Airport Noise in Atlanta: The Inequality of Sound

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Abstract

We examine how changes in the geographic concentrations of Hispanic and African-American populations are correlated with changes in probabilities of airport noise, in Atlanta, during 2003 and 2012. We estimate ordered probit and locally weighted ordered probit regressions for three different noise categories to determine the correlations between these two demographic groups and the aircraft noise levels experienced by people in individual houses that sold. Then we determine the average coefficient for all houses sold in each Census block group, and we plot each year's coefficients for each block group against the percentiles of the minority population. While the absolute level of noise has declined over the geographic area considered in 2012 compared with 2003, we find that the distribution of noise coefficients among Hispanics and blacks became more inequitable in 2012 compared with 2003. At least two potential mechanisms could generate these correlations. Due to residential mobility, income and preferences could combine to produce a concentration of minorities in certain neighborhoods. Or, perhaps noisier flight paths are imposed upon higher minority neighborhoods as a result of discrimination. Our findings contribute to the broader literature on environmental justice, even though we cannot definitively infer the mechanisms at work.

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INTRODUCTION

One undesirable consequence of airplane flights is the associated aircraft noise near airports. This noise can have detrimental impacts on health. In addition to hearing impairment, aircraft noise can adversely affect workers and nearby residents via a number of channels, such as affecting sleep patterns and elevating blood pressure. However, much is unknown about the ultimate effects of airport noise, or about which demographic groups residing near an airport may disproportionately bear the burden of airport noise.

For neighborhoods near the Atlanta airport, we use a nonparametric ordered probit estimation procedure to examine the relationship between higher minority populations (e.g., African American and Hispanic, separately) and the probability of residential properties that sold in 2003 and 2012 being exposed to more airport noise. We develop curves for each of these minority populations, based on the nonparametric regression estimates, to examine how neighborhoods where properties sold are correlated with different marginal effects for the probability of greater airport noise exposure. For instance, we utilize these curves to address these questions, for neighborhoods in Atlanta where residential single family properties sold in 2003 and 2012: Are the more severe levels of airport noise concentrated among the high African-American and Hispanic population neighborhoods? And, are higher African-American population neighborhoods disproportionately more likely to experience higher noise than higher Latino population neighborhoods, or vice-versa?

In a literature review published in 1997, Morrel, Taylor, and Lyle (1997) concluded that high-quality studies on these various health issues related to airport noise were lacking and, thus, definitive conclusions about adverse effects were not possible. However, more recent literature reviews reach somewhat stronger conclusions. Ising and Kruppa (2004) highlight that even during sleep the noise from aircraft may lead to the release of stress hormones and may increase the risk of heart attacks. Moreover, if daytime noise levels exceed 65 dB, a consistent trend toward increased cardiovascular risk is found. This conclusion is reinforced by Lefèvre et al. (2017) in their study of aircraft noise exposure in France. The non-auditory effects of noise pollution are not limited to heart issues. Stansfeld and Matheson (2003) note that children exposed to chronic noise suffer detrimental effects on reading comprehension and long-term memory.

These potential health effects have generated increased attention in recent years. Some of this increased attention has occurred because issues involving environmental justice have become more prominent. The U.S. Environmental Protection Agency defines environmental justice as "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."[1] Environmental justice is achieved when everyone is provided the same protection from environmental and health hazards and has the same access to influence decisions that affect the environments in which they live, learn, and work.

Many economic research studies have examined how airport noise has affected the prices of nearby houses. Not surprisingly, a consistent finding is that more noise is associated with lower prices.[2] Few studies, however, have examined the determinants of airport noise. Our focus is on the distribution of airport noise. We attempt to provide statistical insights

[1] See https://www.epa.gov/environmental justice.
[2] See Cohen and Coughlin (2008; 2009) for numerous references.

concerning the differential impacts of airport noise on selected groups. Our goal is to describe "what is" rather than assessing causality or fairness. In the process, we provide statistical evidence relevant in assessing claims involving environmental justice. We are unable to conclude whether or not a group is affected unfairly by the decisions of others, but we are able to provide suggestive evidence on specific aspects of an environmental justice complaint.

