Hear Ye, Bear Ye: Housing Prices, Noise Levels, and Noise Inequality

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Abstract: Transportation noise – both air and road – is pervasive in major metropolitan areas, and there is heterogeneity in the noise exposure faced by many residents across space. High housing prices can impede some residents in moving from louder to less noisy areas. This paper relies on Census tract-level road and aviation noise data covering the contiguous U.S. for 2016 and 2018, along with American Community Survey data, to address whether house prices can be a barrier to avoiding noise for residents in some demographic groups. In the first known comprehensive analysis of this type combining these datasets over multiple years, we explore which tracts, states and demographic groups have residents who experience disproportionate noise. Then, we use quantile regressions to demonstrate inter-relationships between house prices and demographics, and how these interactions are correlated with noise. We find that White and Black residents tend to avoid noise, and this avoidance intensifies with noise. The estimates also suggest White populations are better able to avoid noise pollution than Black and Hispanic residents, and home values may be an important determinant in shaping unequal ability to avoid noise.

Keywords: noise, inequality, house prices, quantile regression

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Introduction

Documenting disproportionate noise pollution exposure, and considering the relationships between such noise, house prices (that is, affordability), and demographics, are important issues in U.S. urban areas. Which demographic groups bear the most road and aviation noise throughout the U.S., and are lower priced (more affordable) houses associated with more noise? These are the two important focus questions of this paper that have not been thoroughly examined at the Census tract level using comprehensive micro-data for road and aviation noise in the contiguous United States.

Road and aviation noise are pervasive disamenities for those living and working in urban areas. Levels of noise are important because excessive noise can have harmful effects on health (via sleep disruption and hearing deterioration), as well as on learning and household income.[1] [2] Reducing road traffic through urban areas (Chandioa et al., 2010) is one potential way to address racial and ethnic disparities in noise pollution exposure. However, a thorough understanding of where the noise is, whether it occurs in areas with more (or less) affordable house prices, and who bears the greatest burden are important first questions to understand before sustainable planning can be implemented in a broad sense.

A large real estate economics literature demonstrating the extent to which noise, especially noise stemming from airports, is negatively related to home prices exists (e.g., Breidenbach et al., 2022; Cohen et al., 2023). However, little research focuses on the questions of how lower-priced homes are correlated with noise and the associated demographic distributions of noise burdens.

Related to the issue of noise levels and willingness to pay for noise avoidance is the distribution of noise across groups. In other words, are White, Black, and Hispanic residents subjected to differing degrees? An unequal distribution of noise raises potential environmental justice issues. According to the U.S. Environmental Protection Agency:[3]

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[1] Swoboda et al. (2015) identified the following health-related effects: 1) simple annoyance, 2) sleep disturbance, 3) increasing risk for stroke, 4) hypertension, 5) myocardial infarction, 6) overall quality of life. For specific references examining these effects, see Cohen et al. (2019). With respect to airport noise, Issing and Kruppa (2004) highlight that even while sleeping the noise from airplanes may lead to the release of stress hormones that increase the risk of heart attacks. This conclusion is reinforced by Lefèvre at al. (2017) in their study of aircraft noise in France.

[2] While the adverse consequences of noise on health have received relatively more attention, Trudeau and Guastavino (2021) note that sound can be a restorative resource. In other words, access to a soothing sound environment can produce positive health results.

[3] See https://www.epa.gov/environmentaljustice

> “Environmental justice is the fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income, with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies. This goal will be achieved when everyone enjoys:
>
> - The same degree of protection from environmental and health hazards, and
> - Equal access to the decision-making process to have a healthy environment in which to live, learn, and work.”

In the context of the U.S. Department of Transportation (DOT), Order 5610.2(a) requires that environmental justice must be considered in all their programs, policies, and activities.[4]

For road and aviation noise, both the levels and distribution of the burden of such noise are important considerations. Noise in the U.S. is measured by most planners in units of DNL, which are estimates of the decibels of day-night average sound levels. The decibels (dB) scale is logarithmic, which implies the noise level is given as 10^(dB/10). Applying this formula, the linear level of noise (relative to 0 dB) is 1.0 for 0 dB. The U.S. Federal Register (2000) describes annoyance as the adverse psychological response to noise, and notes that 12 percent of people subjected to a DNL of 65 dB report that they are “highly annoyed” while 3 percent are “highly annoyed” with DNL of 55 dB. A much larger share of individuals (40 percent) are highly annoyed at DNL of 75 dB. The U.S. Federal Aviation Administration (FAA) currently uses a cutoff of 65 dB as normally “compatible” with residential use (FAA, 2018).

For levels of noise that pose no threat to sleeping and learning (which in turn, have no impact on health or willingness to pay by homeowners to avoid noise), then sustainable planning actions to mitigate noise inequality are likely unnecessary. But for excessive noise levels, both the levels and distribution of noise across groups pose policy issues.

Our focus is on examining noise levels as well as its distribution across groups. We use noise data at the Census tract level across states in the contiguous United States for 2016 and 2018. While this is a brief period of coverage for road and aviation noise,

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[4] See DOT Order 5610.2(a) (Actions to Address Environmental Justice in Minority Populations and Low-Income Populations) – 2012. https://www.transportation.gov/transportation-policy/environmental-justice/department-transportation-order-56102a#:~:text=DOT%20Order%205610.2(a)%20sets,%2C%20rulemaking%2C%20and%20policy%20formulation

setting a baseline for future studies is important. There is also substantial variation over space with over 73,000 Census tracts in the continental U.S. for which we have noise data in each year.

To address heterogeneity in the relationships between demographics and noise, and between house prices and noise, we use a quantile regression approach. This approach enables us to discern how the relationships differ for various noise quantiles. We find little to no correlation between home values and noise pollution at lower levels of noise but a significant negative relationship in the noisiest areas (i.e., 90^{th} percentile or 40 dB and above). In other words, greater noise tends to occur in tracts with lower house prices for the highest noise quantiles. Also, greater racial and ethnic minority population tracts are associated with higher noise levels; and this tends to become more pronounced in the higher noise quantiles; especially those with high house prices. One interpretation of our findings is that both White and Black residents dislike noise pollution and try to avoid this disamentity. However, rising home values are likely a barrier to one's ability to avoid noise; and we find this barrier does not equally affect White, Black, and Hispanic populations. In locations exposed to significant noise pollution at the 95^{th} percentile, for example, a rise in the population share of Black residents has a statistically significant association with lower noise when the median house price is below $300,000. Above this home-value threshold, the relationship becomes statistically insignificant. In contrast, a rise in the population share of White residents in the same noisy areas is associated with lower noise when the median house price is below $520,000. These results tend to show supporting evidence of an environmental injustice with respect to air and road transport-related noise pollution; especially in the tracts that are already the noisiest.

The remainder of this paper proceeds as follows. First, we thoroughly survey the literature of past research on the related topics of racial and ethnic demographics, house prices, and noise. A part of this literature review covers quantile regression, with some limited research on noise in the context of a quantile approach. Then we describe our data and methods, including a discussion of noise-bearing coefficients and curves in the context of our problem. These measures are constructed in a manner similar to Gini coefficients and Lorenz curves. We present some summary results of the noise-inequality coefficients and some examples of the noise-inequality curves (with a set of curves for all states in both 2016 and 2018 available in an appendix). Finally, we present our quantile regression results. We conclude by summarizing our findings and offering some potential housing policy implications of our results.

Literature Review

Noise and Inequality

The literature focused on the inequality of sound remains rather limited. A recent review by Trudeau and Guastavino (2021) identified 22 studies, the majority of which focused on areas not in the United States. The current review will highlight US studies, some of which were not identified by Trudeau and Guastavino, directly related to our study. Specifically, we explore the connection between demographic and socioeconomic characteristics to noise and noise inequality. In terms of geography, some are based on metropolitan areas, one is based on a state, and others are nationally based.

First, we examine a few studies based on metropolitan areas. Generally, airport noise is stressed. Four such studies are related directly to the current study – Ogneva-Himmelberger and Cooperman (2010), Sobotta et al. (2007), Cohen and Coughlin (2012), and Nega et al. (2013).

Ogneva-Himmelberger and Cooperman (2010), using Boston's Logan International Airport, find that minority and lower-income populations are subjected to relatively higher noise levels than their counterparts. Sobotta et al. (2007) regress airport noise in Phoenix, expressed as a qualitative dependent variable, on various independent variables, including the percentage of neighborhood population that is Hispanic. They find that households in neighborhoods with a greater Hispanic population were subjected to higher noise levels than households in other neighborhoods.

Following techniques in McMillen and McDonald (2004), Cohen and Coughlin (2012) estimate ordered probit locally weighted regressions (OPLWR) to explore the issue of spatial heterogeneity in the context of the determinants of airport noise in Atlanta. Cohen and Coughlin (2012) find notable differences in parameter estimates for different houses in their sample with the OPLWR estimates. In particular, the sign on the coefficient for each explanatory variable contains some positive and some negative values. Also, compared to an ordered probit model, the mean of the magnitudes of the coefficients for some of the other explanatory variables is larger with the OPLWR model, while for other coefficients the mean is smaller. These differences between the OPLWR and ordered probit results imply that focusing exclusively on an ordered probit model for the determinants of noise can lead to biased estimates in our context due to ignored heterogeneity among individual houses in our sample. Overall, the heterogeneity over the relatively small area examined precluded any environmental-justice generalizations with respect to either the black or Hispanic populations.

The fourth metropolitan-based study is focused on the Twin Cities. Nega et al. (2013) uses spatial econometric techniques to examine median noise levels in block groups.

Controlling for spatial autocorrelation, they found noise as related to a number of demographic and socioeconomic variables. Specifically, higher levels of noise were related to lower levels of household income, lower levels of home values, higher percentage levels of non-white population, and lower percentage levels of population less than 18 years old.

Moving to a larger geography, prior work has developed a measure of noise inequality for the state of Georgia and its metropolitan areas (Cohen et al., 2019). Cohen et al. (2019) use various indicators to examine the relative noise burdens from road and air traffic noise of Whites, Blacks, and Hispanics in Georgia, both state-wide and by metropolitan area. They found that Whites bear disproportionately less noise than either Blacks and Hispanics and that Blacks tend to experience relatively more traffic noise than Hispanics. Especially noteworthy is that in areas where there is increased likelihood of health-damaging noise Blacks and Hispanics bear disproportionately larger shares of noise. However, exceptions to these general findings were also found. In some Census tracts, roughly one in twenty for Blacks and one in five for Hispanics, larger Black and Hispanics population shares are associated with relatively less noise. In the present paper, we apply the Cohen et al. (2019) methodology to tracts in 48 U.S. states plus the District of Columbia, for the years 2016 and 2018, in generating noise-inequality curves and coefficients that are similar, but not identical, to Lorenz curves and Gini coefficients.

Last, similar to the current study, Casey et al (2017) and Collins et al. (2020) are nation-wide studies. Using noise estimates in census block groups, Casey et al. (2017) found that nighttime and daytime noise levels were higher in block groups containing higher proportions of non-white and lower socioeconomic status residents. Moreover, block groups in more highly segregated metropolitan areas faced higher estimated noise exposure. Similarly, Collins et al. (2020) found higher noise exposure in census tracts characterized by lower socioeconomic status and greater proportions of Blacks, Hispanic, Asian, Pacific Islander, and middle/working-aged residents.

Quantile Regressions in Housing Research

Given the large degree of heterogeneity in noise exposure throughout the U.S., with some urban areas having noise levels that are close to uninhabitable but rural areas with virtually no noise, it is desirable to use an econometric approach that can allow for heterogeneous effects. Methodologically, we employ quantile regressions to investigate differences in exposure to noise pollution across varying levels of this disamenity. In general, the linear quantile regression model can be written as follows:

$$y = X\lambda_q + \epsilon_q$$

Where

$$\hat{\lambda}_q = \underset{\lambda_q \in \mathbb{R}^K}{\operatorname{argmin}} \sum_{i=1}^{I} \rho_q\left(y_i - x_i \lambda_q\right).$$

Here, $p_q(.)$ represents the tilted absolute value function. The solution to this minimization problem yields a vector of marginal effects of X on y for each quantile (q).[5] $\lambda_{0.5}$, for example, represents the correlation of X and y at its median, whereas $\lambda_{0.1}$ measures the correlation at the 10th percentile of y.

Quantile regressions have a long-standing history in the econometric literature[6] and have been applied extensively in the context of real estate and spatial economics (Coulson and McMillen, 2007; Liao and Wang, 2012; McMillen, 2015)[7] as well as air and transport-related noise pollution (Tonne et al., 2018). McMillen (2008), for example, studies changes in the house price distribution in Chicago between 1995 and 2005. Using a quantile regression, McMillen (2008) shows that the distributional shift leading to a larger right-tail in the distribution cannot be explained by location or other home characteristics. Instead, the distributional shift is caused by systematic variations in appreciation rates across lower to higher valued properties that lead to faster housing wealth accumulation to owners of high-priced homes.

