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

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Abstract: We explore the relationships between house prices and transportation noise in a comprehensive manner – in Census tracts across the entire U.S. as well as separating road and aircraft noise. Using a panel of tract-level noise data for two years (2016 and 2018), along with American Community Survey data on demographics, house prices, and property characteristics, we first explore which tracts, states and demographic groups have residents who experience disproportionate amounts of noise. Then we use a 2017 federal government announcement of quieter commercial aircraft engine noise requirements, as a quasi-experiment to test the hypothesis that this requirement caused a structural shift in the effects of aircraft noise on house prices. We also test the hypothesis that the requirement led to differential changes across demographic groups in the effects of noise on house prices. We find average house prices in tracts with aircraft noise above 50 decibels do not significantly change after the announcement. But we also find that increases in the Black population in tracts with at least 50 decibels of noise, after the announcement, experience significantly higher house price increases relative to the baseline, while the opposite is true for higher Hispanic populations in these noisier tracts. Quantile regressions indicate the positive effect for higher Black population tracts only holds in the 75th quantile, while the negative effect for higher Hispanic population tracts holds throughout the 25th, 50th, and 75th quantiles.

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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 in the context of 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 and how does this impact house prices? 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.

Finally, one way in which the FAA may have attempted to reduce noise exposure was with a 2017 announcement of a noise reduction requirement for Stage 5 aircraft

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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

engines.[5] To the extent homeowners react to this announcement immediately, this may subsequently impact their willingness-to-pay for housing if they anticipate the regulation may have an impact on the level of aircraft noise exposure nearby.

Our focus is on examining how noise levels impact house prices, as well as the distribution of the effects 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, 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, noise, and house prices, we use a quantile regression approach, together with the above-described FAA announcement in 2017 mandating quieter aircraft engines. This quasi-experiment enables us to implement a difference-in-differences approach to discern how the causal relationships differ for various housing price quantiles. We find that in tracts with higher Black population (holding constant other demographic variables and housing characteristics), the regulation had a significant positive effect on house prices in the noisier tracts (i.e., with average aircraft noise of at least 50 LAeq). Whether or not these house price benefits were an intended consequence of the regulation, it is interesting that this statistical significance only holds for the higher-priced houses (i.e., those in the higher quantiles). In contrast, in tracts with higher Hispanic population, the sign of the effect was opposite, and this particular statistical significance is robust throughout the 25^{th}, 50^{th}, and 75^{th} house price quantiles.

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.

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[5] https://www.federalregister.gov/documents/2017/10/04/2017-21092/stage-5-airplane-noise-standards#:~:text=The%20new%20Stage%205%20noise%20standard%20applies%20to,55%2C000%20kg%29%20on%20or%20after%20December%2031%2C%202020.

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

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

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).[6] $\lambda_{0.5}$, 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[7] and have been applied extensively in the context of real estate and spatial economics (Coulson and McMillen, 2007; Liao and Wang, 2012; McMillen, 2015)[8] 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 segments and locations in Sydney, Australia. Similar to the previous work, the author

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

[7] 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.

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

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.

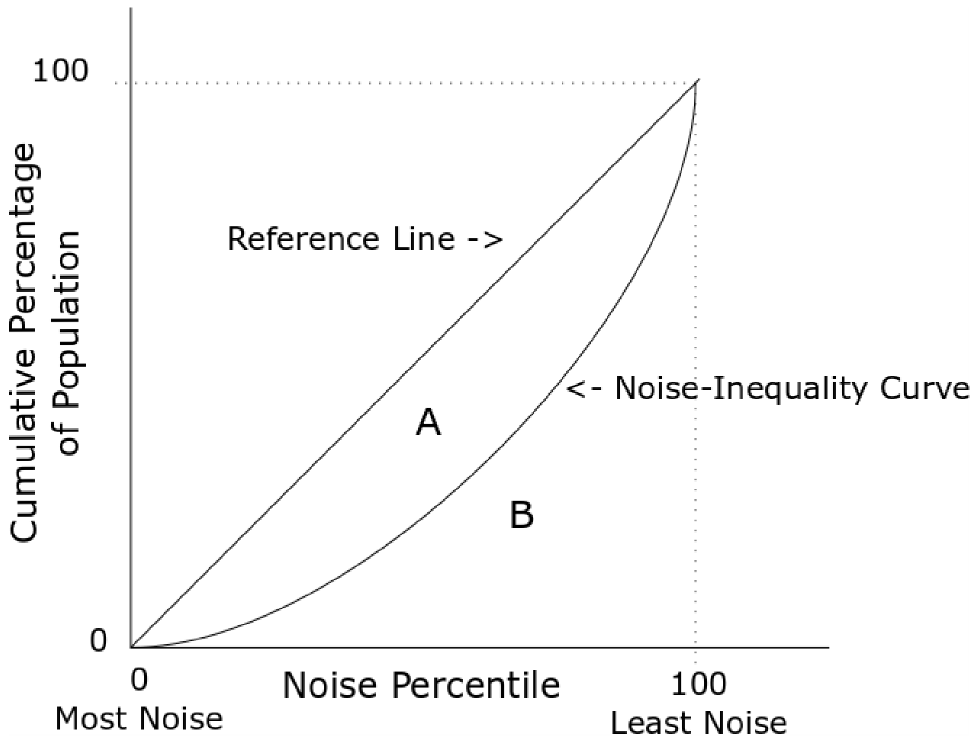
As suggested by the findings in Tonne et al. (2018), the relationship of inequality in exposure to noise pollution is very complex and non-linear. Quantile regression analysis provides a framework to tease out these non-linearities across the entire noise pollution distribution. Similar to Tonne et al. (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 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.