A key challenge in assessing environmental justice in the context of airport noise is that residential mobility likely plays an important role in the observed outcomes.[3] The willingness to pay for less noise may differ across groups. While less airport noise is a good for all groups, it is possible that the willingness to trade other forms of consumption for it differs across groups. For instance, suppose group A's willingness to pay is less than B's. Then, ceteris paribus, one might expect a disproportionate share of A's population residing in noisy areas relative to B's population; such a statement assumes that A's and B's abilities to pay are identical. However, it is reasonable to expect income differentials to drive residential location decisions. If so, then the equitable exposure across groups to airport noise is likely to prove very difficult to define, let alone determine.

From an environmental-justice perspective, we have identified only three airport-noise studies that are related directly to the current study – Ogneva-Himmelberger and Cooperman (2010), Sobotta, Campbell, and Owens (2007), and Cohen and Coughlin (2012).[4] 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

[3] For an analysis of the disproportionate siting versus residential mobility hypotheses in the context of air pollution, see Depro, Timmins, and O'Neil (2015). This reference is also valuable for providing numerous references focused on environmental justice.
[4] For a study examining environmental justice and for additional references in the context of road traffic noise, see Havard et al. (2011).

counterparts. Sobotta, Campbell, and Owens (2007) regress airport noise in Phoenix, expressed as a qualitative dependent variable, on various independent variables, including the percentage of the neighborhood population that is Hispanic. They find that households in neighborhoods with greater Hispanic population were subjected to higher noise levels than households in other neighborhoods. Following 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. OPLWR is a more tractable approach than parametric estimation approaches such as a spatial ordered probit model. It also allows for heterogeneity in each individual parameter estimate by obtaining a separate parameter estimate for each data point (e.g., houses sold). 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.

The current paper extends Cohen and Coughlin (2012) in two noteworthy ways. First, our analysis examines two points in time, roughly a decade apart. This allows for insights into how the distribution of noise has changed for groups over time. Second, our results are used to average the property-level parameter estimates over each Census block group, and then to construct curves showing the inequality of the impact of noise and how the inequality has changed over time.[5] While these curves are different from typical Lorenz curves, in the sense that we plot the coefficients of the minority group population against the cumulative population, we utilize these curves to glean some new insights on how the burden of noise is concentrated among groups of black and Hispanic residents.

The remainder of this paper proceeds as follows. The next section describes the data, followed by the ordered probit model and results. Subsequently, we describe the locally weighted ordered probit model and the corresponding results. We also describe some "heat maps" and construct curves that demonstrate the concentration of minority populations and how these relate to the magnitude of the OPLWR coefficients. Finally, we conclude by summarizing our findings and explain how our results might be generalizable to other settings.

DATA

Our dataset is on airport noise levels surrounding the Atlanta airport in 2003 and 2012. The 2003 airport noise contours were obtained from the Atlanta Department of Aviation. The 2012 contours were obtained from the Hartsfield-Jackson Atlanta International Airport FAR Part 150 Study,[6] which we subsequently geocoded. For the 508 houses near the Atlanta airport that were sold in 2003, we purchased housing sales prices and characteristics data from First American Real Estate. Information for the 199 houses that were sold in 2012 was obtained from CoreLogic. Figure 1 shows the location of the noise contours and a half-mile wide buffer zone as well as the house sales for the two periods. Reflecting a reduction in the size of the noise footprint, the noise contours reveal that the geographic area covered in 2012 is smaller than in

[5] Boyce, Zwickl, and Ash (2016) note that measures traditionally used for income and wealth inequality have been applied to measure the distribution of pollution on minorities and low-income households. They present several inequality measures for industrial air pollution exposure at the state level.
[6] http://www.atl.com/wp-content/uploads/2016/03/Map-4-1.pdf , accessed on May 24, 2017.

2003. All or part of 45 Census block groups comprised the footprint in 2003, while 40 block groups comprised the footprint in 2012. This fact suggests that the number of residents affected by noise levels that are likely to have detrimental effects declined between 2003 and 2012. Also, this is a key reason for the smaller number of house sales in the latter period.

Figure 1 here.

