1985) "The Effects of Traffic Sound and Its Reduction on House Prices," *Transportation Research Record* (1033), 16–22, Issues in Transportion-Related Environmental Quality.

Kim, Kwang Sik, Sung Joong Park, and Young-Jun Kweon (2007) "Highway Traffic Noise Effects on Land Price in an Urban Area," *Transportation Research Part D*, 12, 275–280, 10.1016/j.trd.2007.03.002.

King, E. A. (2017) "Electric vehicles and environmental noise: Assessing the noise impact of an electric fleet through strategic noise mapping," *The Journal of the Acoustical Society of America*, 142, 2636.

Knittel, Christopher R. and Ryan Sandler (2018) "The Welfare Impact of Second-Best Uniform-Pigouvian Taxation: Evidence from Transportation," *American Economic Journal: Economic Policy*, 10 (4), 211–242.

Kuminoff, Nicolai V. and Jaren C. Pope (2014) "Do "Capitalization Effects" for Public Goods Reveal the Public's Willingness to Pay?" *International Economic Review*, 55 (4), 1227–1250.

Kuminoff, Nicolai V., V. Kerry Smith, and Christopher Timmins (2013) "The New Economics of Equilibrium Sorting and Policy Evaluation Using Housing Markets," *Journal of Economic Literature*, 51 (4), 1007–1062.

Lan, Z., M. Cai, F. Li, and W. Yang (2018) "Study of the Traffic Noise Source Emission Model and the Frequency Spectrum Analysis of Electric Vehicles on Urban Roads in China," *Acta Acustica United with Acustica*, 104, 989–998.

Li, H.N., C.K. Chau, M.S. Tse, and S.K. Tang (2009) "Valuing Road Noise for Residents in Hong Kong," *Transportation Research Part D*, 14, 264–271, 10.1016/j.trd.2009.02.001.

Li, Zhaohui, Shanshan Tang, Wei Wang, Yanyan Zhang, and Xiaolu Li (2023) "The impact of urban rail transit on housing prices: Evidence from China," *Sustainable Cities and Society*, 93, 104557, 10.1016/j.scs.2023.104557.

Lindgren, S. (2021) "A Sound Investment? Traffic Noise Mitigation and Property Values," *Journal of Environmental Economics and Policy*, 10 (4), 428–445, 10.1080/21606544.2021.1911861.

Magagnoli, Riccardo and Francesco Tassinari (2024) "The Price of Silence," *Working paper*, https://www.dropbox.com/scl/fi/82ruaseahn7nvi5nm7b62/Magagnoli_Tassinari_The_price_of_silence.pdf?rlkey=bia5xrdsvkivkvg0fl8hyvxtq&e=3&st=ej9jpzky&dl=0.

Marbjerg, Gerd (2013) "Noise from Electric Vehicles: A Literature Survey,"Technical report, Danish Road Directorate, https://www.vejdirektoratet.dk/api/drupal/sites/default/files/publications/noise_from_electric_vehicles.pdf.

Marmolejo-Duarte, Carlos and César A. González-Tamez (2009) "Does noise have a stationary impact on residential values?" *Journal of European Real Estate Research*, 2 (3), 259–279, 10.1108/17539260910999338.

Mieszkowski, Peter and Arthur M. Saper (1978) "An estimate of the effects of airport noise on property values," *Journal of Urban Economics*, 5 (4), 425–440.

MRLC Consortium (2025) "NLCD 2021 Land Cover (CONUS)," https://www.mrlc.gov/data/nlcd-2021-land-cover-conus, Accessed: 2025-02-11.

Murphy, Enda and Eoin A. King (2014) *Noise Mitigation Approaches*, Chap. 7, 203–212: Elsevier, 10.1016/B978-0-12-411595-8.00007-0.

Navrud, Ståle (2002) "The State-Of-The-Art on Economic Valuation of Noise,"Technical report, European Commission DG Environment, https://www.researchgate.net/publication/254318936_The_State-Of-The-Arton_Economic_Valuation_of_Noise, Final Report.

NCEI (2025) "Local Climatological Data (LCD) Version 2," https://www.ncei.noaa.gov/access/search/data-search/local-climatological-data-v2, Accessed: 2025-02-14.

Nelson, Jon P. (2004) "Meta-Analysis of Airport Noise and Hedonic Property Values," *Journal of Transport Economics and Policy*, 38 (1), 1–28.

Pallas, M. A., B. Kennedy, and P. J. T. Filippi (2014) "Noise Emission of Electric and Hybrid Electric Vehicles: Deliverable 5.3," *European Commission*, https://www.semanticscholar.org/paper/Noise-emission-of-electric-and-hybrid-electric-%3A-Pallas-Kennedy/b226051514d0ebd3bcb56c2dad26d23a31bdefef.

Pallas, Marie Agnès, Michel Berengier, Roger Chatagnon, Martin Czuka, Marco Conter, and Matthew Muirhead (2016) "Towards a model for electric vehicle noise emission in the European prediction method CNOSSOS-EU," *Applied Acoustics*, 113, 89–101, 10.1016/j.apacoust.2016.06.012.

Pope, Jaren C. (2008) "Buyer information and the hedonic: the impact of a seller disclosure on the implicit price for airport noise," *Journal of Urban Economics*, 63 (2), 498–516.

Ran, Linlin, Lijuan He, Xinyu Cui, and Feng Chen (2020) "Effects of Wind Speed and Atmospheric Stability on the Air Pollution Reduction Rate Induced by Noise Barriers," *Journal of Wind Engineering and Industrial Aerodynamics*, 200, 104160, 10.1016/j.jweia.2020.104160.

Rich, Jeppe Husted and Otto Anker Nielsen (2004) "Assessment of Traffic Noise Impacts," *International Journal of Environmental Studies*, 61 (1), 19–29, 10.1080/0020723032000113790.

Rochat, Judith L. and Gregg G. Fleming (2002) "Validation of FHWA's Traffic Noise Model (TNM): Phase 1,"Technical Report DOT-VNTSC-FHWA-02-01; FHWA-EP-02-031, John A. Volpe National Transportation Systems Center, https://rosap.ntl.bts.gov/view/dot/8918, Final Report.

Salvi, Massimiliano (2008) "Spatial estimation of the impact of airport noise on residential housing prices," *Swiss Journal of Economics and Statistics*, 144 (4), 577–606.

Seto, Edmund and Ching-Hsuan Huang (2023) "The National Transportation Noise Exposure Map," *medRxiv*, 10.1101/2023.02.02.23285396.

Sugasawa, Takeru, Yuta Kuroda, Kai Nomura, Shohei Yasuda, and Jun Yoshida (2024) "The Impact of Flight Noise on Urban Housing Markets: Evidence from the New Landing Flight Paths of Haneda Airport in Japan," *DSSR Discussion Papers 144, Graduate School of Economics and Management, Tohoku University.*

Swoboda, Alexander, Tigabu Nega, and Matthias Timm (2015) "Hedonic analysis over time and space: The case of house prices and traffic noise," *Journal of Regional Science*, 55, 644–670, https://doi.org/10.1111/jors.12204.

Szczepańska, Agnieszka, Adam Senetra, and Monika Wasilewicz-Pszczółkowska (2018) "The effect of road traffic noise on the prices of residential property – A case study of the Polish city of Olsztyn," *Transportation Research Part D: Transport and Environment*, 65, 472–486, 10.1016/j.trd.2018.09.005.

Tang, C.K. (2021) "The Cost of Traffic: Evidence from the London Congestion Charge," *Journal of Urban Economics*.

Thanos, Sotirios and Jean Dube, "Noise Valuation through the Shock of Airport Closure: Testing a New Causal Identification Strategy for Hedonic Pricing Based on Comparables."

Theebe, Marco A. (2004) "Planes, trains, and automobiles: The impact of traffic noise on house prices," *Journal of Real Estate Finance and Economics*, 28 (2), 209–234, 10.1023/B:REFE.0000017409.91388.4a.

Thiruvenkatachari, R. R., Y. Ding, and D. Pankratz (2022) "A field study to estimate the impact of sound barriers on mitigation of near road air pollution," *Air Quality, Atmosphere and Health*, 15, 363–372, 10.1007/s11869-021-01104-9.

Verhoef, Erik (1994) "External Effects and Social Costs of Road Transport," *Transportation Research Part A*, 28 (4), 273–287, 10.1016/0965-8564(94)90003-5.