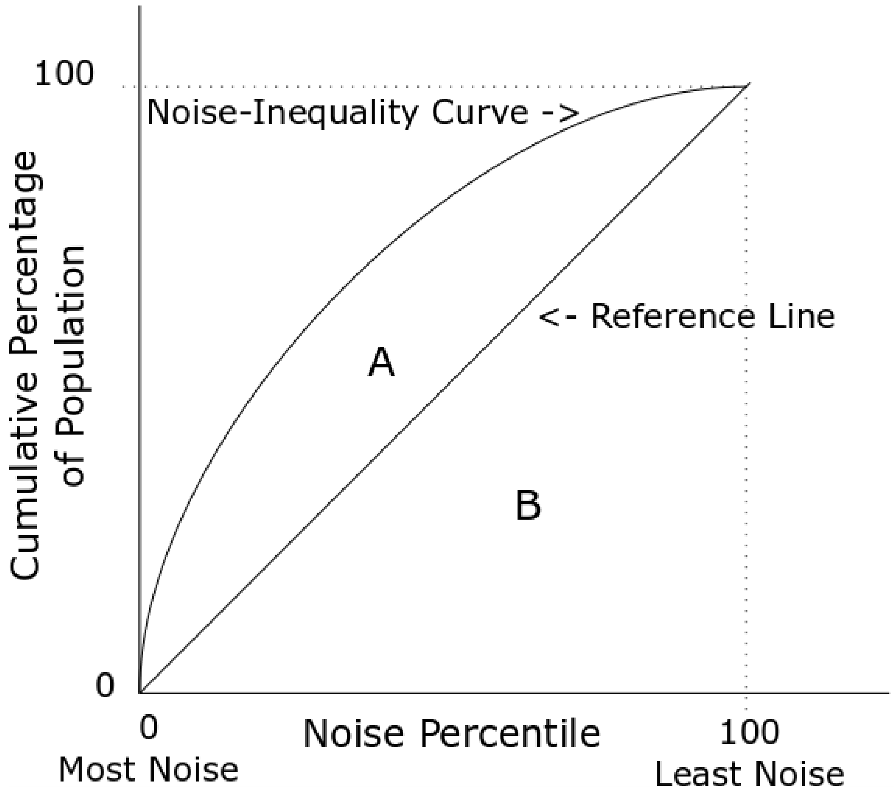
Figure 1 – Noise-Inequality Curve: Less-than-Proportionate



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.[9] 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