Table 1 contains definitions of the variables in our regressions and Table 2 presents the descriptive statistics for the sales prices and characteristics of the data from 2003 and 2012. For 2003, approximately 29 percent of our observations fall in the 65 DNL zone, about 4 percent fall in the 70 DNL zone, and the remainder are in a buffer zone outside of the 65 DNL zone. Meanwhile, for 2012, approximately 10 percent of our observations fall in the 65 DNL zone, about 2 percent fall in the 70 DNL zone, and the remainder are in a buffer zone outside of the 65 DNL zone.

Table 1 and 2 here.

For 2003, the average house sold for approximately $128,400, was nearly 41 years old, and was 3.3 miles from the airport. Block group data on demographics, including percent black, percent Hispanic, and median income, were obtained from the 2000 U.S. Decennial Census. Because the demographic information was from the year 2000 while the noise levels were based on estimates in 2003, it seems reasonable to postulate that previous demographics may have influenced 2003 noise levels. For the neighborhoods under consideration, the average black share of the population was 57 percent, the average Hispanic share of the population was 8.7 percent, and the median household income was $31,900. For 2012, the average house sold for $116,900, was 37 years old, and was 3.3 miles from the airport. Block group data on demographics on percent black and percent Hispanic were obtained from the 2010 U.S. Decennial Census. Median income data are 5-year estimates for the period 2009-2013, and were obtained from the American Community Survey. For the neighborhoods under consideration, the average black share of the population was 70.7 percent, the average Hispanic share of the population was 10 percent, and the median household income was $32,000. Thus, over the period we consider, both areas experienced an increase in their minority populations, with virtually no change in median income. Once again, our use of the 2010 Census data together with 2012 house sales data implies that it is possible the 2010 demographics information had an impact on the 2012 noise levels. A similar statement can be made for any 2009-2011 income data used to calculate the 5-year estimates.

ORDERED PROBIT MODEL AND RESULTS

The first model we estimate, a standard ordered probit (OP) model, is as follows:

$$Noise = \mathrm{f}(X, u) \quad (1)$$

where *Noise* is a categorical variable for a house sold in one of the three noise level groupings described above, ordered from least to most noisy; *X* represents a set of variables measuring: 1) the age of the house in logs – *AgeLog*, 2) the distance in logs from the house to the airport – *DistanceLog*, 3) the percentage of the houses in the neighborhood in which the house was sold with a black head of household – *BlkHH*, 4) the percentage of houses in the neighborhood in which the house was sold with a Hispanic head of household – *HispHH*, and 5) the median household income in the neighborhood in which the house was sold – *MedHHInc*; and 6) the sales price of the house in natural logs – *PriceLog*, and u is an error term with a normal distribution with zero mean and constant variance.

The results produced by estimating equation (1) by ordered probit are presented in Tables 3 and 4. The results in Table 3 indicate that all the variables are statistically significant for 2003, but only *BlkHH*, *HispHH*, and *MedHHInc* are statistically significant for 2012. The results in Table 3 must be transformed before interpreting them as marginal effects.[7] Because there are three categories for the dependent variable, each can be ordered on a line segment under the normal distribution curve, and the width of each sub-segment would depend on the frequency of the observations for each noise level. See Figure 2 for an illustration. The probability of each value of the dependent variable is the area under the curve between the boundaries of each particular sub-segment. The marginal effects of an increase in an exogenous variable on the predicted probabilities of each possible value of the dependent variable can be assessed in the context of a normal distribution that shifts in response to the change in the exogenous variable. This shift leads to a different area under the normal distribution for each of the three possible outcomes.

Table 3, Table 4, and Figure 2 here.

When there is a positive relationship between the dependent variable and the exogenous variable causing the shift, there will be less area under the normal curve for the lowest outcome (noise less than 65 dB), so this probability will decrease. For the largest outcome (noise greater than 70 dB), the area under the normal curve will increase, so the probability that a house is exposed to noise greater than 70 dB increases. The outcome of an increase in an exogenous variable on the area in the middle range (65 up to 70 dB) is ambiguous, as the probability of being in this noise range may either increase or decrease.