Zietz et al. (2008) apply a quantile regression to consider the market segmentation and variation in the valuation of housing attributes across the conditional property price distribution in Orem/Provo, Utah. In this context the authors find evidence of significant systematic variation in the implicit prices of house attributes across low- to high-value homes. The impact of an additional square foot of living space, for example, is much larger for already higher-valued homes than for lower-price houses. Further, the authors conclude that the quantile effects dominate the spatial autocorrelations effects.

A more recent application of quantile regressions in the context of house sale prices was done by Waltl (2019) who studies variations in appreciation rates across price

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[5] For further technical details see Koenker and Bassett (1978).

[6] The methodology was first introduced by Koenker and Bassett (1978). Early influential applications include the work by Chamberlain (1994) or Buchinsky (1994). Koenker and Hallock (2001) provide an excellent overview of the methodology and applications in various contexts.

[7] For an excellent introduction to quantile regression and its application to spatial data see McMillen (2012).

segments and locations in Sydney, Australia. Similar to the previous work, the author finds significant differences in appreciation rates across submarkets and that boom-and-bust cycles are primarily driven by price developments in suburban low-priced houses. Tonne et al. (2018) apply quantile regressions in the context of rail and aircraft noise pollution in London, England. The authors focus on a sample of residents exposed to noise pollution above 50dB. In general, they find that the direction of inequalities in noise exposures was highly variable with respect to sociodemographic characteristics and the type of noise. For example, the authors find little evidence of variations in exposure to road noise across income groups below the 75th exposure quantile. Above this threshold, however, the authors provide some evidence to suggest that households with higher income are less exposed to the most significant levels of noise pollution. Moreover, Asian participants appeared to be more exposed to road traffic noise, while white individuals with high household income were more likely exposed to aircraft noise.

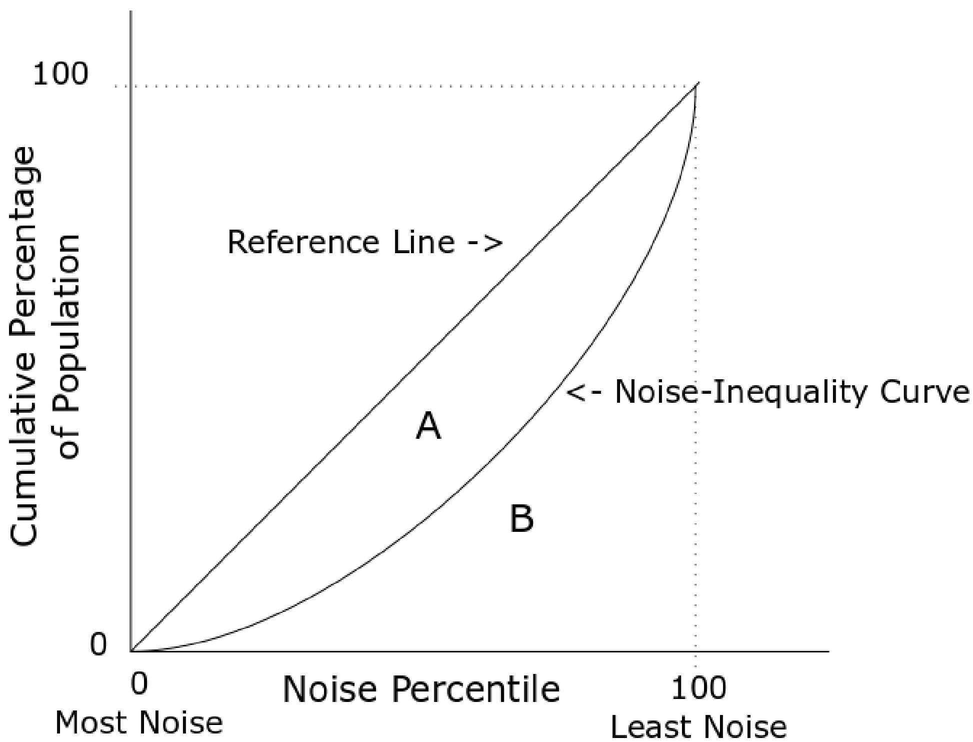
As suggested by the findings in Tonne et al. (2018), the relationship of inequality in exposure to noise pollution is very complex and non-linear. Quantile regression analysis provides a framework to tease out these non-linearities across the entire noise pollution distribution. Similar to Tonne et al. (2018), we apply this methodology to study the inequality-in-noise-pollution-exposure relationship but broaden the study area to the entire continental U.S. over a two-year sample.

Data and Analytical Methods

Before exploring the complexities of the noise-ethnicity-house-price relationship via quantile regressions, we provide a summary measure of the noise borne by one group relative to other groups as well as to the national average. To this end, we use noise-inequality coefficients and curves. These coefficients and curves are constructed in a manner analogous to Gini coefficients and Lorenz curves. These coefficients and curves were used previously in Cohen et al. (2019), although focused on a much narrower geographic area (the state of Georgia) and only for one year of data. As such, these constructs provide numerical and visual indicators of noise inequality.

On the horizonal axis is a measure of noise that orders census tracts in percentiles from the one with the most noise to the census tract with the least noise. On the vertical axis is the cumulative percentage of the relevant population. The reference line uses the entire population of the census tracts under consideration. Similar to the construction of a Lorenz curve in the context of income inequality, this 45-degree line indicates noise equality. Figure 1 illustrates a specific situation with a noise-bearing curve.

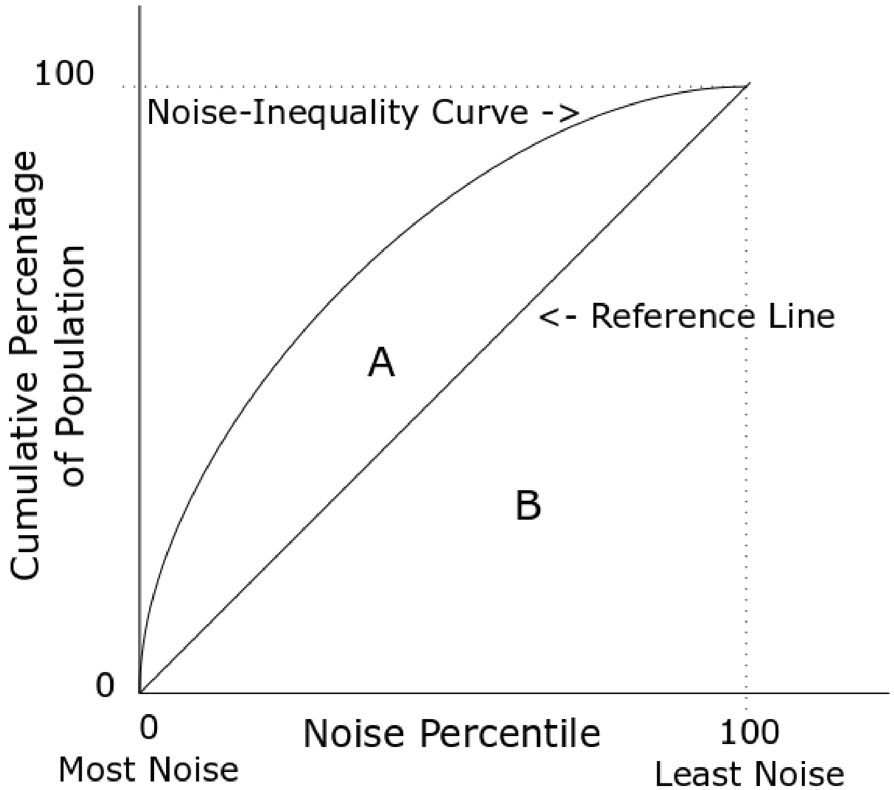
Figure 1 – Noise-Inequality Curve: Less-than-Proportionate



In this figure the noise-inequality curve for a specific group lies below the reference line. At the lowest noise percentiles the noise borne by this group is less than that borne by the population. Let A be the area between the noise-bearing curve and the reference line and B be the area below the noise-bearing curve. The noise-bearing coefficient is defined as follows: NBC = A/(A + B). In the limiting cases, a coefficient of 1 indicates this group bears no noise, while a coefficient of 0 indicates the group bears noise proportionate to its size. Thus, the coefficient must lie between 0 and 1. In this illustration, the specific group bears a less-than-proportionate share of the noise. If A were to shrink, then noise inequality declines.

Now, as represented in Figure 2, consider the case where the noise-bearing curve lies above the reference line. Thus, A is the area above the reference curve and B is the entire area below the reference line. In this case, the noise-inquality coefficient is defined as follows: NBC = -A/B. In the limiting cases, a coefficient of -1 indicates that the specific group bears all the noise, while a coefficient of 0 indicates that the specific group bears noise proportionate to its size. Thus, in this case the coefficient must lie between 0 and -1. The group bears a more-than-proportionate share of the noise. If A were to shrink, then noise inequality declines.

Figure 2 – Noise-Inequality Curve: More-than-Proportionate



In summary, the noise-inequality coefficient for a specific group may range from -1 to +1.[8] Values near -1 indicate that the group bears a very large share of noise, while values near +1 indicate that the group bears a very small share of noise. Values near 0 indicate that the group bears a roughly proportionate noise share (i.e., equality).

Data

To investigate the relationship between exposure to transport-related noise pollution and home values as well as ethnicity we construct a novel dataset that combines information on 2016 and 2018 air and road noise pollution published by the U.S. Department of Transportation's Bureau of Transportation Statistics with Census tract data on local housing markets and socioeconomic characteristics of local residents. The latter data are sourced from the American Community Survey (ACS) published by the US Census

[8] It is also possible that there can be times when A does not lie completely above or below the reference line. The calculation of the numerator is a net of the positive "A" area beneath the line and the negative "A" area above the line. Meanwhile, the denominator is the area beneath the reference line.

Bureau. Noise pollution statistics are available for 2016 and 2018 and are linked to the ACS data for those years with a spatial join, leading to separate tract-level noise and demographics estimates for over 70,000 tracts in each of the 2 years.

Figure 3: Air & Road Noise Quantiles

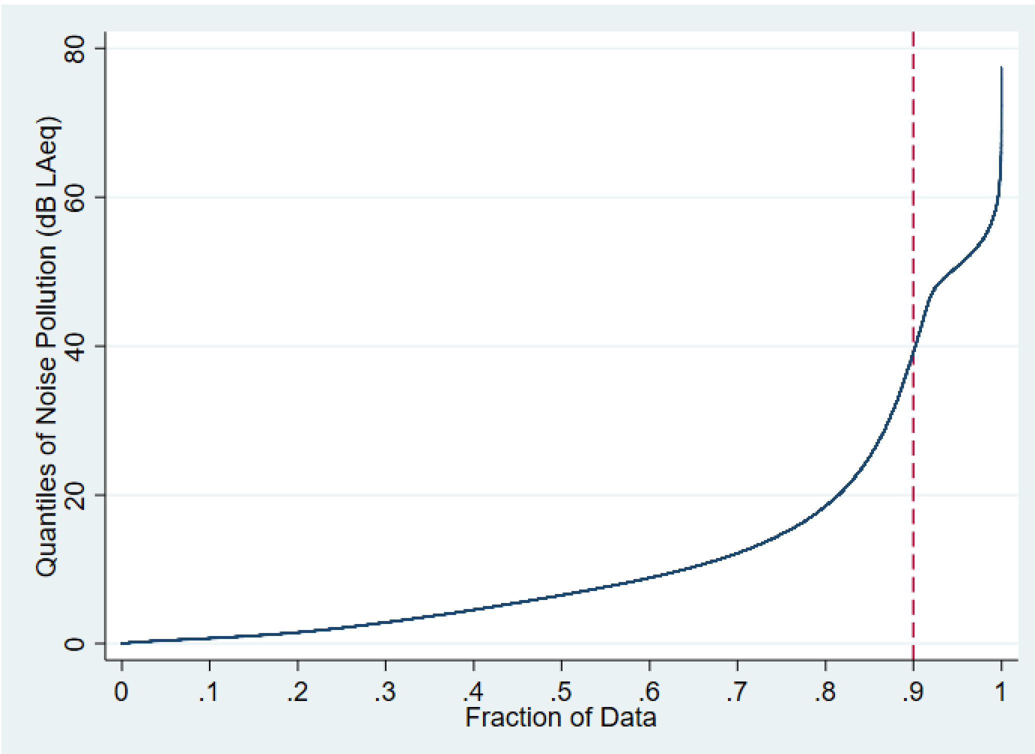


Figure 3 summarizes the distribution of air and road noise across the contiguous United States. The data reveal that the vast majority of census tracts experience very little transport-related noise pollution. More specifically, 90 percent of US census tracts are subject to approximately 40 dB LAeq or less average daily noise pollution. Above this threshold noise ranges widely. While a census tract at the 90th percentile of noise experiences 40 dB LAeq, the noisiest locations are subject to more than 75 dB LAeq in at least one of the two sample years.