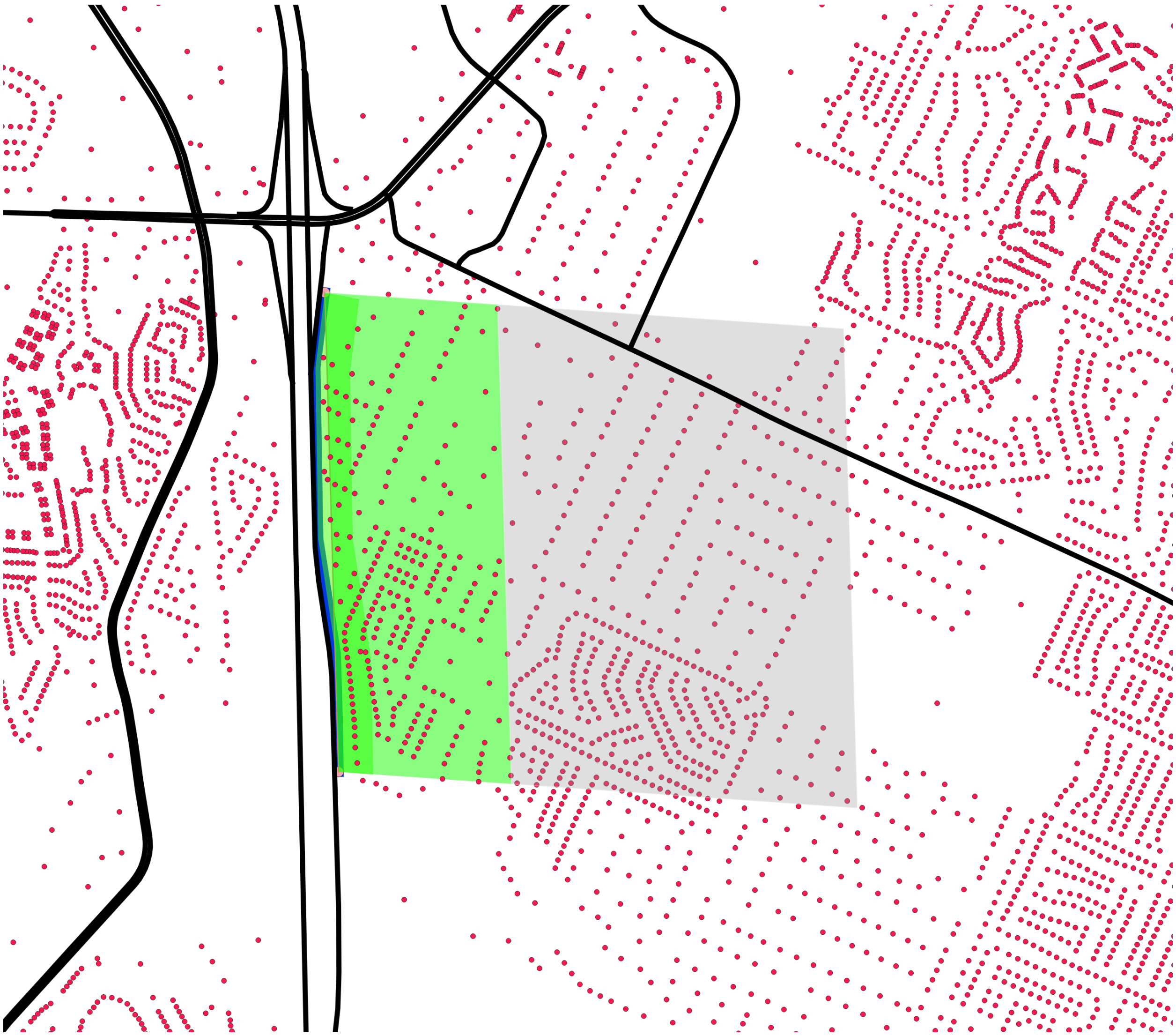
Vestman, Roine, Jesper Bojeryd, Bjorn Tyrefors, and Dany Kessel (2023) "The Housing Wealth Effect: Quasi-Experimental Evidence," `https://roinevestman.com/wp-content/uploads/2023/03/DP18034-compressed.pdf`.

Walker, Bruce et al. (2016) "How Might People Near National Roads Be Affected by Traffic Noise as Electric Vehicles Increase in Number? A Laboratory Study of Subjective Evaluations of Environmental Noise," *PLOS ONE*, 11 (3), e0150516, 10.1371/journal.pone.0150516.

Wang, Yao-pei, Yong Tu, and Yi Fan (2023) "The price of quietness: How a pandemic affects city dwellers' response to road traffic noise," *Sustainable Cities and Society*, 99, 104882, https://doi.org/10.1016/j.scs.2023.104882.

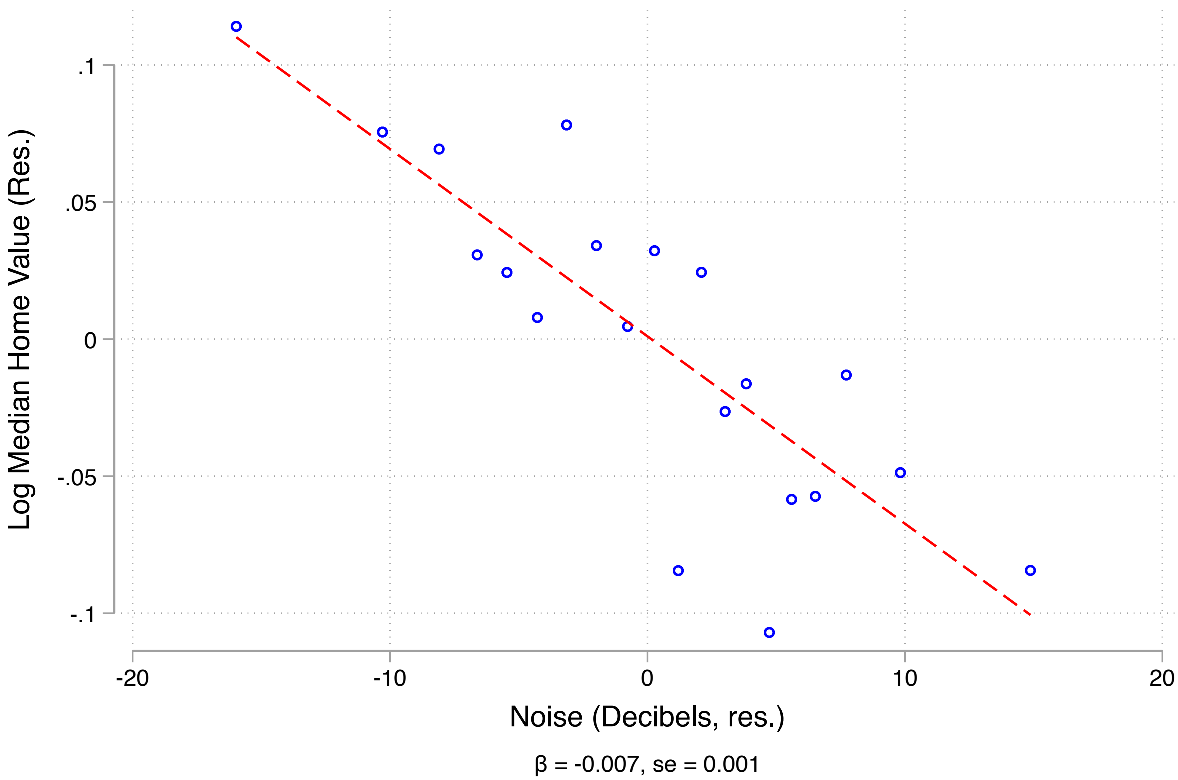
Wilhelmsson, Mats (2000) "The impact of traffic noise on the values of single-family houses," *Journal of Environmental Planning and Management*, 43 (6), 799–815, 10.1080/09640560020000817.