[7] See Greene (2003).

Focusing on the minority populations in the 2003 results, after transforming the results in Table 3, an examination of Table 4 reveals that the marginal effects are negative and significant (at the 10 percent, two-tailed level) in the buffer zone (noise less than 65 dB) for the black (*BlkHH*) and Hispanic (*HispHH*) variables. Because of their positive coefficients in Table 3, increases in these exogenous variables (i.e., larger neighborhood percentages of black and Hispanic heads of households) will shift the entire probability distribution to the right, which decreases the probability of being in the buffer zone and increases the probability of being in the noisiest zone.[8] We also examine the marginal effects for the 65 up to 70 dB noise contour. For percent black and Hispanic households, the signs of their marginal effects imply that for the average house in the 65 up to 70 dB zone, higher percentages of either of these populations in the neighborhood leads to a higher probability that houses in the neighborhood will be exposed to 65 up to 70 dB of noise.

For 2012, the signs and magnitudes are similar for the coefficients on the black and Hispanic variables. Both of these coefficients are positive and are statistically significant at the 10 percent (two-tailed) level. The magnitudes of the marginal effects are virtually identical for Hispanics in 2012 compared with 2003. For blacks, the probability of being in the buffer zone is lower in magnitude in 2012 than in 2003, while the corresponding change in probability of being in the buffer zone with higher black population is lower in 2012 than 2003. On the other hand, the change in probability of being in the 70 dB contour with an increase in black population is higher in 2012 than in 2003.

[8] Using different estimation methods and a different model, Sobotta, Campbell, and Owens (2007) find, similar to our result, that increased Hispanic percentages are significantly associated with more noise. While they find a positive association between higher "non-white" percentages in a neighborhood and more noise, the relationship is not statistically significant.

ORDERED PROBIT LOCALLY WEIGHTED REGRESSIONS: LOCALLY WEIGHTED MAXIMUM LIKELIHOOD

It is possible that some of our variables affect the probability of a given level of airport noise nonlinearly. In other words, the neighborhood characteristics of different houses may have different impacts on the probability of a given level of noise exposure. For instance, some properties may have a higher probability of more noise when Hispanic population increases, while other properties may have a lower probability of more noise with a similar increase in Hispanic population. Even when the direction of the changes is the same across properties, the magnitudes may be different. A standard ordered probit model does not adequately account for such nonlinearities because the parameter estimates are constrained to be equal across all data observations. Thus, ignoring the spatial heterogeneity in the parameter estimates can lead to inaccuracies in interpretation of the magnitude and direction of the distance, age, price, and demographic variables on the probability of greater noise.

McMillen and McDonald (2004) have developed an estimation approach that allows for heterogeneity in the case of an ordered probit model with two dependent variable values, which we call ordered probit locally weighted regressions (OPLWR).[9] They specify a "pseudo log-likelihood function" to estimate a separate set of parameters for each observation, and they describe this as a locally weighted ordinal probit "pseudo log-likelihood function". Cohen and Coughlin (2012) extend their approach for the case where there are 3 possible "regimes" in the ordered probit. In this situation, the pseudo log-likelihood function is:

[9] See Fotheringham, Brunsdon, and Charlton (1998) and Fotheringham, Brunsdon, and Charlton (2002) for general background on locally weighted regressions.

$$\Sigma_j w_{ij} [D_{0j} \log \Phi (- \beta_i' X_j) + D_{1j} [\log \Phi (\mu_i - \beta_i' X_j) - \log \Phi (- \beta_i' X_j)]$$

$$+ D_{2j} \log \Phi (-\mu_i + \beta_i' X_j)] , \qquad i,j = 1,2,\ldots,n, \tag{2}$$

where Φ ( ) is the standard normal cumulative density function; β_i is the parameter vector for observation i; D_{0j} , D_{1j} and D_{2j} are dummy variables taking the value of 1 if observation j is either 0, 1, or 2, respectively, and 0 otherwise; μ_i is a parameter for observation i; and w_{ij} is the weight that house j has on house i.