[9] 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

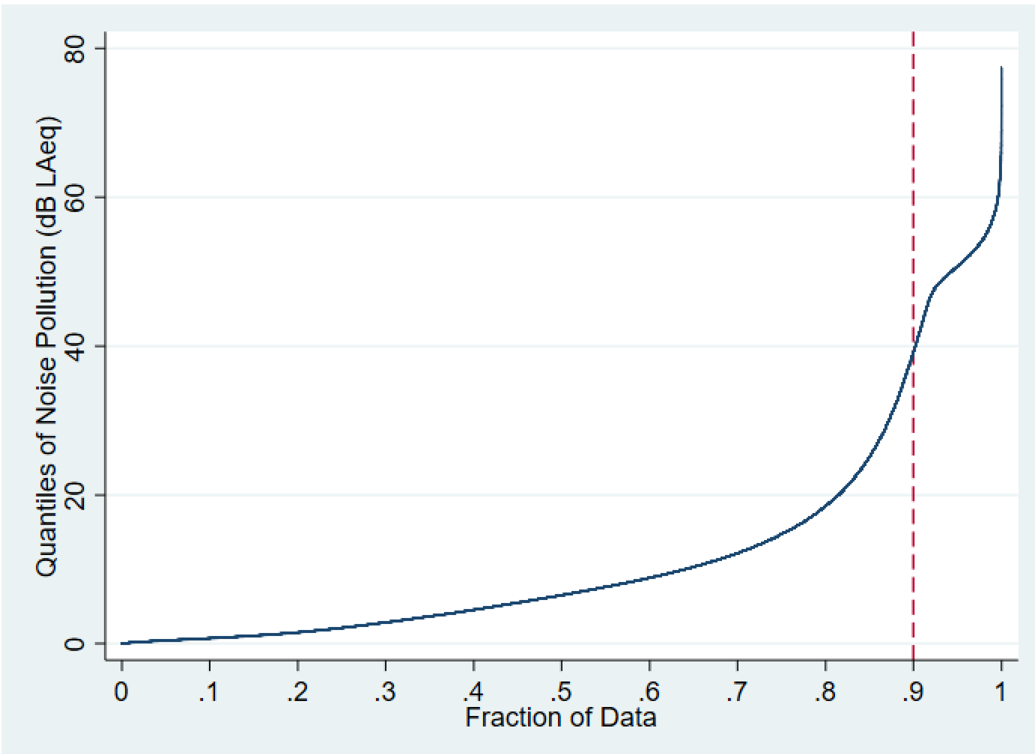


Figure 3 summarizes the distribution of air and road noise across the contiguous United States. The data reveal that the vast majority of census tracts experience very little transport-related noise pollution. More specifically, 90 percent of US census tracts are subject to approximately 40 dB LAeq or 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[10] 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%.

[10] 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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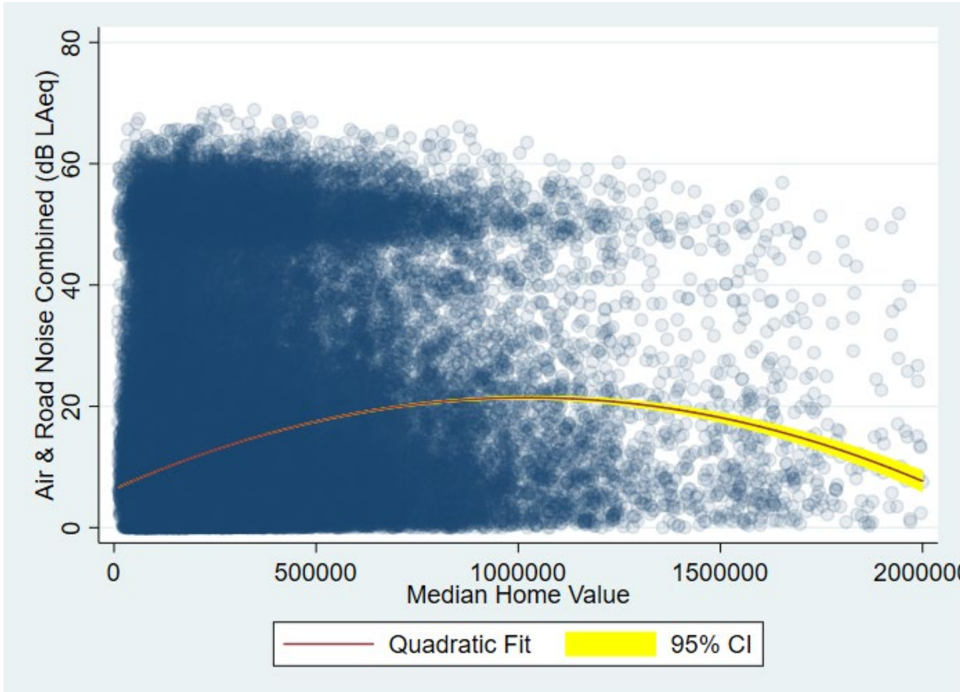
Rank	State	County	Air & Road Noise (dB LAeq)	Air Noise (dB LAeq)	Road Noise (dB LAeq)	Population	Pop. Density	Median Income ($ '000)	Median Home Value ($ '000)	Median Age	Pop. Share White (%)	Pop. Share Black (%)	Pop. Share Hispanic/ Latinx (%)	Pop. Share Bachelor + (%)
1	TX	Webb County	69.45	69.36	2.89	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