Figure 1: Spatial sampling of property transactions



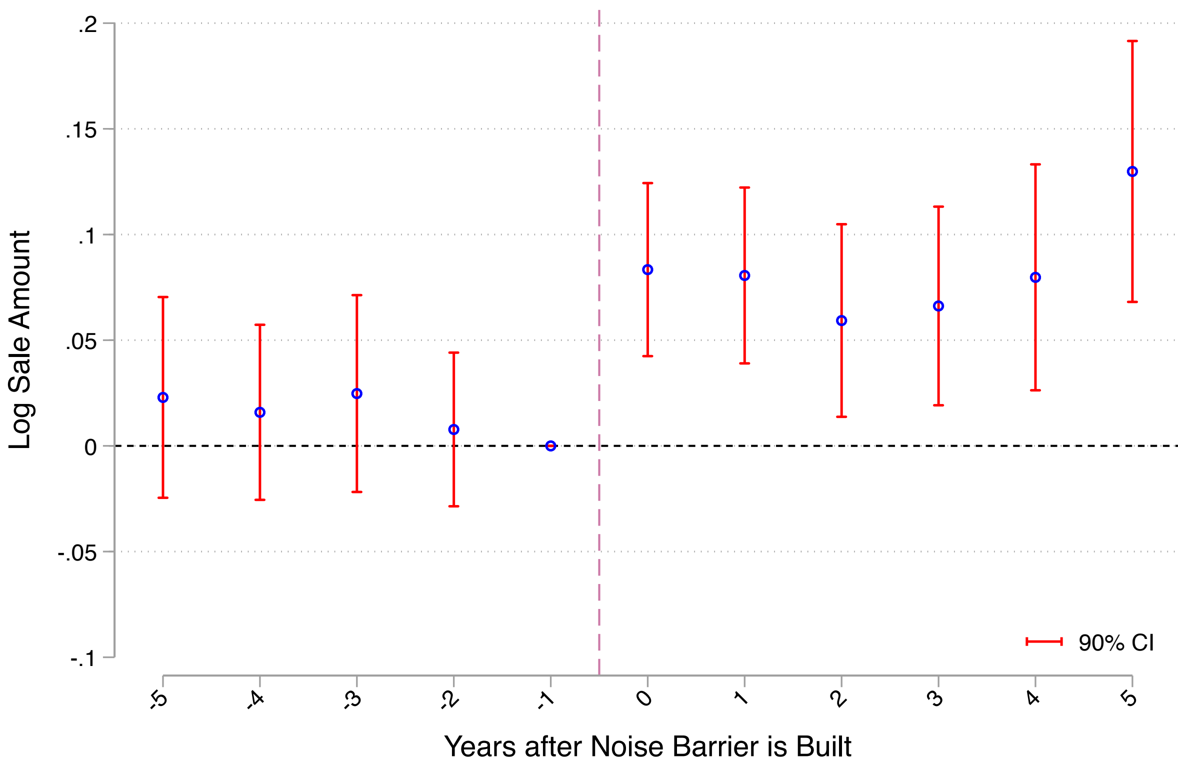
Notes: This figure contains details of the spatial sampling algorithm discussed in Section 3. The depicted barrier is in Daytona Beach, outside of Orlando, Florida. The black lines are a layer of roads from the Florida Department of Transportation. The blue line is a noise barrier built on the side of the road. Dots correspond to property locations from Corelogic. The green shaded areas depict 500 meter buffers on the side of the barrier. For reference, 100 meters from the barrier often contains the first one or two rows of homes. The gray buffer contains properties that are 500–1500 m from the barrier.

Figure 2: Home values and noise



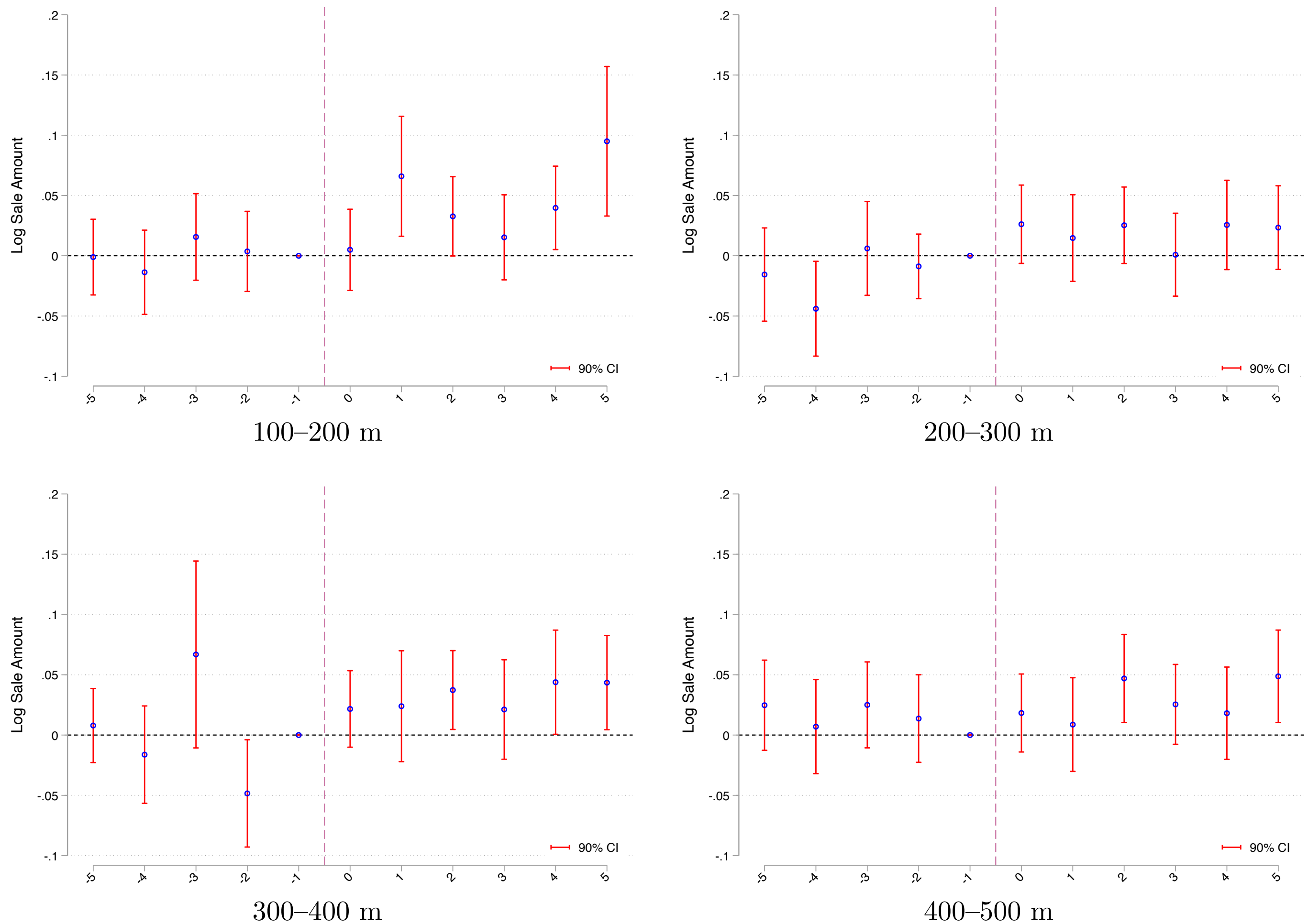
Notes: These figures contain binscatter plots of neighborhood median home values with noise exposure. Our measure of noise is the maximum decibel level, as modeled by the National Transportation Map (2020), across parcels in a 2010 census tract. Median home values come from the 2015-2019 5-year American 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 3: Effects for 0-100m by event time



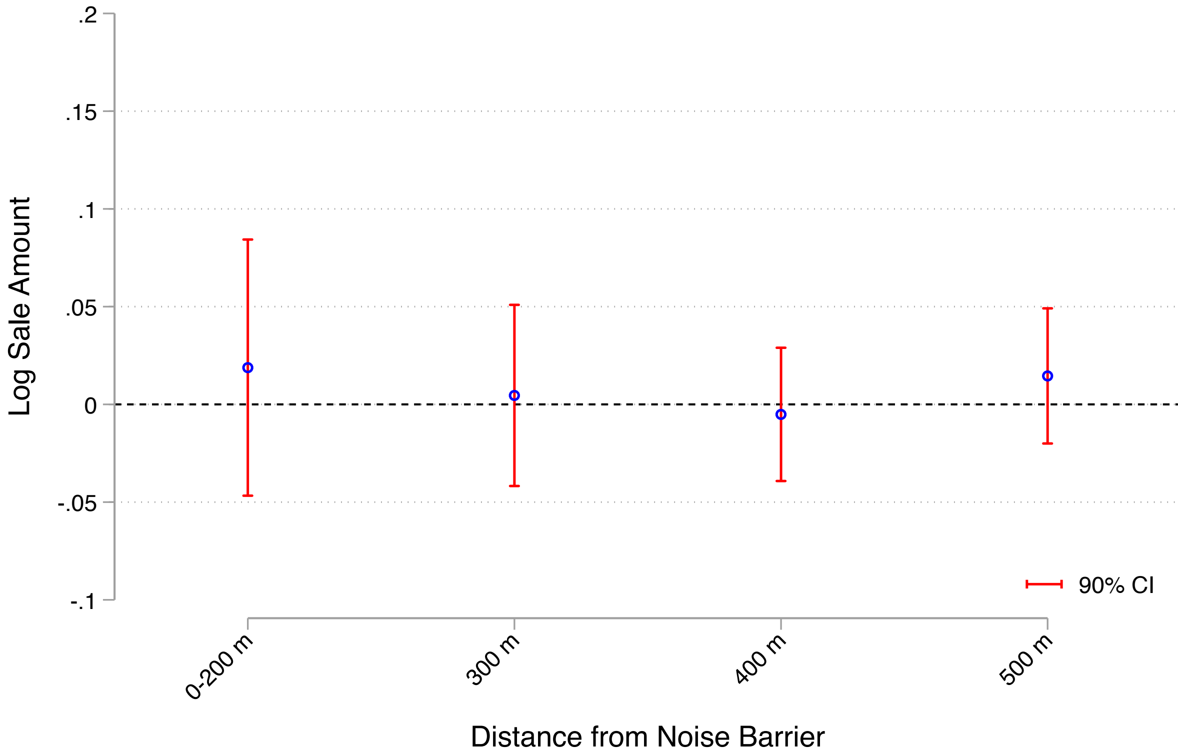
Notes: This figure contains estimates from Equation 2 of the effect on transacted home prices within 100 m of the noise barrier in each year leading up to after the barrier was built. Estimates are in blue and standard errors at the 90% level are in red. Coefficients are plotted for each of the 5 years 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 4: Event studies for further out distances