For several of these heavily noise polluted locations, including the five noisiest tracts with an average 70 dB LAeq or above, the Census data indicate no population. Table 1 lists the top 30 census tracts (and associated states and counties) with the highest levels of noise pollution averaged across the two years conditional on people living in these tracts. The most noise-polluted census tracts where people actually live tend to be located in the states of Texas, New York, and California. But the list also includes census tracts located in Florida, Georgia, Illinois, Mississippi, Missouri, Nevada, New Jersey, Tennessee, Virginia, and Washington. Interestingly, aircraft noise appears to be the primary source of noise pollution in these highly polluted census tracts. Road noise tends to be a lesser contributing factor (even if we do not condition on positive population). But road noise tends to be more constant over time, while aircraft noise is much more intense for very brief periods and then there is typically much less noise in between flyovers.

More specifically, San Diego County, CA, Bronx County, NY and Queens County, NY all have tract(s) with at least 50 dB LAeq[9] in both road noise and air noise. The tract in San Diego has a black population share of less than 5 percent and Hispanic population share of 14 percent. In contrast, the tract in the Bronx County has 21 percent Black population and 54 percent Hispanic population, while the tract in Queens County has nearly 13 percent black and 14 percent Hispanic residents. It is also noteworthy that in some instances, the numbers for the individual race/ethnicity breakdowns do not add to 100 percent. This is because there are other race/ethnicity categories (such as Asian and Native American and others) that are not included in this table, for ease of presentation. Moreover, some Hispanic residents also identify as White, so there is some overlap between the numbers across categories.

Table 1 also shows that population, density, income, and home values, as well as population shares of Black, Hispanic/Latino, and White ethnicities vary greatly across these highly noise-polluted locations. While some census tracts have just 5 residents, others are heavily populated with over 5,000 residents. Similarly, the median family income ranges from around $25,000/year to over $100,000/year, whereas median home values range from just under $35,000 per home to over $800,000 per home. Moreover, these most heavily noise-polluted census tracts have diverse populations. The White population share, for example, ranges from 0% to 100%. Similarly, the Black population share in these locations varies from 0% to 95%.

[9] According to the BTS, the national transportation noise map is developed using a 24-hr equivalent A-weighted sound level noise metric denoted by LAeq. As such, the noise metric represent the approximate average noise energy due to transportation noise sources over a 24-hour period at the receptor locations where noise is computed. https://rosap.ntl.bts.gov/view/dot/53773

Table 1: Top 30 Census Tracts with Highest Noise Pollution

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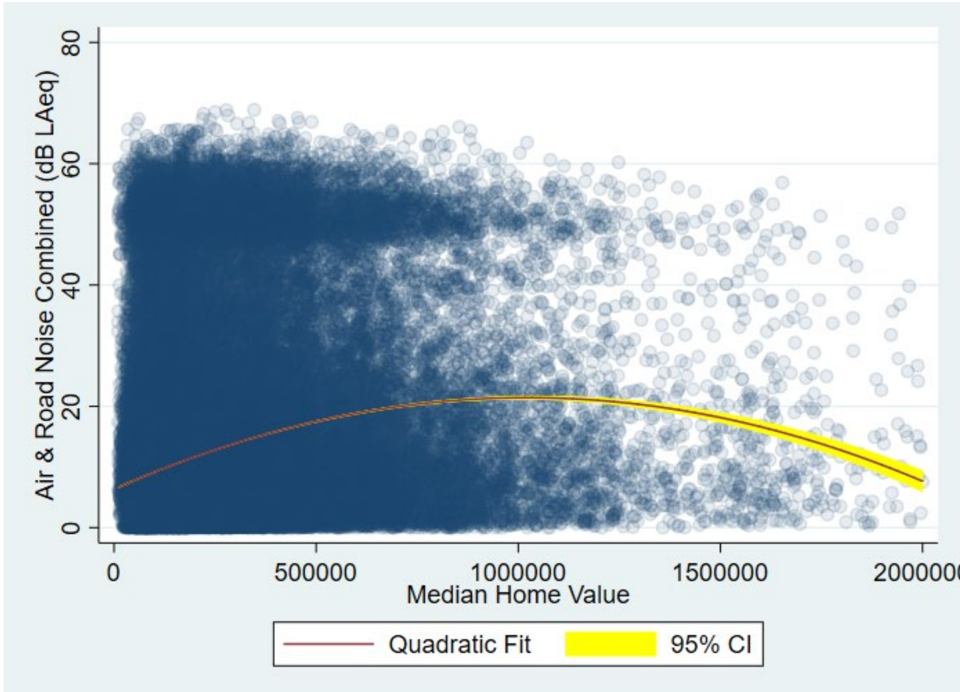
Rank	State	County	Air & Road Noise (dB LAeq)	Air Noise (dB LAeq)	Road Noise (dB LAeq)	Population	Pop. Density	Median Income ($ '000)	Median Home Value ($ '000)	Median Age	Pop. Share White (%)	Pop. Share Black (%)	Pop. Share Hispanic/ Latinx (%)	Pop. Share Bachelor + (%)
1	TX	Webb County	69.45	69.36	2.89	35.00	7.72			50.50	100.00	0.00	34.29	0.00
2	MS	Lauderdale County	69.03	68.88	4.04	62.00	12.97	44.18	34.70	47.30	66.59	33.41	0.00	5.82
3	TX	Dallas County	68.93	68.78	4.29	20.00	3.66			13.80	0.00	0.00	25.00	0.00
4	NY	Bronx County	68.54	50.46	68.15	1254.00	19624.41	20.70	249.70	32.75	14.98	20.98	54.27	35.23
5	CA	Los Angeles County	68.21	67.33	27.34	4006.00	8049.03	42.67	400.40	28.05	56.96	2.39	53.93	18.96
6	MS	Harrison County	67.91	67.87	1.77	94.00	18.58			36.55			0.00	
7	WA	King County	67.60	67.10	10.09	5173.50	621.78	46.69	260.25	33.60	41.86	33.00	4.29	41.41
8	TX	Harris County	67.19	67.06	4.05	6.00	1.06				100.00	0.00	0.00	22.20
9	TN	Blount County	67.04	67.02	1.73	5.00	0.79			23.15			0.00	
10	NY	Queens County	66.86	59.49	60.15	1042.50	1417.79	60.36	473.35	37.05	19.10	12.75	14.21	31.27
11	CA	San Diego County	66.84	63.34	53.31	1626.50	6064.50	35.47	408.50	36.65	76.21	4.73	14.11	61.35
12	VA	Arlington County	66.82	66.48	6.75	6.00	1.62				100.00	0.00	0.00	75.00
13	NJ	Union County	66.79	65.90	19.05	5644.00	10348.37	34.25	238.90	26.05	29.48	42.51	31.98	22.41
14	TX	Harris County	66.46	66.18	3.07	1586.00	87.21	102.83	206.95	42.30	73.48	3.39	8.68	69.77
15	WA	King County	66.38	66.26	6.26	3203.50	613.38	63.98	269.85	39.55	76.51	5.68	9.48	46.63
16	CA	Los Angeles County	65.78	65.63	14.02	4040.00	8297.39	44.93	357.70	29.25	49.88	3.53	60.03	27.91
17	NY	Kings County	65.71	0.00	65.65	2008.50	32818.63	38.48	770.85	31.05	37.15	3.85	38.46	26.60
18	MO	St. Louis County	65.63	64.83	12.15	3598.50	245.98	29.28	54.55	35.05	11.91	87.33	0.00	32.38
19	NV	Clark County	65.50	64.93	8.37	4935.00	320.66	31.04	167.65	33.25	55.39	10.85	32.62	35.80
20	CA	Fresno County	65.48	64.89	14.72	3440.50	1155.27	25.03	149.95	31.90	51.41	7.20	37.31	26.93
21	GA	Fulton County	65.47	65.38	6.50	4305.50	694.63	27.43	135.50	29.70	2.81	94.85	0.29	34.95
22	NY	Bronx County	65.36	50.17	64.51	2202.50	22247.48	27.00	588.75	30.70	11.44	29.50	47.44	22.15
23	IL	Cook County	65.32	65.22	9.20	2298.00	5432.62	40.63	210.30	30.85	63.20	1.06	42.81	21.34
24	CA	Fresno County	65.31	64.98	5.34	4031.00	401.59	46.49	197.15	31.20	67.49	4.14	22.22	49.05
25	NY	Queens County	65.07	19.43	63.61	1814.00	11583.65	68.84	751.15	36.75	78.52	4.77	17.17	59.75
26	CA	San Diego County	65.05	64.96	9.16	5711.00	3113.62	94.15	833.80	37.60	91.33	0.00	9.23	76.30
27	CA	Los Angeles County	65.03	64.59	7.44	81.50	24.10			35.00	14.60	0.00	61.67	0.00
28	IL	Cook County	64.99	63.35	32.12	2544.50	543.28	54.14	336.90	40.65	94.41	1.59	7.55	39.84
29	FL	Broward County	64.99	63.49	16.99	953.00	105.36	54.19	200.55	54.85	95.65	1.60	9.56	49.51
30	CA	San Diego County	64.78	64.62	3.11	3525.00	1723.13			19.85	100.00	0.00	0.00	0.00

Notes: The sample includes 71,954 US Census Tracts with a non-zero population estimate. There are some Census Tracts with higher noise pollution, but no recorded population. These are excluded from the sample. All figures shown in this table are based on the average of the 2016 and 2018 estimates.

Figures 4a through 4d shed more light on some of these noise pollution correlations. Based on the full sample, Figure 3a, for example, plots the combined air and road noise, measured in dB LAeq, against census-tract median home values. As expected, the graph shows a large mass of census tracts with median home values below $500,000 with noise pollution ranging from 0 to over 60dB LAeq. Interestingly a quadratic fit shows a non-linear, “inverse U” relationship between home values and local noise pollution. The graph shows that neighborhoods with low noise pollution can be associated with lower valued homes or the highest value homes. The tipping point is centered around a median value of $1,000,000 per home. Transport-related noise is, of course, linked to human activity. On the one end, low noise pollution may be indicative of an area with little human and economic activity and therefore little housing demand resulting in lower priced homes. As this activity increases, so do home values. However, there is a tipping point after which low noise in high activity areas becomes a desired amenity that commands a house sale price premium helping explain the fact that more of the highest value properties tend to be located in the quietest census tracts.

Figure 4a: Air & Road Noise – Home Value Correlation



Figures 4b through 4d plot the combined air and road noise pollution experienced in each census tract against the local white, black, and Hispanic/Latinx population shares. The fitted quadratic curves reveal a few interesting patterns. First, each plot reveals an "inverse U" shaped relationship suggesting that quieter neighborhoods are also home to less diverse populations. This relationship is most pronounced for the Hispanic/Latino and the White populations compared with the Black populations. Second, neighborhoods with larger shares of white residents experience less noise pollution on average. In contrast, neighborhoods with larger shares of Black residents do not see a pronounced decline in typical noise pollution.

Overall, these figures provide some initial insight into the complexities of the relationships between transport-related noise pollution and local housing market or socioeconomic characteristics. The 95 percent confidence intervals are highlighted in yellow. These confidence intervals are very narrow in some parts of the curves, which is why it appears as if there is no confidence interval in those areas.