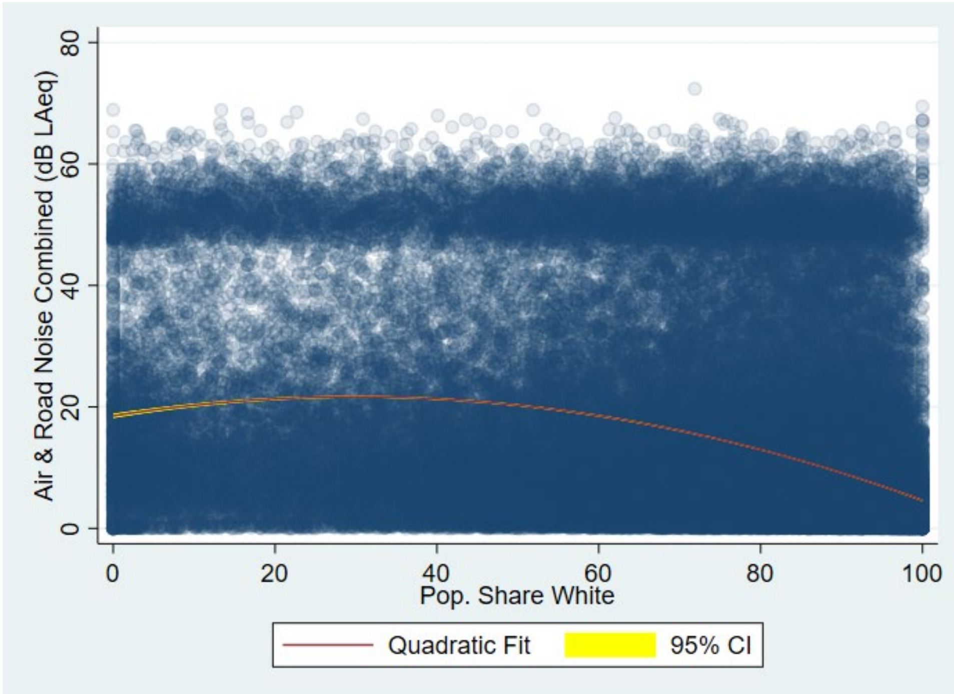


Figure 4c: Air & Road Noise – Black Population Share Correlation

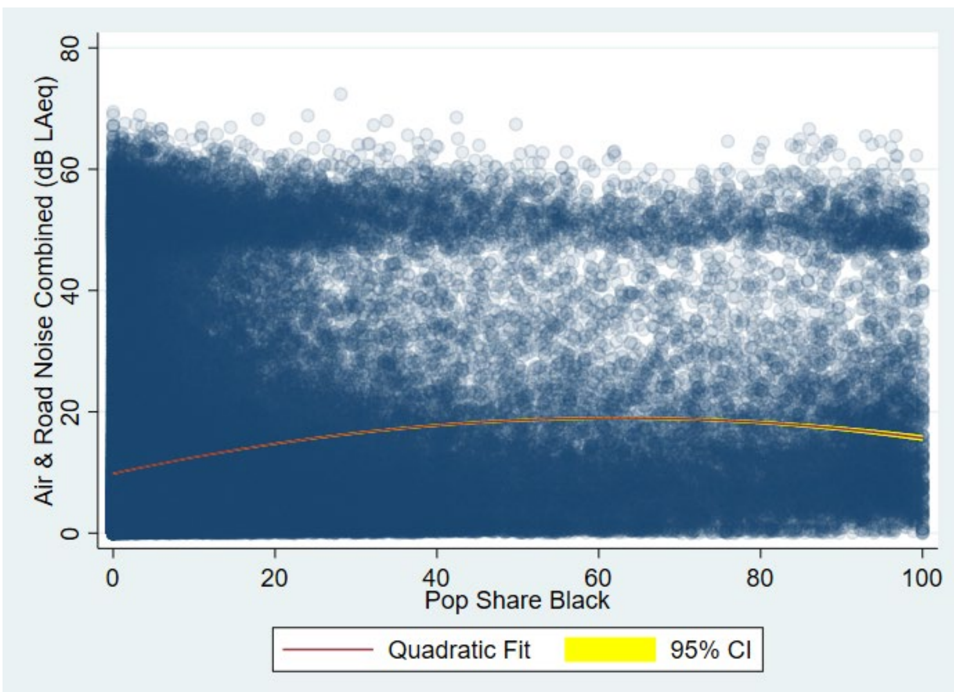
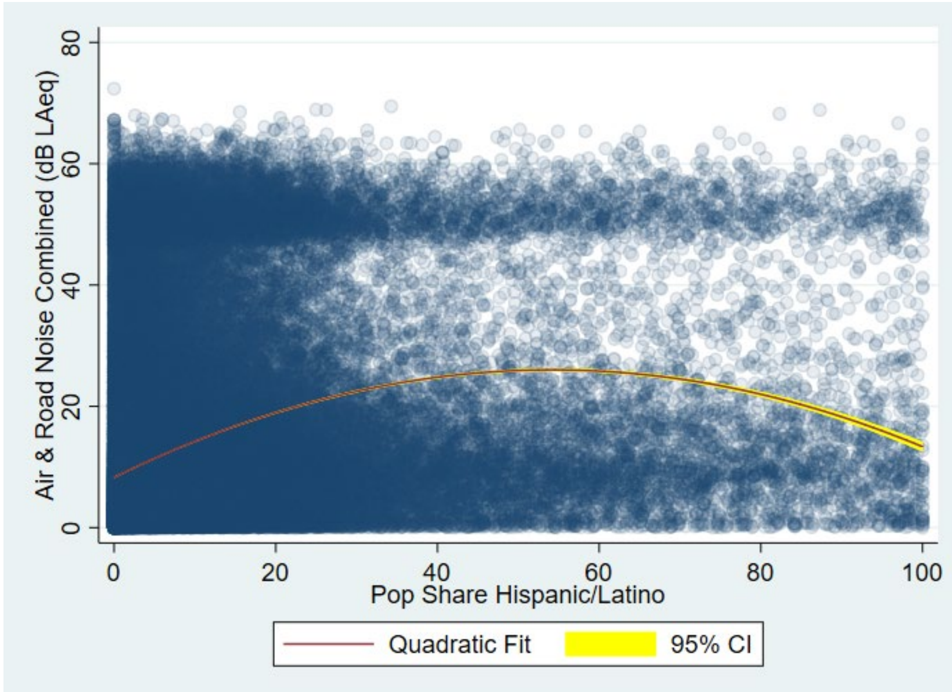