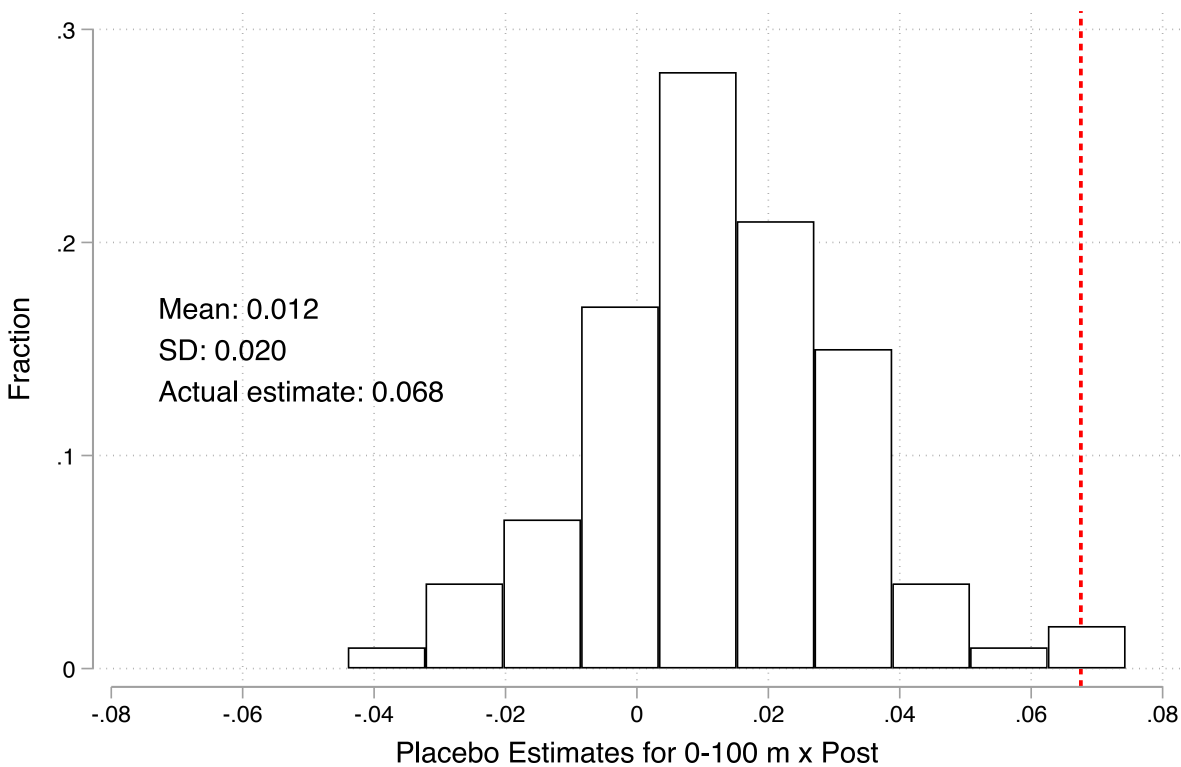
Notes: These figures contains estimates from Equation 2 of the effect on transacted home prices within 100 meter bins of the noise barrier in each year leading up to after the barrier was built. Estimates are in blue and standard errors at the 90% level are in red. Figures are shown for 100–200, 200–300, 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 5: Placebo using "wrong" side of highway difference-in-differences



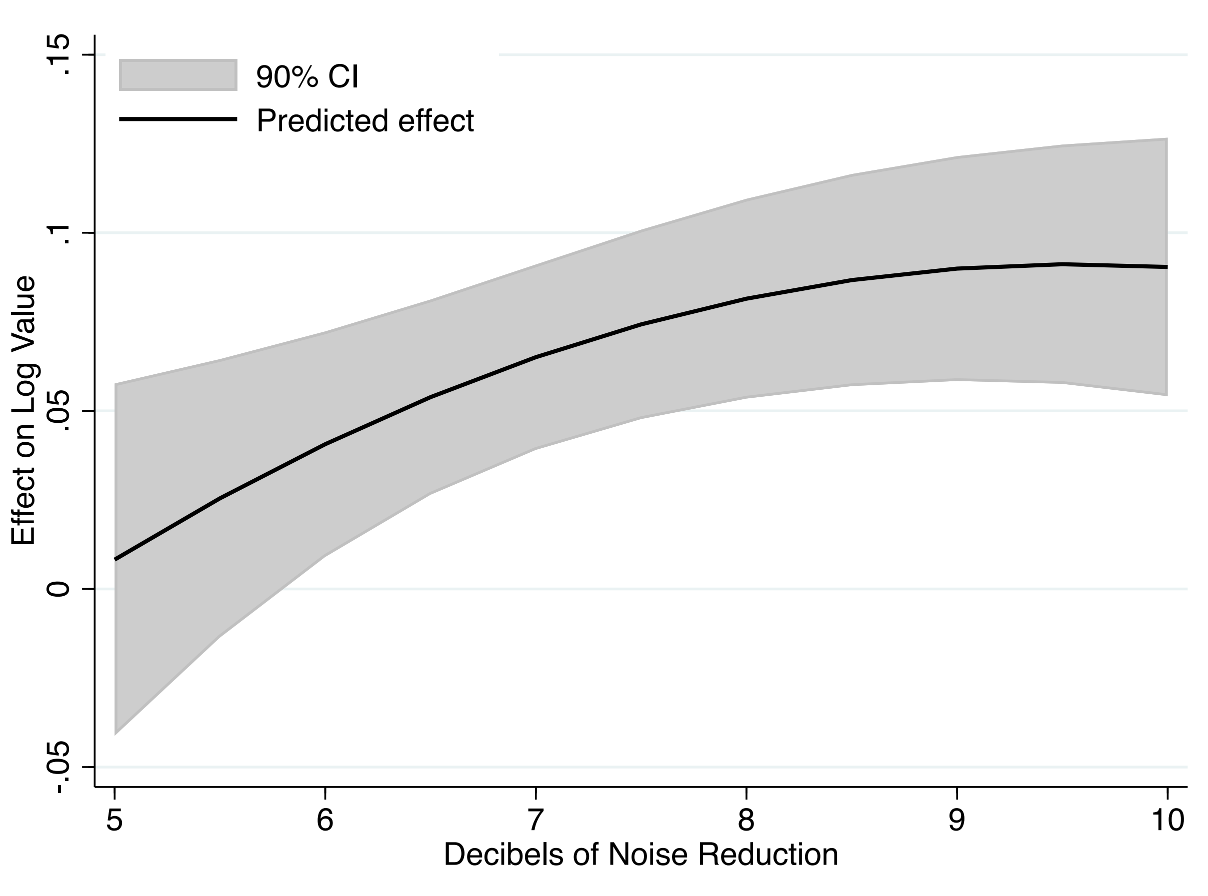
Notes: These figures contains estimates from Equation 3 of the effect on transacted home prices on the "wrong" side of the barrier, within 100 m bins of the noise barrier. The "wrong" side is the one opposite the highway. Details of how we identified it can be found in Section 3. Estimates are in blue 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 6: 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.

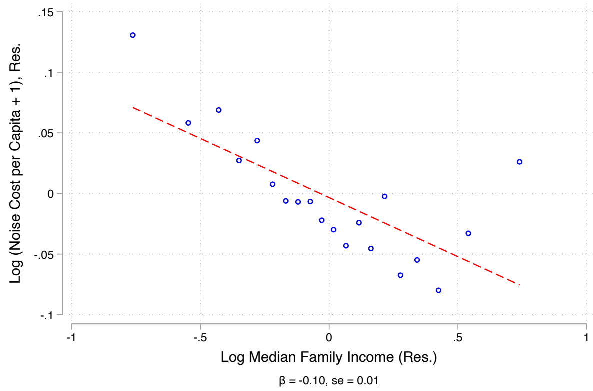
Figure 7: Quadratic effect in noise reduction of barriers on home values



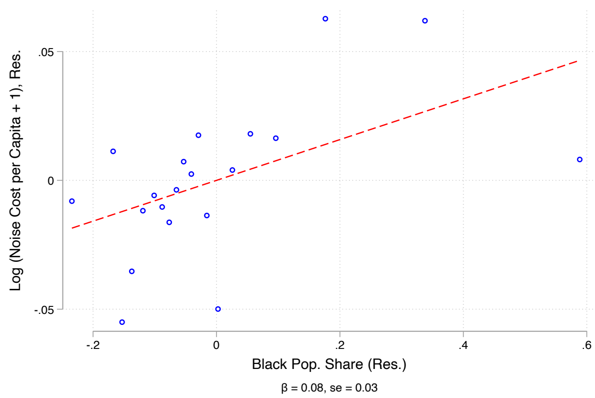
Notes: This figure contains a plot of the quadratic effects estimate from Table 5 in expected noise reduction of the barrier. We use these estimates in our extrapolation exercise (Equation **??**) for the cost of the noise externality and expected benefits from the diffusion of electric vehicles. The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

Figure 8: Noise externality costs (per capita) across neighborhoods

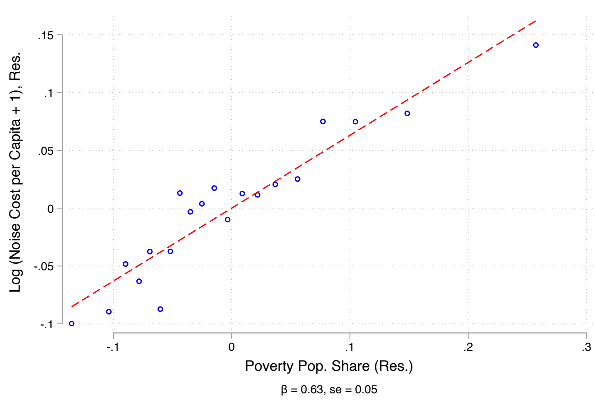
Income



Black share



Poverty



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.