Figure 4b: Air & Road Noise – White Population Share Correlation

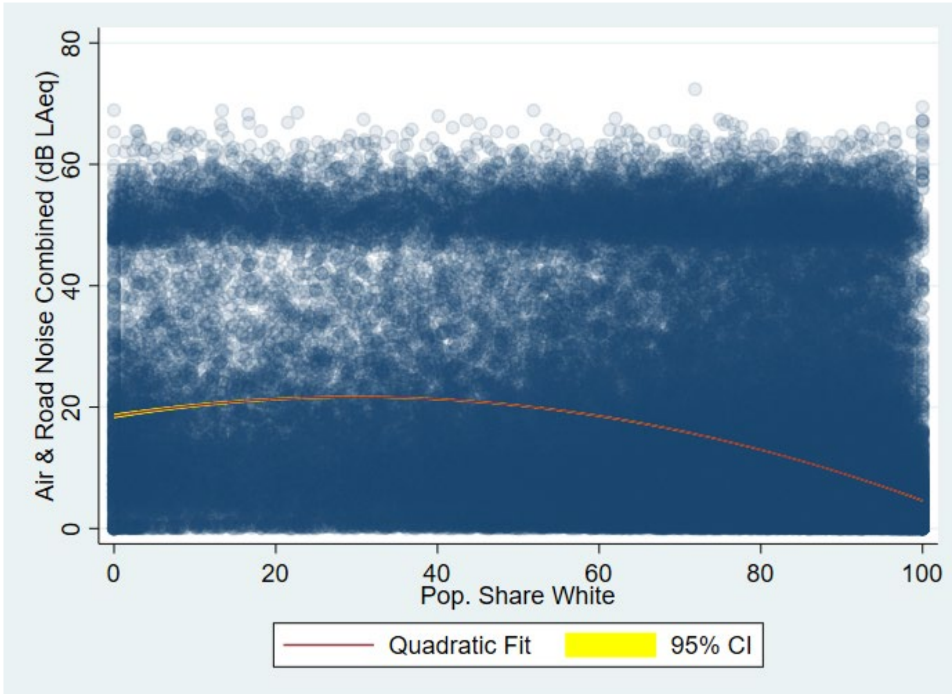


Figure 4c: Air & Road Noise – Black Population Share Correlation

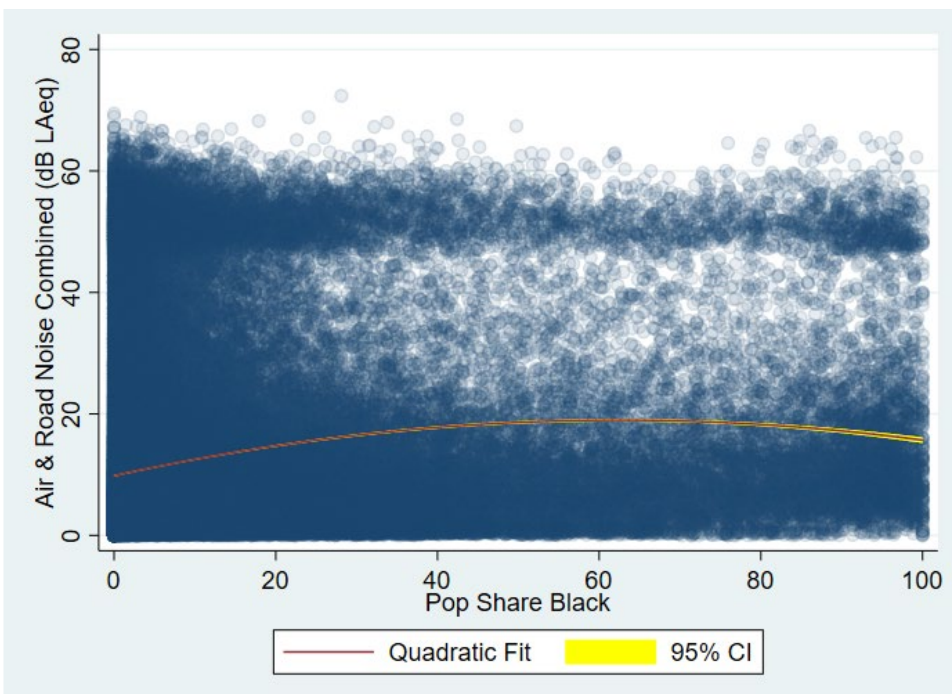
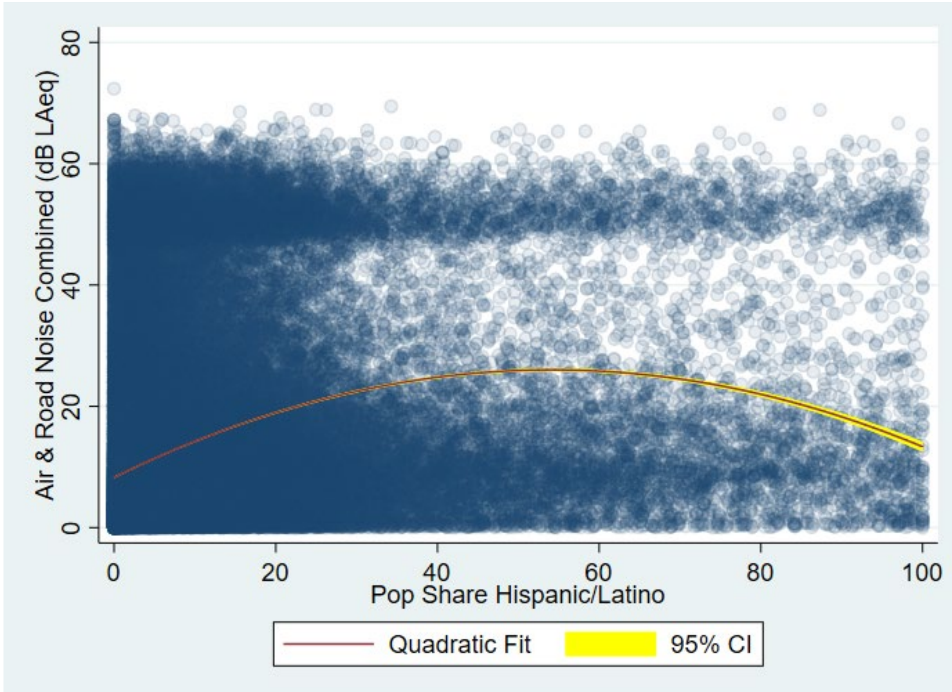


Figure 4d: Air & Road Noise – Hispanic/Latino Population Share Correlation



Results- Noise-Inequality Curves and Coefficients

Noise-inequality coefficient maps and curves

Figures 5a and 5b below are graphical depictions of the noise inequality curves for 2016 and 2018, respectively, at a national level of aggregation. These figures are broken out by the total population, White population, Black population, and Hispanic population. The curves for the Black population and the Hispanic population do not appear to be dramatically different in the two years. But the curve for the White population seems to be closer to the total population in 2018 than in 2016, implying the less than proportionate White population exposure in 2018 is less pronounced than in 2016.

Figure 5a – 2016 National Noise Inequality Curve, by Race/Ethnicity

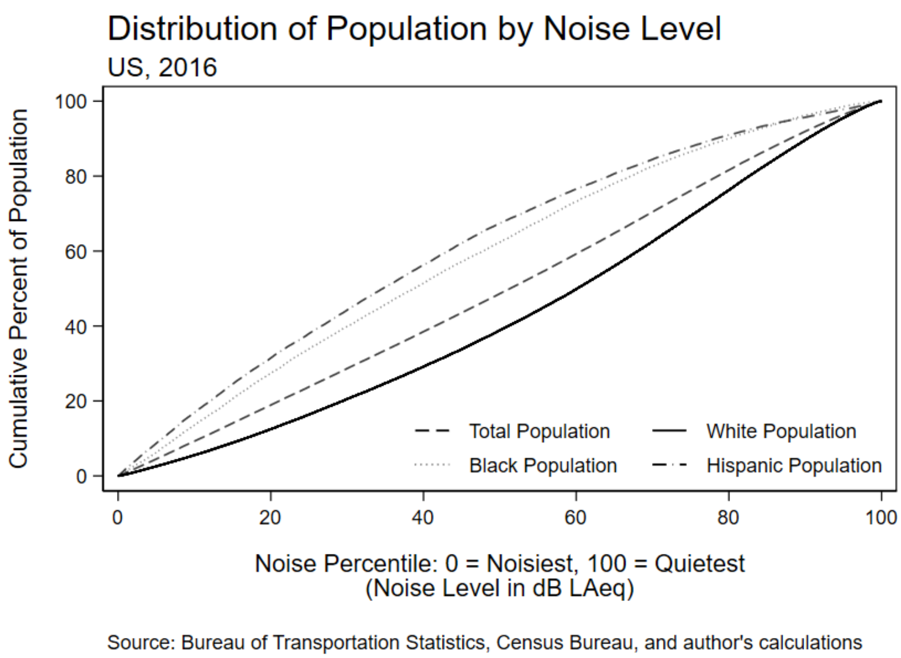
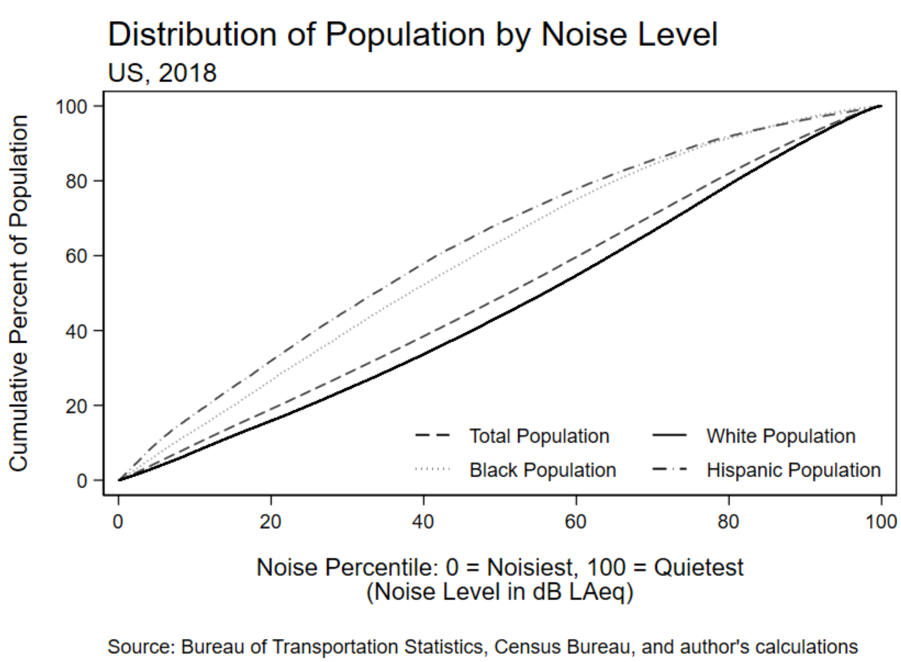


Figure 5b – 2018 National Noise Inequality Curve, by Race/Ethnicity



While the national noise inequality estimates show greater than proportionate exposure for the Black and Hispanic populations, it would be of interest to observe the extent to which this inequality holds up at the sub-national levels. We calculated the noise-inequality coefficients on an average basis, state-by-state, to obtain a sense of which demographic groups experience a more/less equal distribution of noise within each of the states. Figures 6a and 6b show the average noise-inequality coefficients for each demographic group (White, Black, and Hispanic residents), in each year (2016 and 2018), respectively.

Figure 6a: 2016 Noise-Inequality Coefficients, by State

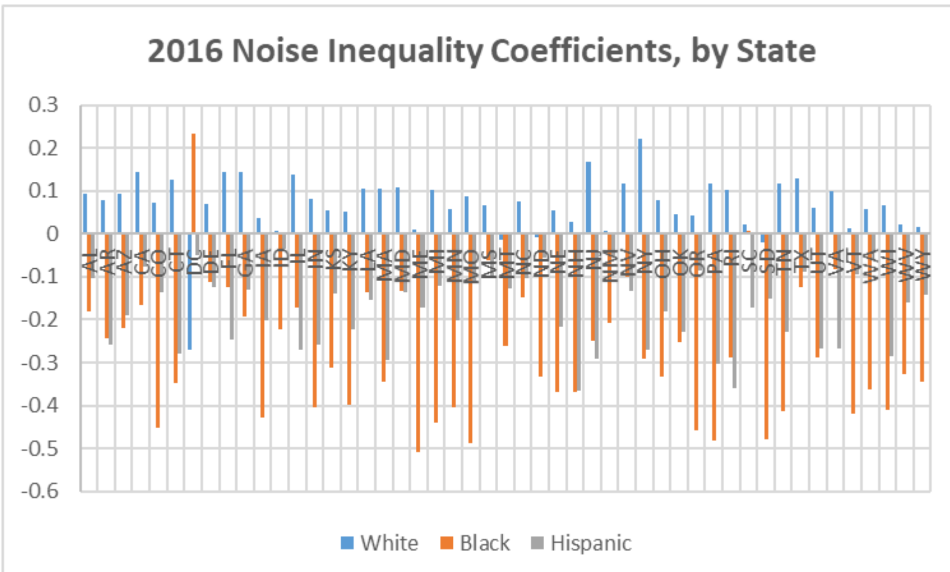
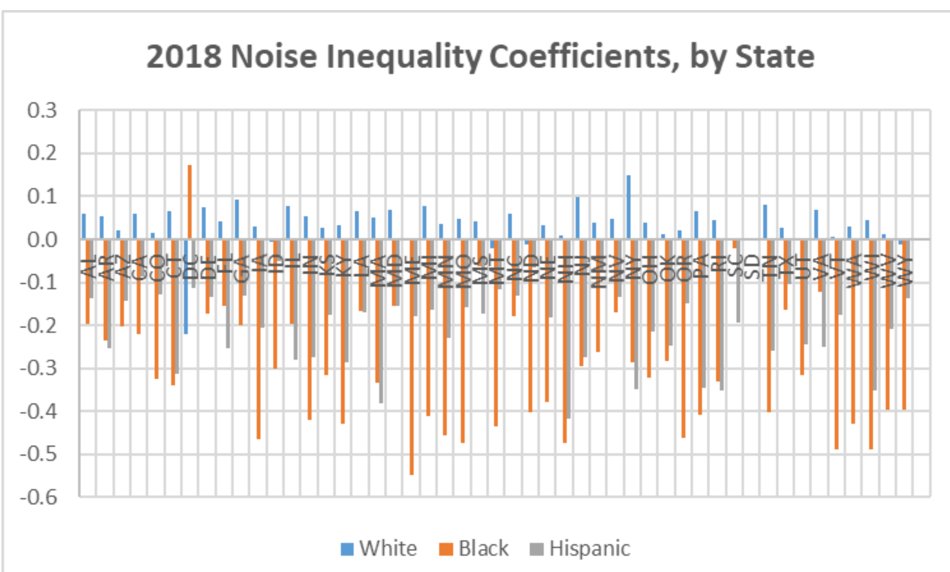


Figure 6b: 2018 Noise-Inequality Coefficients, by State



Note: South Dakota (SD) is missing data from 2018 (in Figure 7b).