Figure 4d: Air & Road Noise – Hispanic/Latino Population Share Correlation

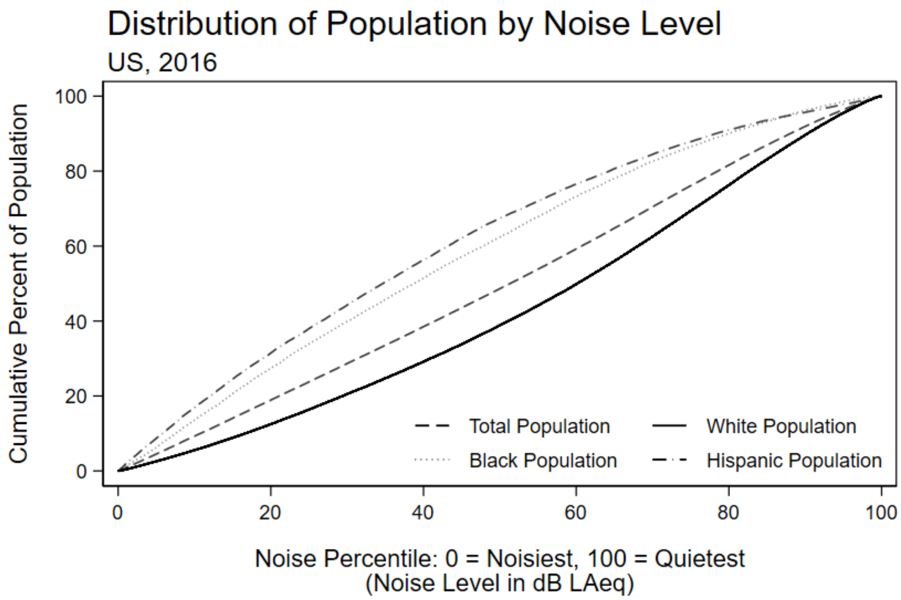


Results- Noise-Inequality Curves and Coefficients

Noise-inequality coefficient maps and curves

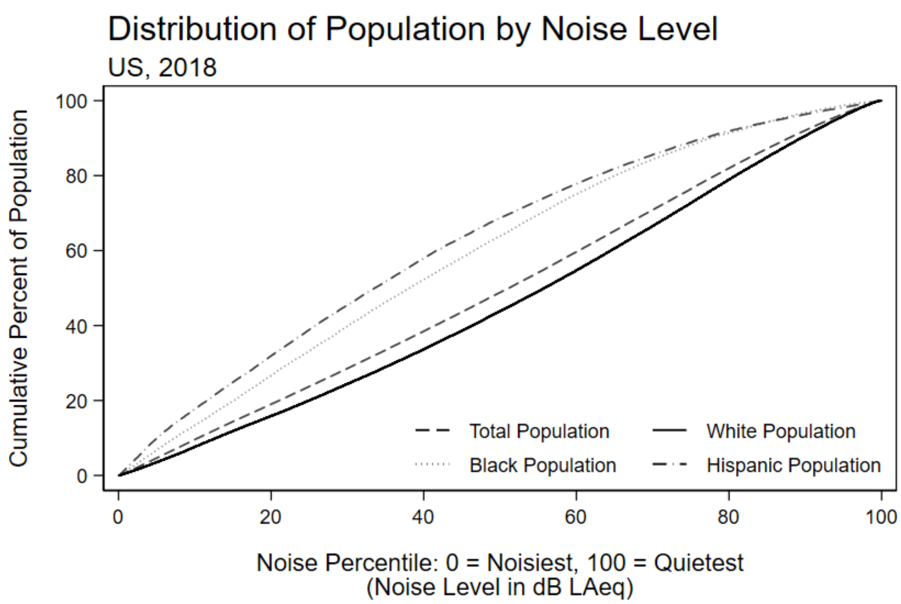
Figures 5a and 5b below are graphical depictions of the noise inequality curves for 2016 and 2018, respectively, at a national level of aggregation. These figures are broken out by the total population, White population, Black population, and