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

	dB > 50	*[46,50]*	*dB < 46*
Florida			
Population (m)	2.2	9.0	8.7
Tracts #	537	2124	2090
Exposure to Any Noise (%)	48.2	1.1	-13.5
Any Exp. to >90 dB (%)	15.7	-0.3	-3.7
Median Fam. Income ($1k)	-12.5	-3.4	6.7
Poverty (%)	3.7	0.6	-1.6
Median Home Val. ($1k)	-48.4	-15.1	27.6
Black (%)	4.8	1.3	-2.5
College Educated (%)	-2.7	-0.8	1.5
Urban (%)	3.1	3.6	-4.5
Density (#/sq. km)	699	32	-213
United States			
Population (m)	42.1	133.6	132.5
Tracts #	11,644	33,020	34,336
Exposure to Any Noise (%)	39.0	-0.5	-12.7
Any Exp. to >90 dB (%)	13.9	-1.0	-3.8
Median Fam. Income ($1k)	-13.2	-2.2	6.4
Poverty (%)	4.0	0.6	-1.9
Median Home Val. ($1k)	-42.5	-5.6	18.7
Black (%)	3.1	0.9	-1.9
College Educated (%)	-2.7	-0.2	1.1
Urban (%)	4.8	8.2	-9.5
Density (#/sq. km)	564	102	-290

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. Row (1) contains the total population. Row (2) contains the total number of census tracts. Each subsequent 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 (3) contains the share of the population exposed to any noise. Row (4) contains the share of the population exposed to extreme noise (greater than 90 dB). Row (5) through (11) 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 top panel contains values for Florida, whereas the bottom panel contains values for the entire U.S. 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	DD	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)	(2)	(3)
	Log. Value	Log. Value	Log. Value
$\mathbb{1}(d \leq 100\mathbf{m}) * \mathbf{post} \times$ **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: Aggregate costs of the noise externality

	Noise Costs			
	Total ($1b)	Cost ($1k) per Capita	Costs pc per MFI (%)	Costs per Prop. Val (%)
Florida	7.00	0.33	0.47	0.26
Q1 MFI (FL)	2.31	0.47	1.18	0.60
Q4 MFI (FL)	1.56	0.30	0.26	0.13
Q1 Black % (FL)	1.50	0.36	0.40	0.17
Q4 Black % (FL)	2.06	0.38	0.74	0.46
United States	109.75	0.34	0.42	0.32
Q1 MFI (U.S.)	24.25	0.35	0.83	0.67
Q4 MFI (U.S.)	39.13	0.44	0.33	0.24
Q1 Black % (U.S.)	20.24	0.27	0.31	0.22
Q4 Black % (U.S.)	23.37	0.30	0.52	0.44

Notes: This table contains estimates of the dollar value of the noise externality. Column (1) contains the aggregate of those costs in billions of 2022 U.S. dollars. Column (2) contains estimates of the cost per capita. Columns (3) and (4) contain estimates of those costs as a percentage of local median incomes and total assessed property values, respectively. 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. Row (6) reports totals for the United States, and rows (7) through (10) perform the same disaggregation as for Florida. These measures are at the 2010 census tract level and come from the 2015-2019 American Community Survey.

Table 9: Costs of traffic noise for the most populous counties

Counties	Noise Costs			
	Total ($1b)	Cost ($1k) per Capita	Costs pc per MFI (%)	Costs per Prop. Val (%)
Los Angeles	8.80	0.87	1.04	0.48
Cook	0.48	0.09	0.11	0.75
Harris	2.07	0.45	0.56	0.33
Maricopa	0.24	0.05	0.07	0.30
San Diego	1.69	0.51	0.54	0.26
Orange	2.23	0.71	0.66	0.31
Miami-Dade	1.69	0.63	0.91	0.41
Kings	0.50	0.19	0.24	0.59
Dallas	1.83	0.70	0.88	0.46
Riverside	0.71	0.29	0.38	0.20

Notes: This table contains estimates of the dollar value of the noise externality for the top 10 most populous U.S. counties. Column (1) contains the aggregate of those costs in billions of 2022 U.S. dollars. Column (2) contains estimates of the cost per capita. Columns (3) and (4) contain estimates of those costs as a percentage of local median incomes and total assessed property values, respectively. These measures are at the 2010 census tract level and come from the 2015-2019 American Community Survey.

Table 10: Potential benefits of electric vehicles

	EV Benefits			
	Total ($1b)	Benefit ($1k) per Capita	Benefit pc per MFI (%)	Benefit per Prop. Val (%)
Florida	5.39	0.26	0.36	0.20
Q1 MFI (FL)	1.94	0.40	0.99	0.50
Q4 MFI (FL)	0.96	0.19	0.16	0.08
Q1 Black % (FL)	1.03	0.24	0.28	0.12
Q4 Black % (FL)	1.71	0.32	0.62	0.38
United States	77.28	0.24	0.30	0.22
Q1 MFI (U.S.)	19.72	0.28	0.68	0.54
Q4 MFI (U.S.)	22.63	0.25	0.19	0.14
Q1 Black % (U.S.)	14.13	0.19	0.22	0.15
Q4 Black % (U.S.)	18.29	0.24	0.40	0.35

Notes: This table contains estimates of 100% diffusion of electric vehicles (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. Columns (3) and (4) contain estimates of those benefits as a percentage of local median incomes and total assessed property values, respectively. 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. Row (6) reports totals for the United States, and rows (7) through (10) perform the same disaggregation as for Florida. These measures are at the 2010 census tract level and come from the 2015-2019 American Community Survey.

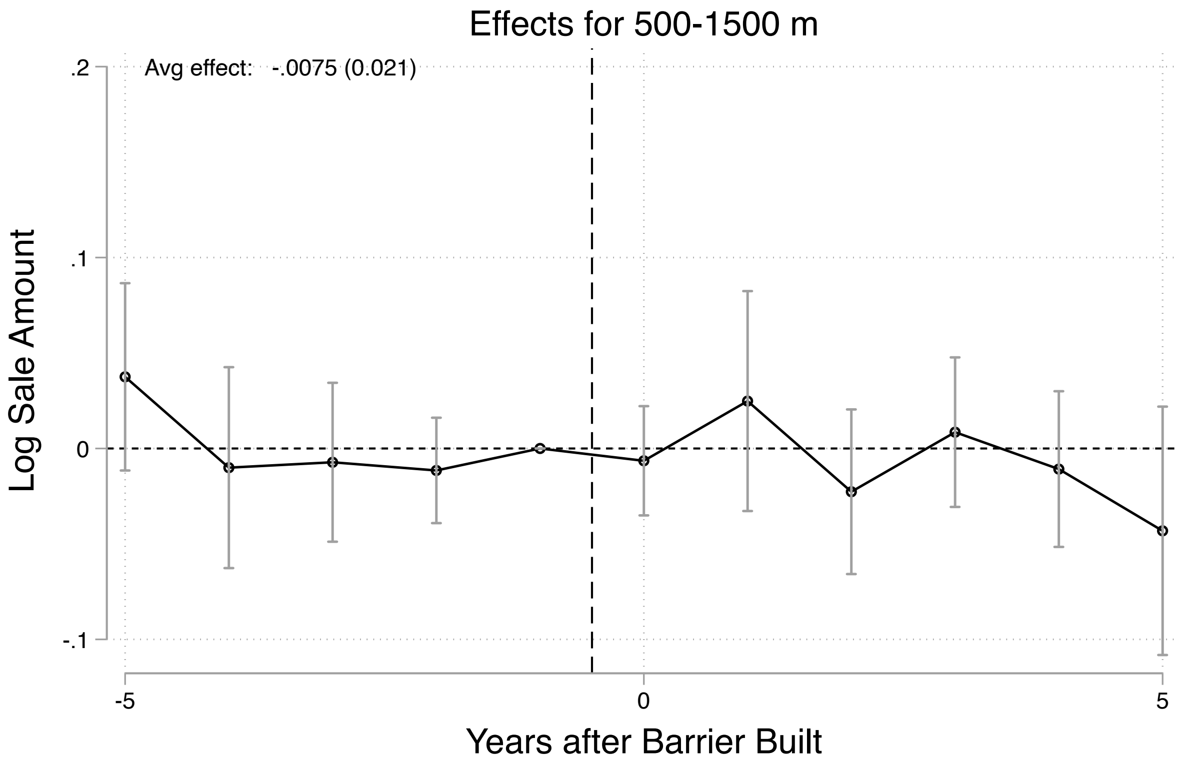
Table 11: Realized EV benefits for top/bottom counties by EV adoption