To determine the overall (U.S.-wide) noise exposure for each of the 3 groups, we calculate that New York has the highest overall average noise exposure (averaged over the two years, 2016 and 2018), while West Virginia is the quietest state. The most unequal state for noise exposure by Black residents is Missouri, while the corresponding most unequal state for Hispanic/Latinx residents is New Hampshire, with Rhode Island and Connecticut close behind. [10]

A full set of noise inequality curves at the state-level, annually in 2016 and 2018, is available in an appendix.

Results – Econometrics

Given the flexibility of quantile regressions in understanding heterogeneity in the data, and the lack of other studies that have already used these approaches to consider the same dataset as ours, we focus on quantile regressions for our regression analysis. Using quantile regressions enables us to uncover heterogeneity that is not apparent with OLS.

In general, the quantile regression results, discussed below, provide evidence of systematic variation in the exposure to transport-related noise pollution across Black, Hispanic, and White populations. These relationships are found to be negative and statistically significant among higher White and higher Black populations, for most quantiles, while they are positive and statistically significant among higher shares of Hispanic populations for most quantiles. While the positive sign on the Hispanic coefficient implies tracts with higher Hispanic population are associated with greater noise, the negative sign on the Black population coefficient implies the opposite relationship, which is somewhat unexpected a priori.

We present our quantile regression findings for two distinct models. In the first we regress the combined air and road noise pollution on census-tract-level house prices, population shares by ethnicity (including white, black, and Hispanic), and a number of control variables including: 1) additional socioeconomic factors (i.e., total population, median family income, age, family size and educational attainment); and 2) housing market characteristics (i.e., median rent, renter occupation rates, share of multi-unit housing, population share of recent movers, and the number of two- to five-or-more-bedroom homes).

In the second model, we further explore the complexities of the relationship between noise exposure and ethnicity given the interplay with house prices. Specifically, we integrate interaction terms between White, Black, and Hispanic population shares and

[10] While at first glance there appears to be some discrepancies between Table 1 and Figures 7a and 7b, the estimates in Table 1 are at the census tract level, while Figures 7a and 7b show the noise inequality coefficients aggregated for entire U.S. states.

local house prices. We continue to control for the aforementioned socioeconomic and housing market characteristics in this *interaction* model.

We estimate both models across the 5th to the 95th noise quantile and present our findings in numerous coefficient plots.[11] Each of these graphs depicts the parameter estimate function (black line) as well as the associated 95 percent confidence interval (CI), which are based on bootstrapped standard errors clustered at the state level. Here we differentiate between the pointwise CI (dark grey shaded area) and the functional CI (light gray shaded area). Pointwise CIs are used to describe the range of values that will cover the true parameter for a single estimate with the pre-specified coverage probability (i.e., 95 percent). Applications include, for example, Ordinary Least Squares (OLS) regressions, which produce a single parameter estimate representing the average effect/association between the dependent (Y) and independent variable (X). In contrast, quantile regression produces a function of parameter estimates describing the relationship between Y and X over the distribution of Y. Functional CIs are the analog to pointwise CIs in the quantile regression context and have been derived by Chernozhukov et al. (2013) and implemented in STATA by Chernozhukov et al. (forthcoming).

Although the empirical findings provide rich insights into the noise-ethnicity-house-price relationships, we are careful not to mistake correlation for causation throughout the discussion that follows. Figures 7 and A1a through A1d illustrate the quantile regression parameter estimates for model one *(no interaction).* The parameter function estimates of interest involve the relationships between noise pollution and house prices as well as White, Black, and Hispanic population shares. The results shown in Figure 6 are striking. Home values are found to have little to no statistically or economically significant association with noise pollution below the 90th percentile of noise. For the noisiest 5 percent of census tracts in the sample, however, the estimates point to a significant negative relationship between noise pollution and house prices that intensifies quickly as noise rises. This finding is, of course, in agreement with much of the real estate literature that has produced convincing evidence of significant price discounts resulting from transport-related noise pollution (Friedt and Cohen, 2021; Cohen and Coughlin, 2008).

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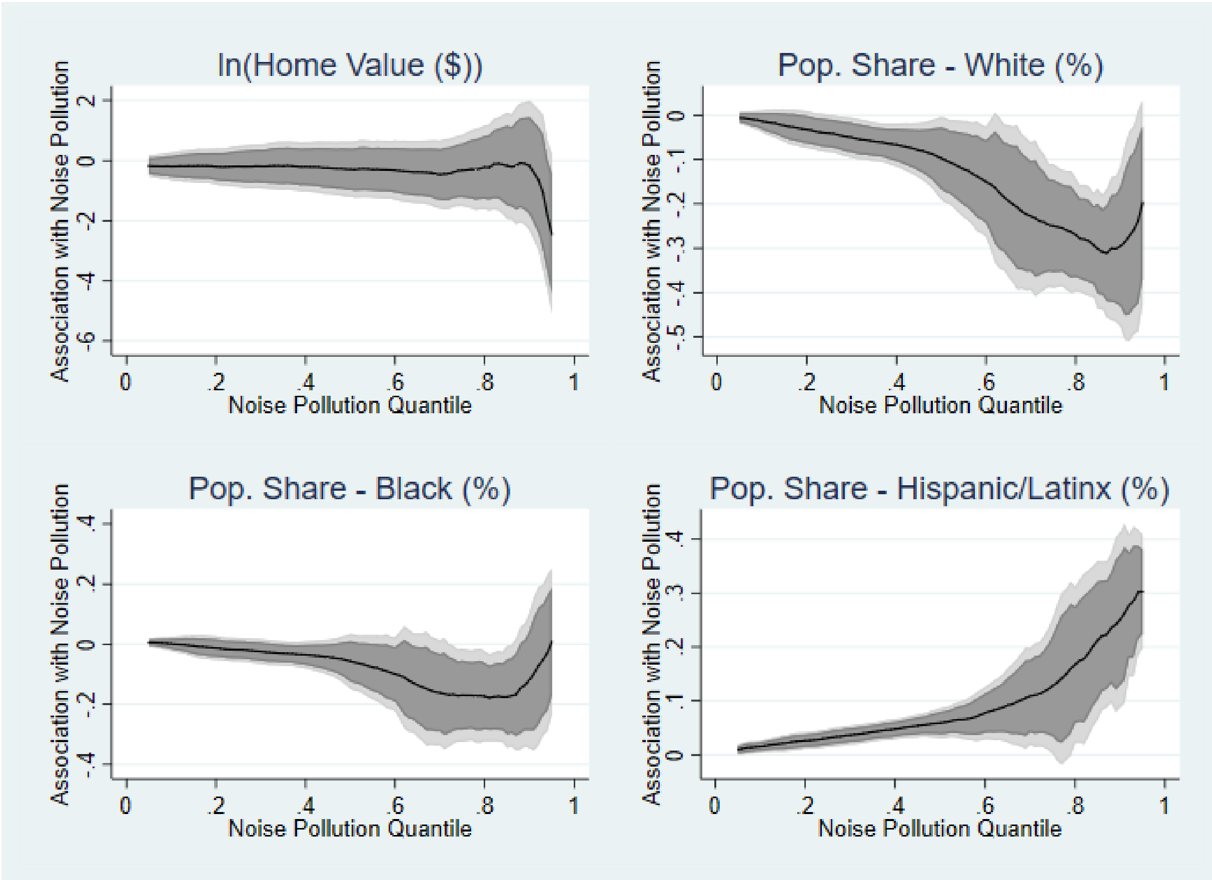
[11] This is common practice in the quantile regression literature. The estimation at each of the 91 quantiles produces 91 coefficient estimates for each of the independent variables. These are most efficiently summarized in coefficient plots.

Figure 7– Quantile Regression Coefficients (Model 1: No Interaction)



Although house prices exhibit no statistically significant relationship with transport-related noise in less polluted areas, variation in the ethnic population shares appears non-random across the entire distribution of noise pollution. White population shares, for example, are found to have a negative relationship with transport noise; and this inverse relation tends to intensify until around the 90th noise quantile when the relationship starts to attenuate towards zero. Overall, this finding agrees with our noise-bearing curves and coefficients for White populations. One way to interpret this finding is that White residents successfully manage to avoid exposure to noise pollution at any level of this disamenity and that this behavior tends to escalate as noise intensifies.

Black population shares also exhibit a negative correlation with noise pollution. However, the point estimates tend to be smaller in absolute magnitude (relative to coefficients for White population shares) and statistically insignificant at the 95 percent threshold. Potential explanations of these estimates include a lesser ability and/or desire to avoid transport-related noise pollution.

Of course, if transport-related noise pollution is a meaningful disamenity, abatement or avoidance is costly. And, similar to the desire to avoid exposure to noise pollution, this avoidance cost may be rising with greater levels of noise. This, perhaps, explains the change in coefficient estimates towards the highest levels of noise in the estimation sample (i.e., 90^{th}-95^{th} percentile).

The coefficient estimates on Hispanic/Latinx population shares tell a very different story. Across all levels of noise pollution, we find a positive relationship between noise and Hispanic/Latinx population shares; and this relationship also intensifies at greater levels of noise. One potential interpretation is that, in contrast to White and Black populations, Hispanic/Latinx residents appear unsuccessful in avoiding transport-related noise pollution.

Parameter estimates for the control variables are presented in Figures A1a through A1d and demonstrate several statistically and economically significant relationships. For example, as one might expect we find a negative association between noise pollution and the total population. In contrast the association between family size and noise pollution is positive and tends to increase at greater levels of noise. Interestingly, the estimates also show a strongly positive and intensifying relationship between noise pollution and rent as well as the share of multi-unit homes.

Finally, Table 3 presents the Kolmogov-Smirnov (K-S) and Cramer-von-Mises (C-M) type tests across five functional null hypotheses of interest ranging from no effect to a positive or negative effect, to a constant or location-scale shift effect. Rather than separately test the coefficients estimates at each of the 91 noise quantiles, which would suffer from a multiple testing problem, we employ the K-S and C-M type tests which consider all of the quantile regressions simultaneously to detect a systematic violation of any of the five null hypotheses (see Kroenker and Xiao, 2002 and Chernozhukov et al., forthcoming).

Table 3 – Quantile Regression Hypothesis Tests (Model 1: No Interaction)

Dependent Variables	Kolmogov-Smirnov Type Tests					Cramer-von-Mises type tests				
	No Effect	Constant Effect	Positive Effect	Negative Effect	Location-Scale Shift	No Effect	Constant Effect	Positive Effect	Negative Effect	Location-Scale Shift
ln(Home Value ($))	0.076	0.169	0.031	1.000	0.382	0.396	0.650	0.193	1.000	0.872
Pop. Share White (%)	0.000	0.001	0.000	1.000	0.000	0.001	0.003	0.001	1.000	0.000
Pop. Share Black (%)	0.017	0.016	0.009	0.438	0.000	0.029	0.026	0.013	0.712	0.001
Pop. Share HSP/LTX (%)	0.000	0.000	1.000	0.000	0.000	0.000	0.003	1.000	0.000	0.001
ln(Total Population)	0.006	0.003	0.001	0.006	0.001	0.013	0.001	0.009	0.136	0.015
ln(Median Income ($))	0.120	0.023	0.648	0.059	0.595	0.282	0.020	0.641	0.142	0.489
Median Age	0.327	0.388	0.158	1.000	0.769	0.317	0.586	0.150	1.000	0.729
Median Family Size	0.002	0.001	1.000	0.002	0.000	0.001	0.002	1.000	0.001	0.005
ln(Median Rent ($))	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000
# of Renter-occup. Homes	0.097	0.008	0.444	0.043	0.075	0.230	0.042	0.458	0.119	0.332
Share of Multi-unit Homes	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000
ln(# of Movers 2010-2014)	0.000	0.553	0.901	0.000	0.368	0.003	0.716	0.903	0.000	0.893
# of 1-BDRM Homes	0.200	0.642	0.752	0.103	0.977	0.333	0.627	0.773	0.152	0.990
# of 2-BDRM Homes	0.000	0.013	0.000	0.313	0.259	0.000	0.015	0.000	0.489	0.656
# of 3-BDRM Homes	0.142	0.001	0.076	0.301	0.169	0.283	0.076	0.160	0.418	0.275
# of 4+-BDRM Homes	0.002	0.002	0.002	1.000	0.003	0.002	0.001	0.002	1.000	0.167
Pop. Share No HS Dipl. (%)	0.022	0.091	0.017	1.000	0.020	0.015	0.098	0.011	1.000	0.338
Pop. Share HS Dipl. (%)	0.019	0.017	0.006	0.533	0.131	0.554	0.345	0.297	0.505	0.460
Pop. Share Some College (%)	0.002	0.261	0.001	1.000	0.000	0.001	0.353	0.001	1.000	0.141
2018 Fixed Effect	0.021	0.021	0.008	0.559	0.354	0.289	0.141	0.142	0.552	0.329

Notes: The reported statistics represent p-values on the Kolmogove-Smirnov or Cramer-von-Mises type test statistics (see Chernoshukov and Fernandez-Val, 2005; Chernozhukov et al., forthcoming) regarding five hypothesis tests on each of the coefficient estimates across the 0.05 to 0.95 quantiles. The hypotheses include no effect, a constant (or location shitf) effect, positive effect, negative effect, and location-scale shift effect as defined by Kroenker and Xiao (2002).