Hispanic population. The curves for the Black population and 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



Source: Bureau of Transportation Statistics, Census Bureau, and author's calculations

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



Source: Bureau of Transportation Statistics, Census Bureau, and author's calculations

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

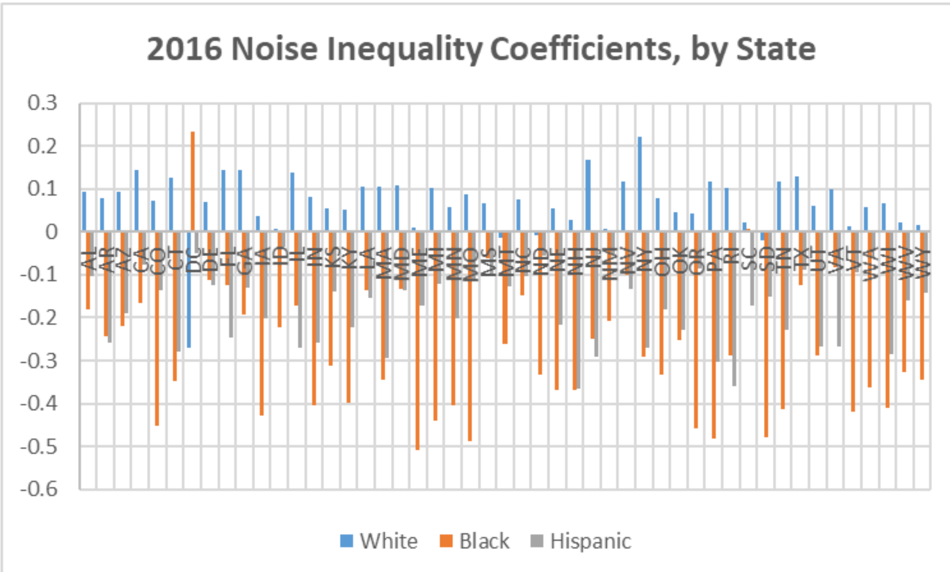
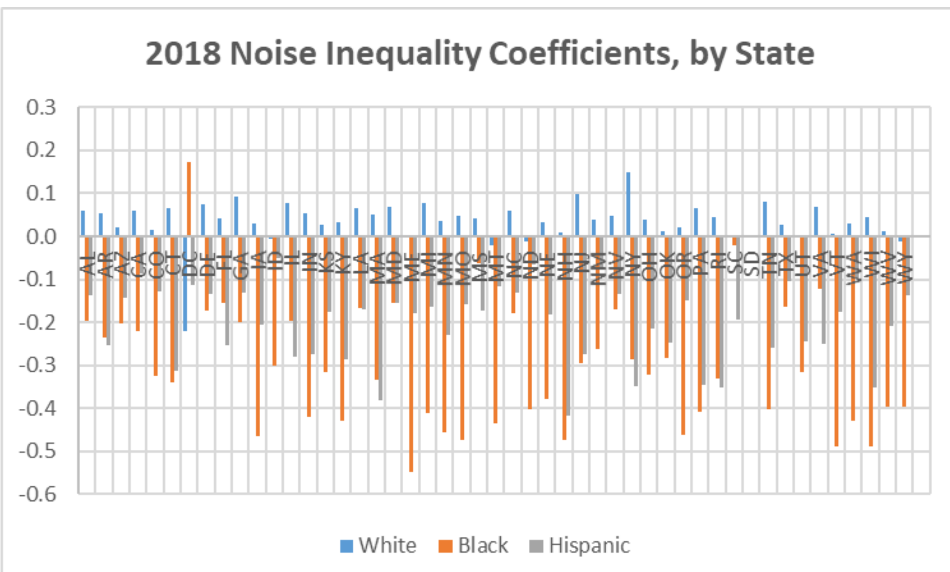