Top / Bottom 7 Counties	EV Share	Total ($1m)	Benefit ($) per Capita	Benefit pc per MFI (%)	Benefit per Prop. Val (%)
Santa Clara	0.230	264.70	137.37	0.10	0.04
San Francisco	0.186	275.86	315.28	0.22	0.09
Alameda	0.178	123.62	74.61	0.06	0.03
Orange	0.156	192.58	60.79	0.06	0.03
King	0.141	168.75	76.86	0.06	0.02
Contra Costa	0.132	43.20	37.82	0.03	0.02
San Diego	0.108	102.83	31.11	0.03	0.02
Hidalgo	0.004	0.90	1.05	0.00	0.00
Macomb	0.004	0.58	0.67	0.00	0.00
El Paso	0.004	1.47	1.76	0.00	0.00
St. Louis	0.003	0.25	0.25	0.00	0.00
Cuyahoga	0.003	0.28	0.22	0.00	0.00
Jefferson	0.002	0.80	1.05	0.00	0.00
Wayne	0.002	0.98	0.56	0.00	0.00

Notes: This table contains estimates of the dollar value of the current diffusion of EVs in U.S. counties. The top and bottom panels include the top and bottom 7 counties by 2023 share of vehicles that are EVs, respectively. Column (1) contains the share of vehicles that are EVs. Column (2) contains the aggregate of those benefits in millions of 2022 U.S. dollars. Column (3) contains estimates of the benefit per capita. Columns (4) and (5) contains estimates of those benefits as a percentage of local median incomes and total assessed property values, respectively. These measures are aggregated up from the 2010 census tract level.

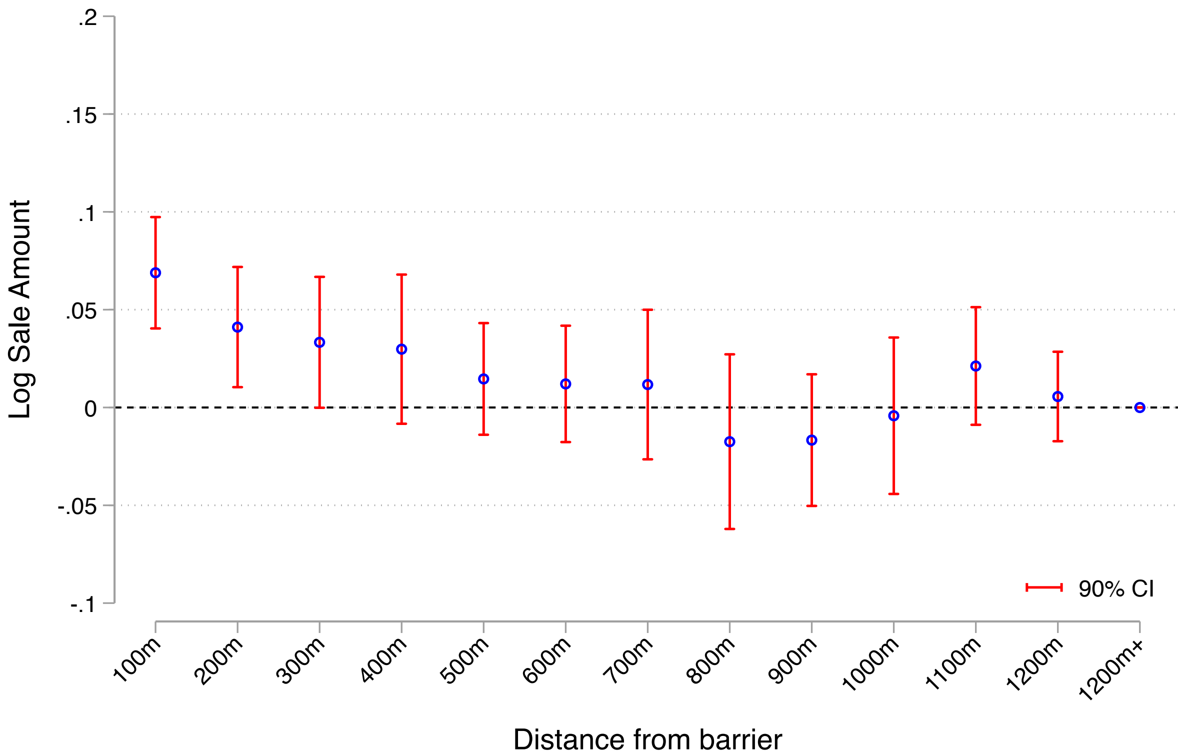
Appendix

Appendix Figure A1: Event study effects for 500–1500 m from the noise barrier



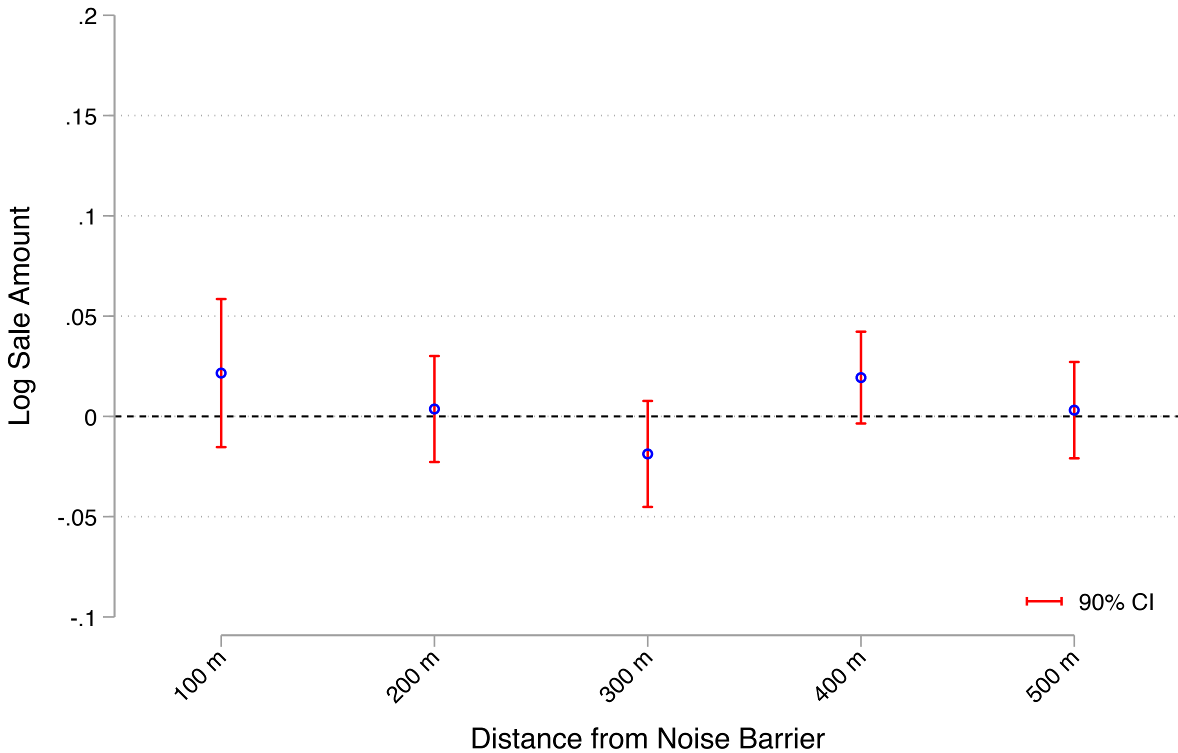
Notes: This figure plots event study estimates of the effect of the barrier on transacted home value prices 500–1500 m away from the barrier. To do this, we use transactions 500–1500 m way from barriers that have yet to be constructed as the control group. This design is subject to concerns over two-way 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 A2: Difference-in-differences estimates by distance