Table 3 reports the p-values across both types of tests across all five hypotheses for each of the parameter estimates. In general, the C-M tests tend to be more conservative than the K-S tests and the results further support the aforementioned patterns seen in Figure 6. There is only marginal evidence to suggest a statistically significant, non-positive noise-house-price relationship across the 5th to 95th noise quantiles. In contrast, the tests strongly reject all but one hypothesis regarding the estimated noise-ethnicity relationships. White, Black, and Hispanic population shares exhibit statistically significant and non-constant relationships with transport-related noise pollution. While White and Black population shares are inversely related to noise, Hispanic population shares are positively related to the same noise pollution.

Interaction Effects

One other important consideration, however, is that of the dynamics between race, ethnicity, and house prices. It is our hypothesis that the relationships between White, Black, and Hispanic populations and noise exposure are different in tracts with higher average house prices than in tracts with lower average house prices. To allow for this possibility, we include interaction terms between housing prices and each of the race/ethnicity percentage variables.

Figures 8a, 8b, and 8c depict the parameter function estimates for the White, Black, and Hispanic population shares and their interactions with home values, respectively. Across all three ethnicities, we observe a relative stagnant and economically and/or statistically insignificant relationship between population shares and noise pollution when this disamenity is roughly below the 80th quantile.

Figure 8a – Quantile Regression Coefficients – White (Model 2: With Interaction)

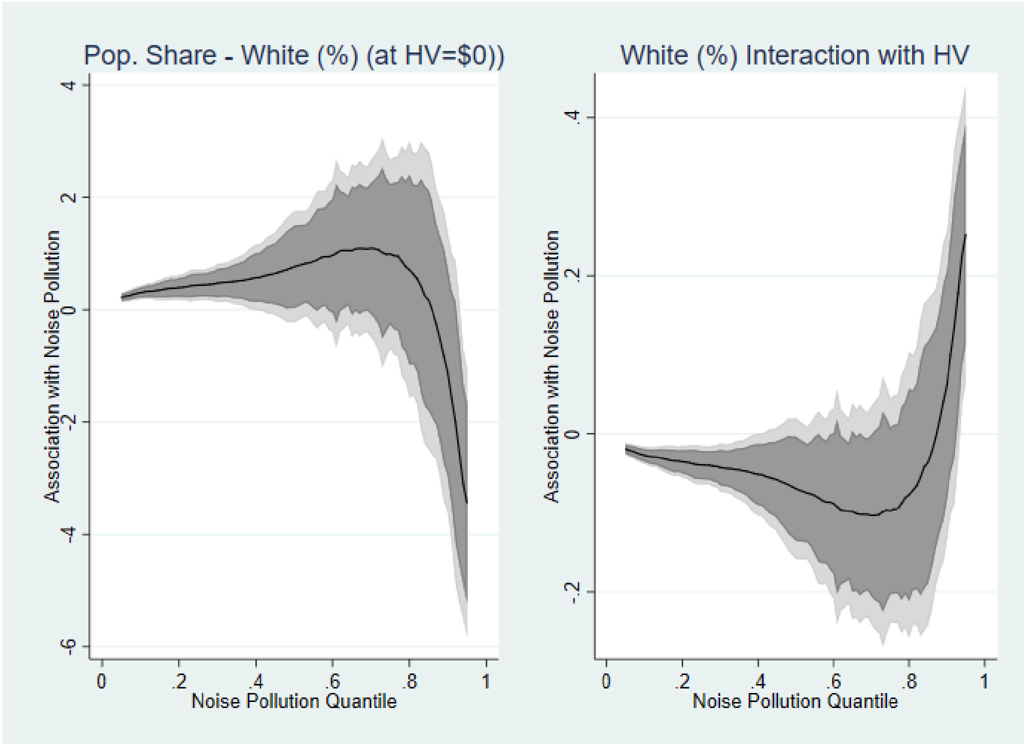


Figure 8b – Quantile Regression Coefficients – Black (Model 2: With Interaction)

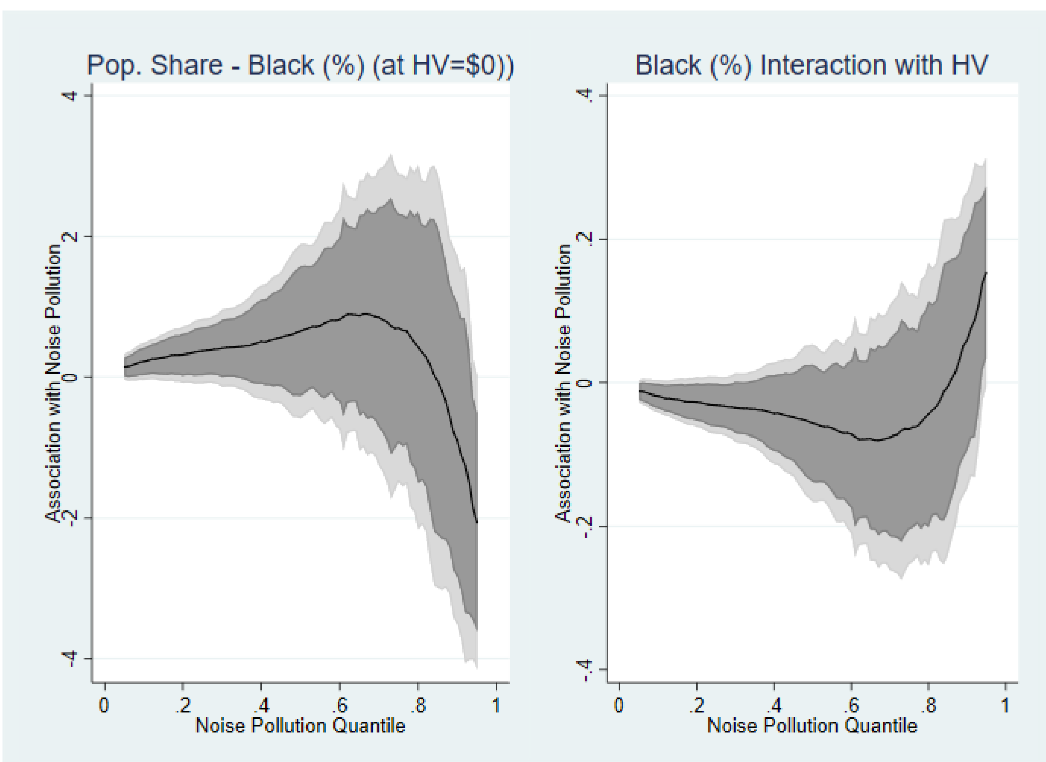
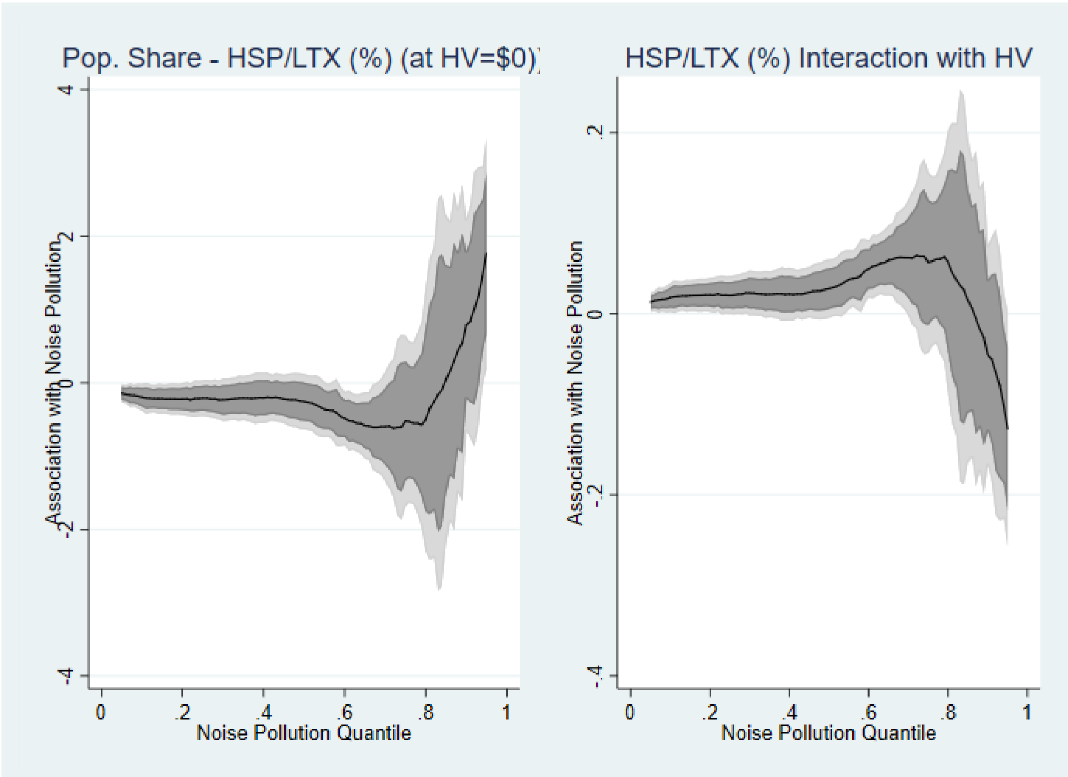


Figure 8c – Quantile Regression Coefficients – Hispanic/Latinx (Model 2: with Interaction)



Above this threshold, however, residential behavior changes. The White and Black coefficients (left-hand plots in Figures 8a and 8b) are negative, whereas the interaction term coefficients are positive (right panels in Figures 8a, 8b). This relationship is more pronounced and statistically significant for White relative to Black residents. The marginal effects imply that in neighborhoods with below average house prices, White and Black residents appear to be able to avoid noise exposure in these very noisy areas (95^{th} noise quantile). In other words, when barriers to relocate (i.e., low house prices) to quieter neighborhoods are low, White and Black residents successfully manage to reduce their exposure to transport-related noise pollution and reside in quieter areas. In contrast, in the left panel of Figure 8c, Hispanic population shares are positively related with noise pollution above the 80^{th} noise quantile when house prices are low. It seems more difficult for Hispanic residents to relocate and avoid noise in a similar manner as the Black and White populations tend to do, on average.

Interaction term estimates reveal rising house prices offset this avoidance behavior for White and Black populations (the right panels in Figures 8a, 8b, and 8c). One possible interpretation is that rising home values may become a barrier to noise avoidance for White and Black residents and thereby also mitigate noise exposure for Hispanic populations. In other words, when barriers to relocate (i.e., high house prices) to quieter areas in a given neighborhood are high, more White and Black residents tend to locate in the more noise polluted areas, and are therefore more exposed to transport noise.

Table 4 reports the p-values across the K-S and C-M tests for the parameter function estimates of interest. Across most coefficient estimates the hypothesis of a null and/or constant effect is strongly rejected.

Table 4 – Quantile Regression Hypothesis Tests (Model 2: With Interaction)

Dependent Variables	Kolmogov-Smirnov Type Tests					Cramer-von-Mises type tests				
	No Effect	Constant Effect	Positive Effect	Negative Effect	Location-Scale Shift	No Effect	Constant Effect	Positive Effect	Negative Effect	Location-Scale Shift
ln(Home Value ($))	0.002	0.009	0.003	0.155	0.009	0.309	0.001	0.003	0.001	0.136
Pop. Share White (%)	0.000	0.002	0.002	0.096	0.006	0.265	0.000	0.001	0.000	0.006
White x ln(Home Value)	0.000	0.003	0.002	0.108	0.000	0.001	0.008	0.296	0.000	0.051
Pop. Share Black (%)	0.054	0.068	0.013	0.194	0.035	0.364	0.032	0.029	0.052	0.386
Black x ln(Home Value)	0.062	0.077	0.013	0.208	0.037	0.033	0.040	0.377	0.329	0.658
Pop. Share HSP/LTX (%)	0.008	0.011	0.004	0.110	0.007	0.010	0.009	0.372	0.002	0.071
HSP/LTX x ln(Home Value)	0.003	0.006	0.003	0.106	0.023	0.466	0.003	0.006	0.029	0.335

Notes: The reported statistics represent p-values on the Kolmogove-Smirnov or Cramer-von-Mises type test statistics (see Chernoshukov and Fernandez-Val, 2005; Chernozhukov et al., forthcoming) regarding five hypothesis tests on each of the coefficient estimates across the 0.05 to 0.95 quantiles. The hypotheses include no effect, a constant (or location shift) effect, positive effect, negative effect, and location-scale shift effect as defined by Kroenker and Xiao (2002). P-values on test statistics for hypothesis tests regarding parameter estimates for other control variables are omitted for brevity.

We further investigate the thresholds at which house prices become prohibitively high for White and Black residents to avoid transport-related noise pollution by deriving the marginal effects for each population group at the 95th quantile of air and road noise. The results are shown in Figures 9a, 9b, and 9c. In each figure, the solid blue curves represent the marginal noise-ethnicity relationship over house prices ranging from $0 to $2 million. Grey shaded areas represent the 95th percent CI based on the delta method.