Figure 6b: 2018 Noise-Inequality Coefficients, by State



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. [11]

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

Results – Econometrics

We first present difference-in-differences hedonic regressions, with tract-level price as the dependent variable. We include in our sample all tracts with non-zero noise levels, and the treatment group is those tracts with at least 50 LAeq of aircraft noise in one or both of the two year (2016 and 2018).

Overall, we find the treatment effect is statistically insignificant. This is robust to clustering standard errors at the county level, and to including a variety of covariates such as the average number of homes in the tract that have 2 bedrooms, 3 bedrooms, …, and share with 5 or more bedrooms; controlling for road noise, average age of the homeowners, family size, share of housing that is one-unit and share that is multi-unit; and share that is renter-occupied. While these covariate estimates are not shown in the results tables, all except renter-occupied share are statistically significant. These results are in the second column of Table 2.

[11] 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 6a and 6b show the noise inequality coefficients aggregated for entire U.S. states.

Table 2 – Hedonic Difference-In-Differences Regression Results

	(1)	(2)
Dependent Variable:	Log house value	Log house value
Air noise > 50 LAeq	0.00385	0.00579
	(0.37)	(0.55)
Air noise > 50 LAeq × Post-2017	-0.0317	-0.0132*
	(-0.38)	(-1.69)
% White×Air noise > 50 LAeq×Post-2017	0.00122	
	(1.43)	
% Black×Air noise > 50 LAeq×Post-2017	0.00216**	
	(2.33)	
% Hispanic×Air noise > 50 LAeq×Post-2017	-0.0106***	
	(-9.27)	
% Other×Air noise > 50 LAeq×Post-2017	0.000000133	
	(0.22)	
Road noise > 50 LAeq	0.204***	0.201***
	(5.76)	(5.54)
N	27082	27082
R^2	0.615	0.613

Notes: t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.01
Regressions include county and year fixed effects;
Standard errors are clustered at the Census tract level.

We next turn to the set of results that include both the treatment effect, and an additional set of treatment effects with interaction terms for the percent of the population that are Black, percent of the population that are White, percent that are Hispanic, and percent that are “other”. In these results (shown in column 1 of Table 2), the interaction between the percent White and the treatment effects is insignificant. But the interaction between the percent Black and the treatment effects is positive and significant. This implies that when moving from tracts with less Black population to more Black population, the effect of the 2017 noise regulation leads to higher house prices. The opposite can be said when moving from tracts with less Hispanic population to more Hispanic population, that is, the effect of the 2017 noise regulation in those tracts leads to lower house prices. There is no significant effect of this aircraft noise regulation from moving from tracts with lower to higher White populations.

The nonlinearities between noise and house values are apparent in Figure 4a above. Therefore, it might shed additional light on these relationships if we were to estimate these difference-in-differences models with quantile regressions. 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. These results are shown in Table 3.

Specifically, when running quantile regressions, we see that there is significant heterogeneity among the different demographic groups. For instance, in the 25th and 50th quantiles, there is an insignificant coefficient on the interaction term between the Black percent of population and the treatment variables. But for the 75th quantile, we see that there is a significant positive relationship on the interaction between the treatment variables and the Black population share with respect to housing prices. For the Hispanic population interacted with the treatment variables, that coefficient estimate is negative throughout for all quantiles that we have estimated, and the magnitude of the coefficient is fairly constant in the range of around -0.01. This indicates that while there's not much heterogeneity in the price effects due to this policy change in 2017 for Hispanic households, there is heterogeneity for Black households. In other words, as the Black population percentage in a tract increases, we see that higher valued houses are impacted more by this policy change, than lower valued houses. The coefficient on the interaction between White population and the treatment effects are insignificant in all three quantiles estimated (i.e., the 25th, 50th, and 75th quantiles). The base treatment effect is insignificant throughout. This implies that considering heterogeneity among racial and ethnic demographics, as well as with differences among house prices across tracks, are important in assessing the impacts of this aircraft engine noise reduction policy.