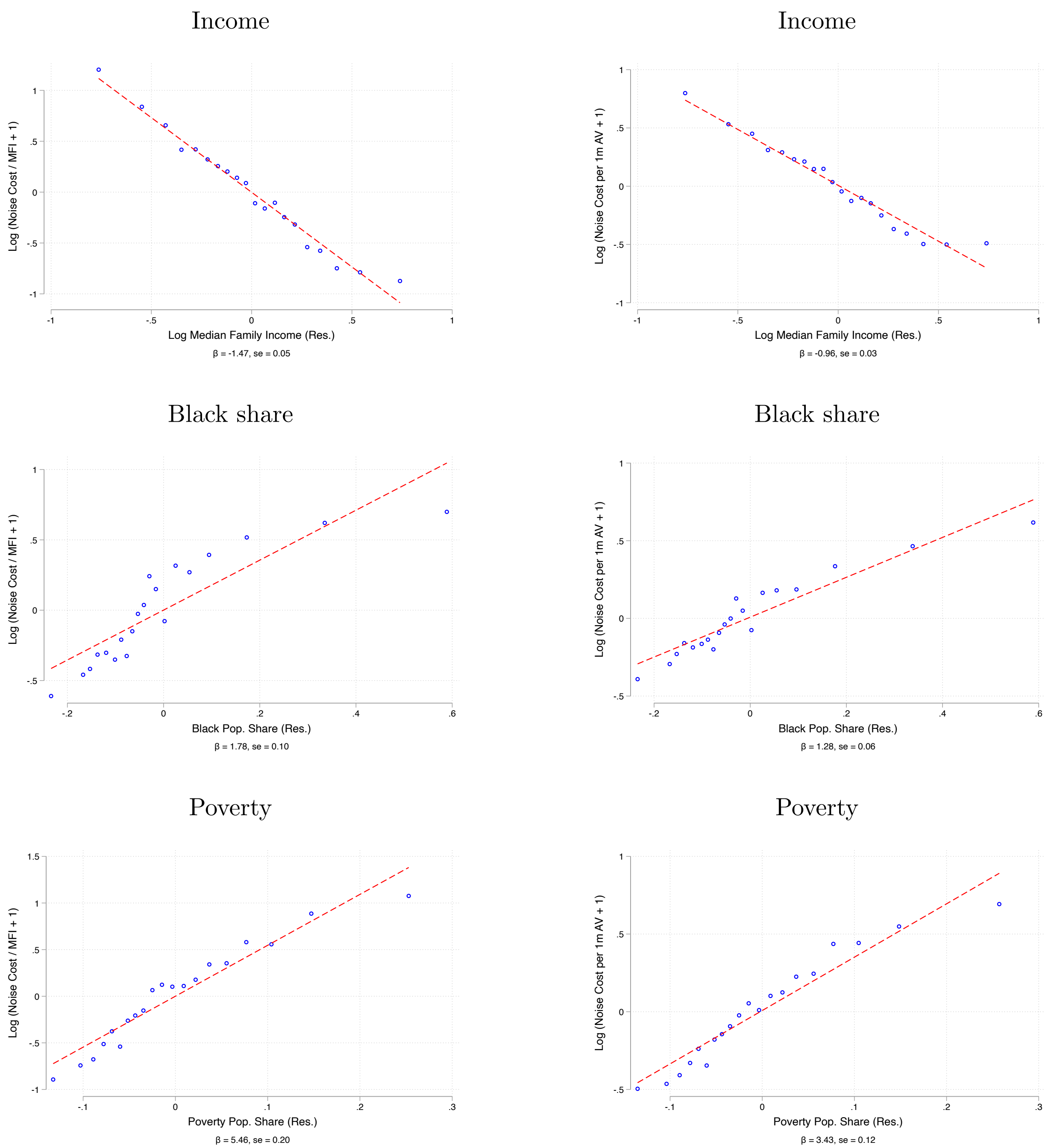
Notes: This figure contains estimates from Equation 3 of the average effect on transacted home prices in 100 meter bins from the noise barrier. Estimates are in blue and standard errors at the 90% level are in red. The difference-in-differences design considers changes in transaction values five years 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 A3: Placebo estimates using proposed barriers



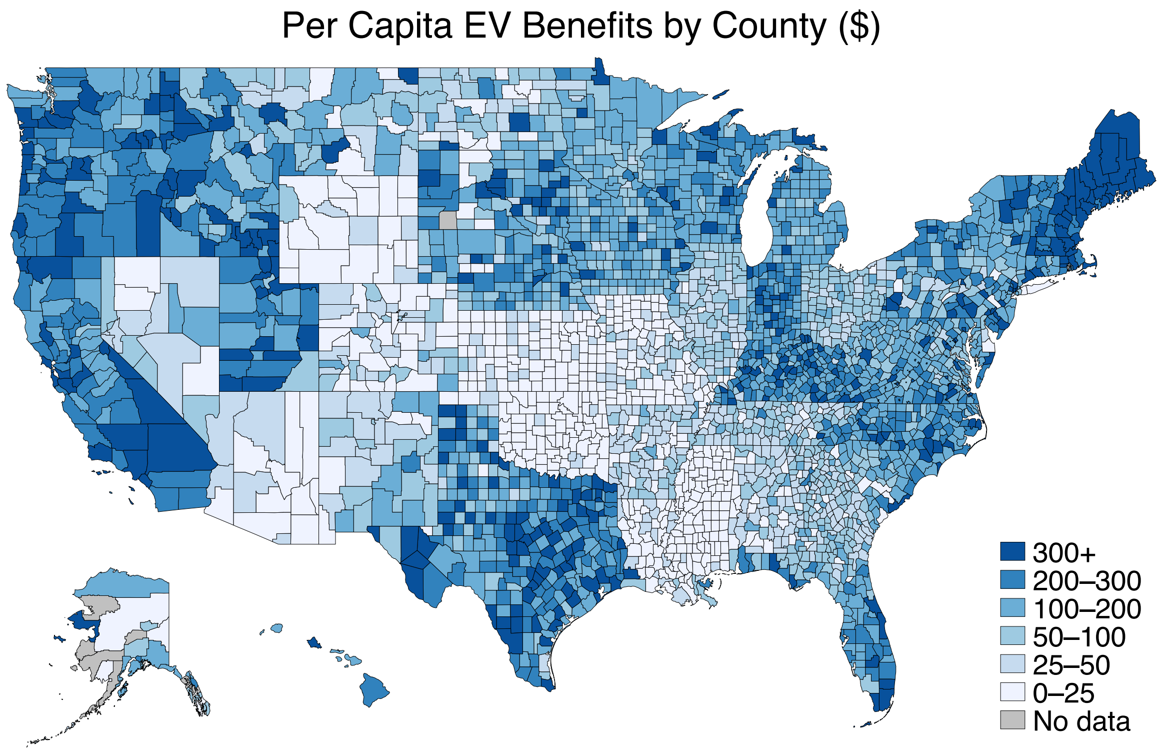
Notes: This figures contains estimates from Equation 3 of the effect on transacted home prices for proposed (but not built) barriers within 100 meter bins of the proposed barrier. Estimates are in blue and standard errors at the 90% level are in red. Figures are shown for 0–100, 100–200, 200–300, 300–400, 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 A4: Noise externality costs (per capita as a fraction of income and as a fraction of property values) 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 (on the left) and by assessed property values (on the right) 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.

Appendix Figure A5: Realized EV benefits by county



Notes: This figures contains estimates of the current per capita benefits of EVs in counties across the U.S. We use the statewide total number of EVs from the U.S. Department of Energy for 2023. We include plug-in Hybrid EVs in this calculation. We allocate EVs across all counties according to the share of EV charging ports within the state located in that county. The locations of EV charging ports are from the Joint Office of Energy and Transportation and are current as of March 2025. We then calculate the share of all personal vehicles in the county that are EVs using the 2019-2023 American Community Survey. We then multiply this share by the potential benefits of 100% EVs according to the analysis in Table 10.

Appendix Table A1: Sound barrier summary statistics

Summary Statistics					
	Constructed		*Recommended*		*Diff.*
	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
Noise Reduction (dB)	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			
Population (m)	2	9	9
Tracts #	537	2124	2090
Exposure to Any Noise (%)	90	31	5
Any Exp. to >90 dB (%)	26	10	7
Median Fam. Income ($1k)	64	72	79
Poverty (%)	17	14	11
Median Home Val. ($1k)	239	251	260
Black (%)	23	17	10
College Educated (%)	21	23	23
Urban (%)	99	98	80
Density (#/sq. km)	3,212	1,902	930
United States			
Population (m)	42	134	133
Tracts #	11,644	33,020	34,336
Exposure to Any Noise (%)	88	33	5
Any Exp. to >90 dB (%)	31	17	20
Median Fam. Income ($1k)	80	86	85
Poverty (%)	18	13	11
Median Home Val. ($1k)	368	312	247
Black (%)	20	15	9
College Educated (%)	23	24	21
Urban (%)	99	96	52
Density (#/sq. km)	5,272	2,479	589

Notes: This table contains summary statistics for neighborhoods across Florida and 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 total population. Row (2) contains the total number of census tracts. Row (3) contains the share of the population exposed to any noise. Row (4) contains the share of the population exposed to extreme noise (greater than 90 dB). Row (5) through (11) 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 top panel contains values for Florida, whereas the bottom panel contains values for the entire U.S. 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: Intensity of treatment under alternative controls

	(1)	(2)	(3)
	Log. Value	Log. Value	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 A5: 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.