Figure 9a – Marginal Effects – White

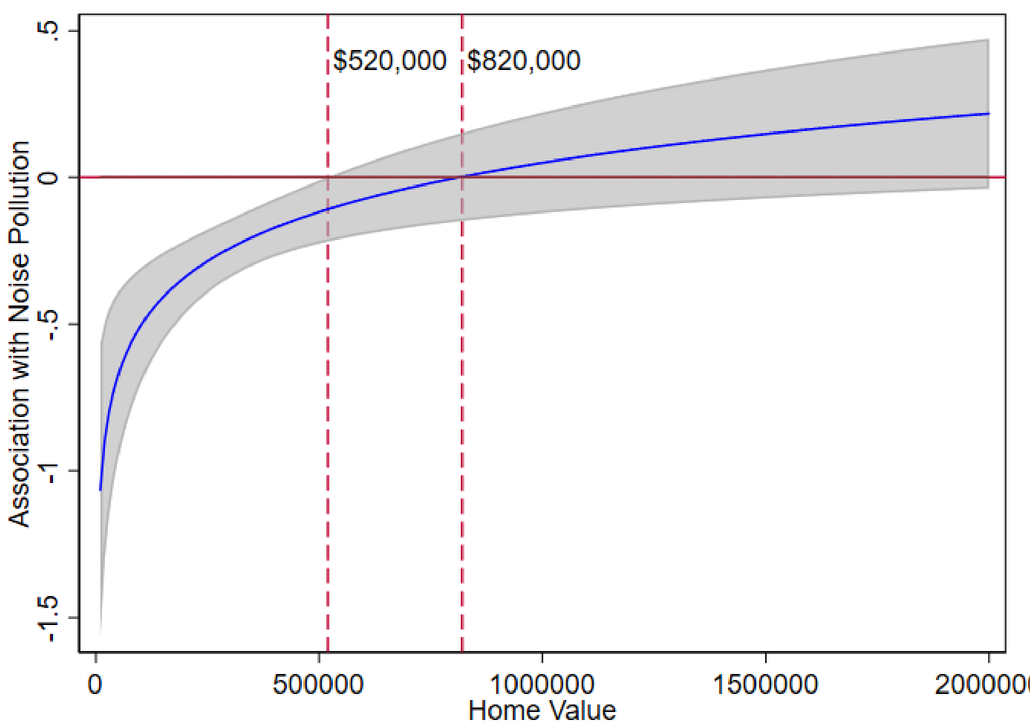


Figure 9b – Marginal Effects – Black

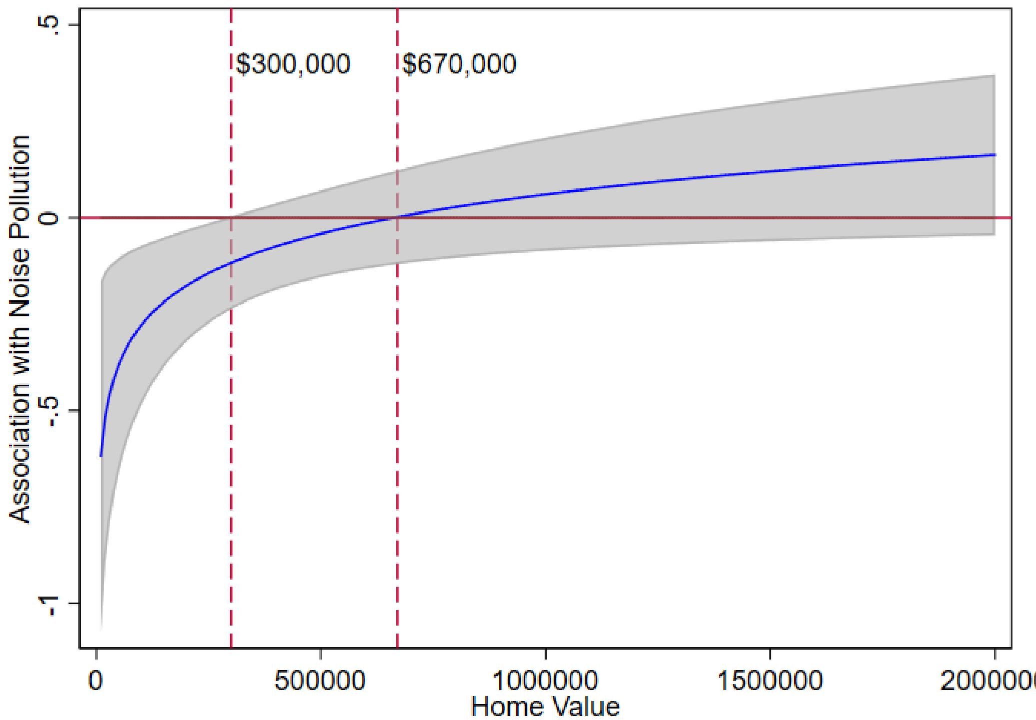
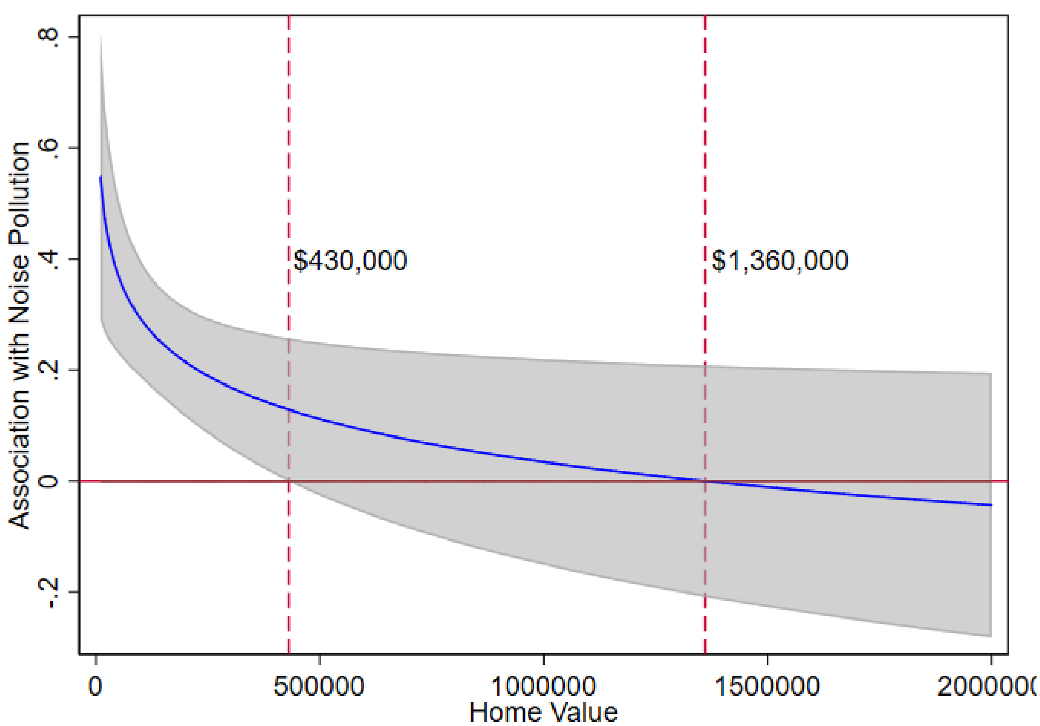


Figure 9c – Marginal Effects – Hispanic/Latinx



The most striking result is that the house price thresholds for a null effect varies across the White and Black populations. Figure 9a illustrates that the marginal relationship between noise pollution and White population shares becomes statistically insignificant at a typical house price of around \$520,000. The point estimate is 0 at a typical house price of \$820,000.

In contrast, Figure 9b shows that the marginal relationship between noise pollution and Black population shares becomes statistically insignificant at a typical house price of around \$300,000. And the point estimate is 0 at a typical house price of \$670,000. These thresholds for Black residents are much lower than those observed for White residents and perhaps explain the more pronounced avoidance behavior of White population shares found in the estimation without interaction terms. More importantly though, one way to interpret these findings is that home values represent a barrier to one's ability to avoid transport-related noise pollution, but that these barriers are unequal across White and Black residents.

Conclusion

In sum, exposure to noise pollution may be a source of racial and demographic inequality rooted in income and wealth. A potential mechanism of the apparent inequality may be the varying affordability of homes in quieter neighborhoods. In past studies, noise has been associated with lower property values and poor health outcomes. Less research has demonstrated the heterogeneity in how noise is correlated with house prices, average demographics of the neighborhoods, and their interactions. Differences between road noise and aircraft noise are also important to consider, given that aircraft noise is very intense for a short amount of time, while road noise is more consistent but typically at a lower intensity.

In this paper, we have tackled these issues using a relatively new dataset with multiple years of observations on noise levels for the entire U.S., which also breaks down the noise levels into separate estimates for aircraft opposed to road noise. We merge the noise data, at the Census tract level, with demographics and house prices data at the Census tract level, for the years 2016 and 2018. We present the data in multiple dimensions.

Specifically, we apply a set of noise-inequality curves and coefficients, which are based on the approach of Cohen et al. (2019). This enables us to demonstrate how the average burden of noise falls unequally in some locations (that is, U.S. states) but more equitably in others. We present graphs, tables, and maps of these noise inequality estimates. Maine, Missouri, Oregon, Vermont, and Pennsylvania are among the states with the greatest degree of inequality among Black residents. This inequality becomes worse for some states (e.g., Maine) in 2018 compared with 2016.

We also use quantile regressions to demonstrate the heterogeneity in the correlations between noise and house prices, broken out for various demographic groups. This enables us to estimate the abilities of the members of these groups to avoid noise by moving to different neighborhoods where noise may be less pervasive.

Our results suggest that when house prices are low (below national average), both the Black and White populations may successfully avoid noise pollution at any level of this negative externality. However, when in neighborhoods where house prices are high (above the national average), greater shares of Black residents are exposed to greater levels of noise pollution.

These results may be interpreted as evidence of racial and ethnic inequality, if one accepts the hypotheses that: 1) increases in noise pollution represent a significant dis-amenity in already noisy neighborhoods (i.e., those above the tipping point); and 2) increase in transport-related noise indicate better accessibility in the least noisy census tracts (i.e., those below the tipping point). In the first case, on average, the White population seems to be systematically sorting into the quietest neighborhoods within the census tracts with highest average house prices that tend to be most heavily affected by transport-noise pollution. The ability of White residents to better avoid transport-related noise pollution than Black and Hispanic residents in the most "expensive” areas, leads to significant inequality across these populations in terms of their exposure to transport-related noise pollution. In the second case, in quieter and perhaps more rural areas, some of which have lower average house prices, White and Black populations are able to sort towards areas with greater accessibility, which is captured by increases in transport-related noise. However, the inequality remains due to the inability of Hispanic residents to successfully sort in the same manner as White and Black residents.
The fact that these inequality patterns arise, even when controlling for local income and house prices, suggests that there are other mechanisms at play that may induce such sorting. Possible explanations may include hysteresis arising from historically discriminatory land use policies or transport infrastructure investments, among others. Another explanation may be based on the theory of market segmentation in the sense that Black and Hispanic populations hold lower implicit prices for noise pollution than White populations. Another possible explanation is discriminatory zoning, as in a paper by Schertzer et al. (2016) on race, ethnicity, and discriminatory zoning. They find evidence that “exclusionary zoning” in Chicago, IL was predated by industrial zoning that was focused primarily on higher black and Hispanic population neighborhoods. If similar patterns exist throughout the U.S., it is possible that highway construction (which cuts through major U.S. population centers that had predominantly high numbers of racial and ethnic minorities, as in Cohen et al., 2022), continued to exhibit high degrees of noise moving forward and are associated with lower house prices. In this respect, it may be a challenge to identify a causal effect between minority population and noise levels, or between housing prices and noise levels, when relying on contemporary data, but the correlations are of interest.

Overall, the identification of and delineation across these mechanisms is beyond the scope of this paper, but an interesting and important topic for future research.