Table 3 – Difference-in-Differences Quantile Regression Results (for the 25th, 50th, and 75th quantiles)

Dependent Variable	Log house value	Log house value
q25		
Air noise > 50 LAeq	0.0228	0.0212**
	(1.50)	(2.11)
Air noise > 50 LAeq × Post-2017	0.172	-0.00574
	(1.26)	(-0.28)
% White×Air noise > 50 LAeq×Post-2017	-0.00115	
	(-0.79)	
% Black×Air noise > 50 LAeq×Post-2017	-0.000954	
	(-0.72)	
% Hispanic×Air noise > 50 LAeq×Post-2017	-0.00933***	
	(-5.73)	
% Other×Air noise > 50 LAeq×Post-2017	-0.000000168	
	(-0.17)	
Road noise > 50 LAeq	-0.203***	-0.223***
	(-4.98)	(-5.48)
q50		
Air noise > 50 LAeq	-0.000467	0.00397
	(-0.02)	(0.20)
Air noise > 50 LAeq × Post-2017	0.0409	-0.00318
	(0.33)	(-0.11)
% White×Air noise > 50 LAeq×Post-2017	0.000380	
	(0.30)	
% Black×Air noise > 50 LAeq×Post-2017	0.00180	
	(1.54)	
% Hispanic×Air noise > 50 LAeq×Post-2017	-0.0123***	
	(-5.82)	
% Other×Air noise > 50 LAeq×Post-2017	0.000000734	
	(0.77)	
Road noise > 50 LAeq	-0.137***	-0.134***
	(-3.88)	(-2.75)
q75		
Air noise > 50 LAeq	-0.0310**	-0.0215
	(-2.18)	(-0.99)
Air noise > 50 LAeq × Post-2017	-0.0832	0.00707
	(-0.70)	(0.27)
% White×Air noise > 50 LAeq×Post-2017	0.00203*	
	(1.66)	
% Black×Air noise > 50 LAeq×Post-2017	0.00445***	
	(2.72)	
% Hispanic×Air noise > 50 LAeq×Post-2017	-0.0111***	
	(-6.28)	
% Other×Air noise > 50 LAeq×Post-2017	0.000000435	
	(0.44)	
Road noise > 50 LAeq	-0.0347	-0.0205
	(-0.88)	(-0.59)
N	27,082	27,082

Notes: t statistics in parentheses;
* p<0.10, ** p<0.05, *** p<0.01

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 some neighborhoods. In past studies, noise has been associated with lower property values and poor health outcomes. Less research has demonstrated the heterogeneity in how house prices are correlated with noise, 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. Finally, a quasi-natural experiment might allow for some analysis of causality between noise and house prices, which could add to the existing literature.

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.

In terms of empirics, we implement a difference-in-differences model where the "event" date is in 2017, based on the announcement of a new Federal Aviation Administration announcement of a new requirement for lower aircraft engine noise. We explore how house prices after this event, for tracts with noise levels of at least 50 LAeq, are impacted differently, and we find no direct effect. But when we break out the treatment effects by interacting them with the population percent that is Black, White, and Hispanic, we find a significant positive effect on house prices when Black population increases, and a significant negative effect on house prices when Hispanic population increases. This implies that perhaps the aircraft engine noise regulation is one approach in the direction of achieving environmental justice in tracts with higher Black population, while the evidence is the opposite in tracts with higher Hispanic population.

Since prices vary dramatically across tracts and within neighborhoods with different demographics, we explore a quantile regression approach to drill down deeper into the causal relationships between how the aircraft engine noise regulation impacts house prices differently across demographically diverse neighborhoods. While we find the positive treatment effect for the interaction with the Black population in a tract holds for the higher quantile tracts, the negative treatment effects for the interactions with Hispanic population is consistently significant across the 25th, 50th, and 75th quantiles of house prices. This finding is particularly intriguing because it implies that in tracts with higher Black population, the aircraft engine noise policy announcement only significantly enhances house prices in the tracts with already relatively high house prices. This finding leads to the question of how tracts with large Black populations that are renters are impacted by the noise regulation announcement.

Future work should explore the extent to which Black residents own homes in the tracts with the 75th quantile of home prices, opposed to the 25th quantile. Also, an examination of the impacts of this aircraft noise regulation announcement on apartment rental prices could be of interest. Although some other work (such as Breidenbach et al., 2021) have shown that apartment rents react immediately from announcements that impact the current noise levels, it is not obvious how such announcements for future noise level changes would impact apartment prices.
The fact that these inequality patterns arise, even when controlling for other covariates, suggests that there may be other mechanisms at play. Possible explanations may include hysteresis arising from historically discriminatory land use policies or transport infrastructure investments, among others.

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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
	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.	Home Value ($ '000)
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.