Appendix Table A6: Effect of barrier construction on transaction, residence, and property characteristics

Panel A: Transaction Outcomes	Investor	Resale	New Bldg	Cash	Mortg.	Forcl.
100 meters × 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 × 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 × 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 × 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 × 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)
Panel B: Land Use Outcomes	SFR	Condo	Duplex	Apt.		
100 meters × Post	0.00720	-0.00477	-0.000745	-0.00168		
	(0.00670)	(0.00619)	(0.00231)	(0.00195)		
200 meters × Post	-0.00723	0.00522	0.000965	0.00105		
	(0.00763)	(0.00730)	(0.00182)	(0.00182)		
300 meters × Post	-0.00252	0.00238	-0.000307	0.000453		
	(0.00503)	(0.00446)	(0.00186)	(0.00184)		
400 meters × Post	-0.00419	0.00103	0.00414**	-0.000976		
	(0.00680)	(0.00624)	(0.00195)	(0.00176)		
500 meters × Post	-0.0000995	-0.00386	0.00467**	-0.000706		
	(0.00491)	(0.00417)	(0.00208)	(0.00169)		
Panel C: Building Characteristics	Bedrooms	Stories	Pool	Central AC	Fin. Garage	
100 meters × Post	-0.0105	-0.00873	0.00527	-0.00382	0.00134	
	(0.0204)	(0.00835)	(0.00520)	(0.00290)	(0.00470)	
200 meters × Post	-0.0236	-0.0184	0.00329	-0.000875	0.00524	
	(0.0171)	(0.0129)	(0.00405)	(0.00256)	(0.00421)	
300 meters × Post	-0.0104	0.00315	0.0120**	0.000471	0.00275	
	(0.0166)	(0.00737)	(0.00493)	(0.00265)	(0.00428)	
400 meters × Post	-0.0283	-0.000326	0.000247	-0.00651	0.00143	
	(0.0217)	(0.00893)	(0.00502)	(0.00470)	(0.00520)	
500 meters × Post	0.00518	-0.000496	0.00859	-0.00235	-0.000290	
	(0.0154)	(0.00653)	(0.00531)	(0.00316)	(0.00422)	

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 (Panel A), land use characteristics (Panel B), and property characteristics (Panel C). Thus, the table assesses whether the construction of the barrier induces any change in the types of transactions, residences, or properties that are sold at various distances from the barrier. For Panel A, 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. For Panel B, columns (1) through (4) consider whether there is a change in whether the property is a single family residence, a condominium, a duplex, or an apartment, respectively. For Panel C, 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 A7: Robustness to outliers and varying distance and time horizons

Panel A: Lower Outliers	> $1k	> $5k	> $10k	> $20k
100 meters × post	0.0676***	0.0608***	0.0585***	0.0575***
	(0.0139)	(0.0126)	(0.0122)	(0.0118)
200 meters × post	0.0399***	0.0372***	0.0357***	0.0369***
	(0.0141)	(0.0131)	(0.0129)	(0.0128)
300 meters × post	0.0318**	0.0297**	0.0248**	0.0280**
	(0.0131)	(0.0127)	(0.0123)	(0.0114)
400 meters × post	0.0285	0.0265	0.0266	0.0291
	(0.0196)	(0.0189)	(0.0186)	(0.0181)
500 meters × post	0.0132	0.00557	0.00756	0.00674
	(0.0111)	(0.0102)	(0.00995)	(0.00942)
Panel B: Upper Outliers	< $7.5m	< $5m	< $2.5m	< $1m
100 meters × post	0.0676***	0.0603***	0.0415***	0.0387***
	(0.0139)	(0.0133)	(0.0112)	(0.0109)
200 meters × post	0.0399***	0.0298**	0.0144	0.0159
	(0.0141)	(0.0129)	(0.0106)	(0.0105)
300 meters × post	0.0318**	0.0253**	0.0141	0.0158
	(0.0131)	(0.0123)	(0.0107)	(0.0100)
400 meters × post	0.0285	0.0156	0.0119	0.00191
	(0.0196)	(0.0178)	(0.0121)	(0.0108)
500 meters × post	0.0132	0.00938	0.00125	0.00183
	(0.0111)	(0.0107)	(0.0103)	(0.0108)
Panel C: Distance Sensitivity	≤ 1500m	≤ 800m	≤ 1000m	≤ 1200m
100 meters × post	0.0676***	0.0460***	0.0637***	0.0664***
	(0.0139)	(0.0153)	(0.0155)	(0.0146)
200 meters × post	0.0399***	0.0240*	0.0364***	0.0367***
	(0.0141)	(0.0144)	(0.0138)	(0.0141)
300 meters × post	0.0318**	0.0187*	0.0290***	0.0280**
	(0.0131)	(0.0109)	(0.0106)	(0.0114)
400 meters × post	0.0285	0.00658	0.0189	0.0244
	(0.0196)	(0.0186)	(0.0180)	(0.0190)
500 meters × post	0.0132	0.00549	0.0133	0.0124
	(0.0111)	(0.0120)	(0.0112)	(0.0109)
Panel D: Event Time Window	-10 to 10	-5 to 5	-8 to 8	-12 to 12
100 meters × post	0.0676***	0.0603***	0.0684***	0.0674***
	(0.0139)	(0.0133)	(0.0136)	(0.0143)
200 meters × post	0.0399***	0.0347***	0.0403***	0.0396***
	(0.0141)	(0.0134)	(0.0141)	(0.0146)
300 meters × post	0.0318**	0.0302**	0.0327**	0.0306**
	(0.0131)	(0.0123)	(0.0128)	(0.0134)
400 meters × post	0.0285	0.0266	0.0283	0.0276
	(0.0196)	(0.0177)	(0.0194)	(0.0200)
500 meters × post	0.0132	0.0158	0.0162	0.0133
	(0.0111)	(0.0107)	(0.0109)	(0.0113)

Notes: This table contains estimates of Equation 3 using 500–1500 m as the control group under different restrictions on outliers (Panels A and B), distances included in our estimation sample (Panel C), and event times included in our estimation sample (Panel D). All specifications include our main set of fixed effects and controls. All errors are clustered at the barrier-level.

Appendix Table A8: Price effect as a function of expected noise reduction interacted with property value

Interaction with dB reduction			
	Base	Linear	Squared
Base	0.0590***	0.0186*	-0.0036
	(0.0146)	(0.0095)	(0.0024)
Log Median Home Val.	-0.0649**	0.0165	-0.0058
	(0.0305)	(0.0198)	(0.0057)
Observations = 585083			

Notes: This table contains a version of our main specification given in Equation 3 where the effects are allowed to vary with housing price 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 home values 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.

To use these estimates to measure the cost of the noise externality in Section 6, we proceed as follows. We are concerned that extrapolating our estimates to neighborhoods with home values well below or above those observed in Florida will lead to issues over external validity, as well as the influence of outliers. To address this, we censor tract-level log median home values symmetrically so that 10% of Florida's neighborhoods are censored. This comes out to ± 0.75 around the mean of 12.2 (in logged terms). We then perform the same censoring for neighborhoods in the U.S. nationally. This censors 32% of tracts nationally, so can be thought of approximately censoring at 1 standard deviation. We continue to censor the estimated price effects on the lower range to be positive, and on the upper range, to be equal to their value at 10 dB for any value greater than 10 dB.

Appendix Table A9: Costs of traffic noise without adjusting for heterogeneity in price effects across neighborhoods

	Noise Costs			
	Total ($1b)	Cost ($1k) per Capita	Costs pc per MFI (%)	Costs per Prop. Val (%)
Florida	8.09	0.39	0.54	0.30
Q1 MFI (FL)	1.86	0.38	0.94	0.48
Q4 MFI (FL)	3.06	0.59	0.52	0.26
Q1 Black % (FL)	2.42	0.57	0.65	0.28
Q4 Black % (FL)	1.73	0.32	0.62	0.39
United States	163.97	0.51	0.63	0.48
Q1 MFI (U.S.)	22.76	0.33	0.78	0.63
Q4 MFI (U.S.)	83.46	0.94	0.70	0.51
Q1 Black % (U.S.)	30.85	0.41	0.47	0.33
Q4 Black % (U.S.)	25.61	0.33	0.57	0.49

Notes: This table contains estimates of the dollar value of the noise externality. Column (1) contains the aggregate of those costs in billions of 2022 U.S. dollars. Column (2) contains estimates of the cost per capita. Columns (3) and (4) contain estimates of those costs as a percentage of local median incomes and total assessed property values, respectively. 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. Row (6) reports totals for the United States, and rows (7) through (10) perform the same disaggregation as for Florida. These measures are at the 2010 census tract level and come from the 2015-2019 American Community Survey.