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Appendix

Table A1: State-level ranking of Air & Road Noise Pollution and Inequality in Noise Pollution Exposure, Averaged over 2016 and 2018 Noise Values

State	Noise Pollution				Noise Pollution Exposure Inequality					Median Home Value ($ '000)
	Rank (Highest Pollution to Lowest)	Air & Road Noise (dB LAeq)	Air Noise (dB LAeq)	Road Noise (dB LAeq)	Rank (Highest Inequality to Lowest)	Overall	White Pop.	Black Pop.	Hispanic/ Latinx Pop.	
New York	1	47.87	44.65	38.54	4	0.78	0.19	-0.29	-0.31	403.52
Nevada	2	46.89	45.88	12.29	41	0.35	0.08	-0.13	-0.13	219.28
Illinois	3	46.81	45.56	26.57	22	0.56	0.11	-0.18	-0.27	204.86
Massachusetts	4	45.83	43.84	32.65	5	0.75	0.08	-0.34	-0.34	385.11
Washington	5	45.73	44.40	28.35	30	0.51	0.04	-0.40	-0.07	314.87
New Jersey	6	45.59	44.01	22.39	13	0.69	0.13	-0.27	-0.28	337.16
California	7	45.49	43.77	26.63	40	0.38	0.10	-0.19	-0.08	495.86
District of Columbia	8	43.91	40.20	29.86	27	0.53	-0.24	0.20	-0.08	531.23
Minnesota	9	43.32	41.43	23.80	12	0.69	0.05	-0.43	-0.22	204.75
Florida	10	42.78	41.14	16.75	32	0.48	0.09	-0.14	-0.25	204.99
Arizona	11	42.51	41.05	15.73	36	0.44	0.06	-0.21	-0.17	204.88
Texas	12	41.90	40.53	15.73	45	0.32	0.08	-0.14	-0.10	164.41
Georgia	13	41.61	40.31	22.57	34	0.45	0.12	-0.20	-0.13	165.30
Vermont	14	41.36	40.55	4.49	19	0.60	0.01	-0.45	-0.14	227.05
Oregon	15	41.07	39.74	19.28	18	0.61	0.03	-0.46	-0.12	280.31
Kentucky	16	40.06	37.61	13.30	11	0.71	0.04	-0.41	-0.25	131.66
South Dakota	17	39.93	38.22	7.29	-	-	-	-	-	139.10
Wyoming	18	39.92	38.65	6.33	28	0.52	0.00	-0.37	-0.14	220.40
Colorado	19	39.83	38.36	14.40	23	0.56	0.04	-0.39	-0.13	305.95
Virginia	20	39.57	37.60	15.53	33	0.45	0.08	-0.10	-0.26	291.52
Utah	21	39.44	35.99	21.20	20	0.59	0.03	-0.30	-0.26	256.04
Tennessee	22	39.41	37.48	12.59	6	0.75	0.10	-0.41	-0.24	156.80
Maryland	23	39.31	37.85	18.46	39	0.38	0.09	-0.14	-0.15	305.21
Missouri	24	38.98	37.60	14.41	15	0.68	0.07	-0.48	-0.13	143.52
Wisconsin	25	38.56	36.90	23.33	3	0.82	0.05	-0.45	-0.32	168.63
Mississippi	26	38.16	37.10	4.32	47	0.25	0.05	-0.06	-0.14	106.49
New Mexico	27	37.82	35.81	10.53	44	0.32	0.02	-0.24	-0.07	172.49
Delaware	28	37.61	36.01	10.23	43	0.34	0.07	-0.14	-0.13	253.35
Rhode Island	29	37.19	35.26	21.04	8	0.74	0.07	-0.31	-0.36	258.49
South Carolina	30	36.63	34.60	7.47	48	0.21	0.01	-0.01	-0.18	160.31
Oklahoma	31	36.28	34.39	8.80	26	0.53	0.03	-0.27	-0.24	121.30
Ohio	32	35.93	34.16	15.12	21	0.58	0.06	-0.33	-0.20	131.45
Montana	33	35.89	34.36	5.32	31	0.49	-0.02	-0.35	-0.12	204.65
Alabama	34	35.85	33.84	14.15	38	0.39	0.08	-0.19	-0.12	128.84
Louisiana	35	35.81	34.14	14.31	37	0.40	0.08	-0.15	-0.16	156.09
Michigan	36	35.71	34.27	12.91	16	0.66	0.09	-0.42	-0.14	136.21
Idaho	37	34.98	33.21	7.86	46	0.31	0.00	-0.26	-0.04	185.70
Pennsylvania	38	34.73	31.17	24.50	1	0.86	0.09	-0.45	-0.32	179.61
North Carolina	39	34.30	33.13	7.49	42	0.35	0.07	-0.16	-0.12	176.14
Indiana	40	34.29	31.99	13.81	7	0.75	0.07	-0.41	-0.27	123.11
Nebraska	41	33.53	31.30	12.94	17	0.62	0.04	-0.37	-0.20	140.75
Iowa	42	33.14	31.68	9.59	14	0.68	0.03	-0.45	-0.20	131.79
Kansas	43	32.31	29.87	9.98	29	0.51	0.04	-0.31	-0.16	133.80
North Dakota	44	32.01	29.08	7.27	35	0.44	-0.01	-0.37	-0.06	158.89
New Hampshire	45	32.00	28.37	8.66	2	0.83	0.02	-0.42	-0.39	246.27
Arkansas	46	29.19	26.89	7.92	25	0.56	0.07	-0.24	-0.26	114.96
Maine	47	28.43	24.54	7.52	10	0.71	0.01	-0.53	-0.18	182.68
Connecticut	48	27.92	25.11	16.77	9	0.73	0.10	-0.34	-0.30	299.62
West Virginia	49	23.28	19.84	8.36	24	0.56	0.02	-0.36	-0.18	112.61

Notes: Noise pollution statistics represent the average noise levels across 2016 and 2018 weighted by census tract populations. Inequality statistics are calculated as discussed in section ADD SECTION. The overall inequality measure is the sum of the absolute values across the black, hispanic/latinx, and white populations.

Figure A1a – Quantile Regression Coefficients – Socioeconomic Characteristics (No Interaction)

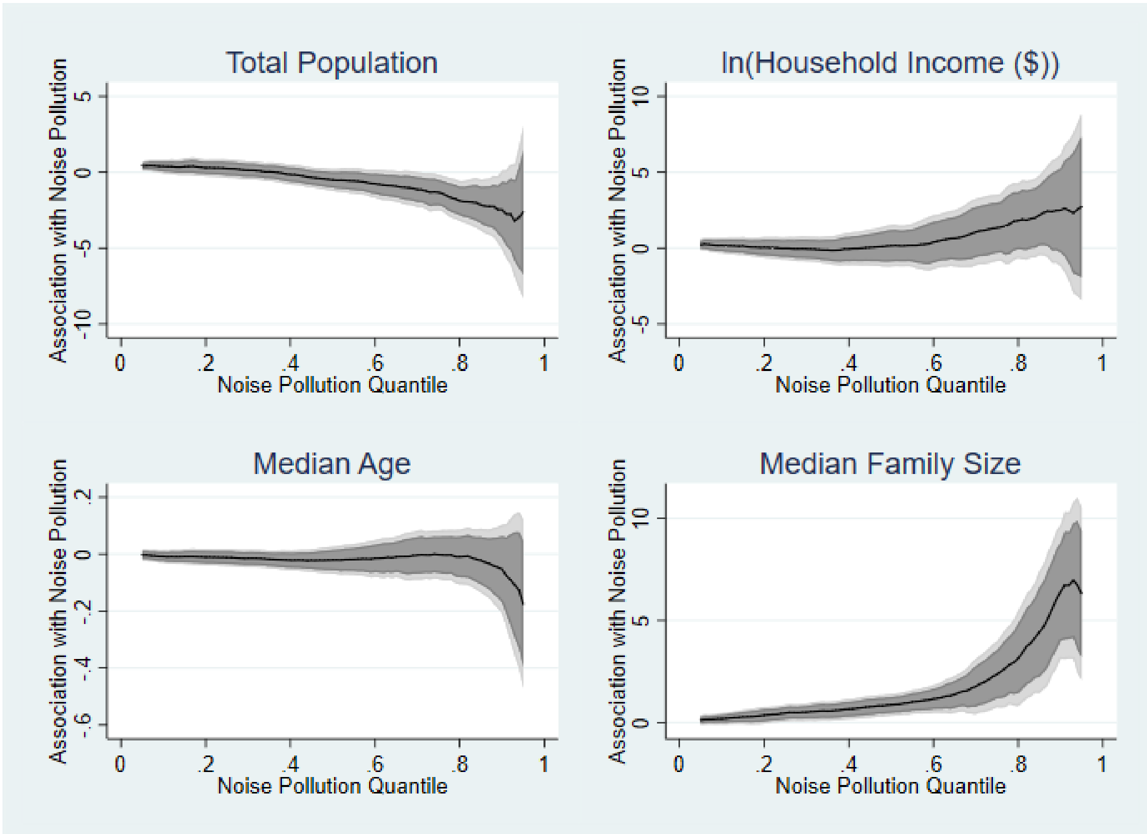

Figure A1b – Quantile Regression Coefficients – Housing Market Characteristics (No Interaction)

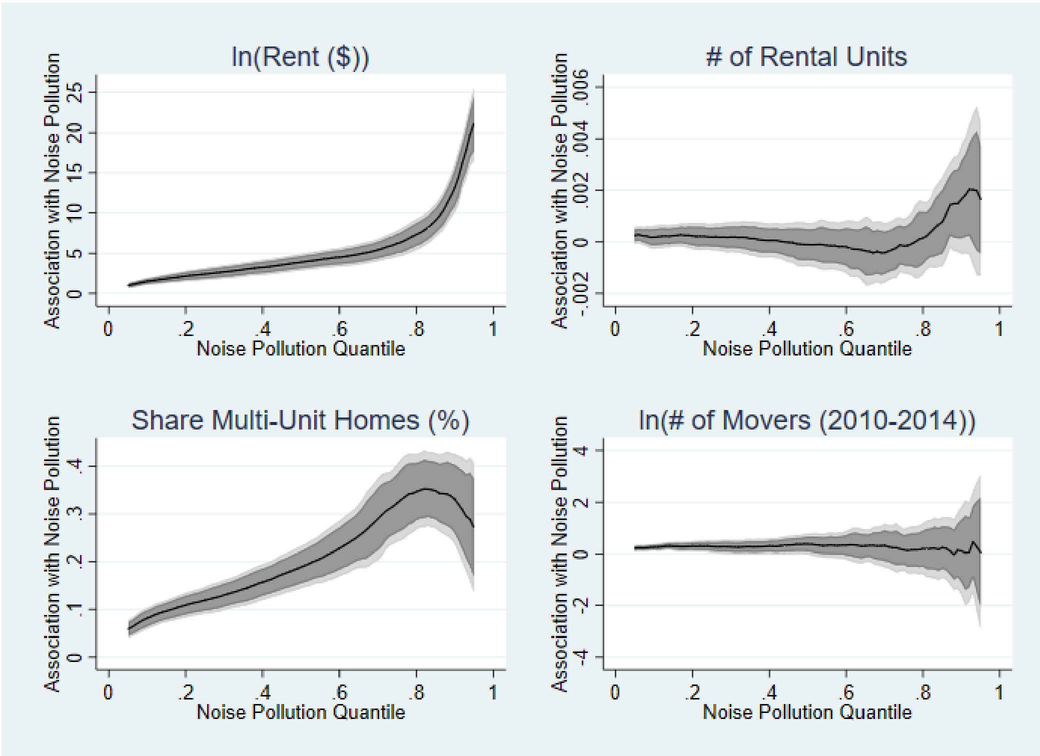

Figure A1c – Quantile Regression Coefficients – House Characteristics (No Interaction)

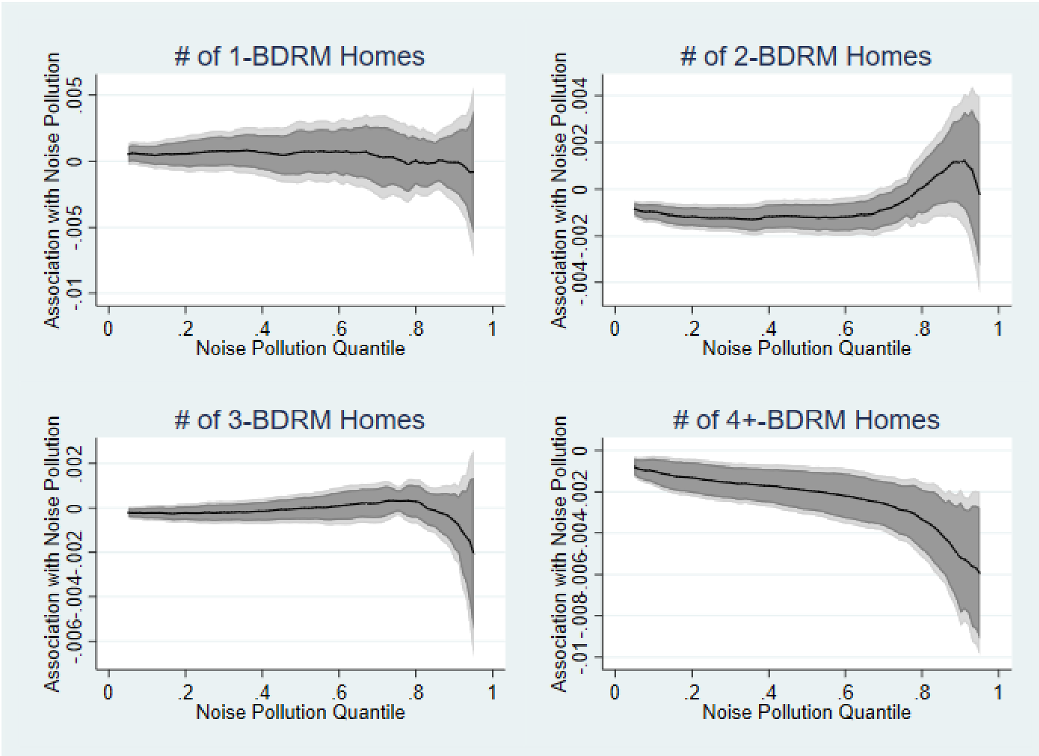

Figure A1d – Quantile Regression Coefficients – Education & Year FE (No Interaction)