The weight structure is important for estimating the nonparametric version of the log likelihood function. One possibility, which we use in our analysis, relies on the "Gaussian function", and is represented as:

$$w_{ij} = \phi (d_{ij}/(b)) \tag{3}$$

where ϕ is the standard normal (Gaussian) density function; d_{ij} is distance (as the crow flies) between house i and house j; and b represents the "bandwidth".[10]

Many locally weighted regression applications have used the Gaussian function, including recent analyses such as Barr and Cohen (2014) and Cohen, Osleeb, and Yang (2014). The determination of the bandwidth tends to be more important than the choice of the weighting function.[11] In our models, we selected the bandwidths as described below.

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[10] See Thorsnes and McMillen (1998) and McMillen and McDonald (2004) for details on the Gaussian function.

[11] For example, the results in Thorsnes and McMillen (1998) are essentially invariant to choosing among several different weighting functions. McMillen and McDonald (2004) suggest the "cross-validation" approach for selecting the appropriate bandwidth. This approach consists of estimating the OPLWR model for several different bandwidths (and setting $w_{ii} = 0$), and choosing the bandwidth for which the pseudo-likelihood function is maximized. Other studies, such as McMillen and Redfearn (2010), present results for more than one bandwidth rather than selecting one preferred bandwidth.

ORDERED PROBIT LOCALLY WEIGHTED REGRESSIONS: RESULTS

Table 5 contains results for the OPLWR estimations, based on a bandwidth of b = 1.5 for 2003 and b = 1.0 for 2012. These bandwidths are calculated based on a value of approximately 10 percent of the greatest distance between observations in each sample. In this context, the greatest distance for 2003 was approximately 11.3 miles for 2003 and 9.9 miles for 2012.[12] For 2003, we started with a bandwidth of 1.2, but with this choice the model had difficulty converging because of the relative sparseness of observations receiving positive weight in some locations. Therefore, we incrementally raised that bandwidth until we reached a value that converged, which was 1.5.

Table 5 here.

Similar to the previous discussion, we focus our discussion on specific results for the two minority populations. While Table 5 reports statistics on the property-level OPLWR results, the following discussion focuses on Census block-level average coefficients in order to directly analyze the relationships between the minority percent coefficients and the dispersion of the minority groups in the neighborhoods surrounding the airport.

For the variable measuring percentage of houses in the neighborhood with a black head of household (*BlkHH*), the mean from the OPLWR for 2003 is nearly twice as large as the coefficient estimate of the OP. The range of the OPLWR results is 0.037 to 0.060.[13] Thus, for all block groups an increase in *BlkHH* tends to be associated with a reduced probability of being

[12] Once again, these discrepancies reflect the decrease in the number of houses exposed to noise levels of 65dB or more in 2012 versus 2003.

[13] The average coefficient for a block group is based on one or more regressions. For multiple house sales in a block group, we simply average the OPLWR coefficients.

in the buffer zone and an increased probability of being located in a noisier zone. A similar conclusion is supported by the results for 2012 as all coefficients are estimated to be positive, while the average coefficient for the black variable from OPLWR for 2012 is roughly equal in magnitude to the same coefficient from OP in 2012. An important difference, however, is that the values of the estimated coefficients are smaller than in 2003, ranging from 0.010 to 0.022.

Meanwhile, the estimates for the Hispanic variable (*HispHH*) also demonstrate a substantial amount of heterogeneity, but with a notable mix of both positive and negative coefficients. The mean OPLWR for 2003 is about two-thirds the magnitude, and the same sign as, the OP coefficient estimate. The range of the OPLWR results is -0.028 to 0.225. Of these 45 coefficients, 19 are negative. These negative coefficients indicate that an increase in *HispHH* tends to be associated with an increased probability of being in the buffer zone and a reduced probability of being located in the noisiest zone.

There is a sharp contrast between the 2012 OP and the 2012 OPLWR mean for the Hispanic variable. The mean OPLWR coefficient in 2012 is negative, while the OP estimate is positive. A mixture of negative and positive coefficients was also produced by the OPLWR for 2012. The range of the OPLWR results is -0.175 to 0.051. Of these 40 coefficients, 23 are negative. Once again, these negative coefficients indicate that an increase in *HispHH* tends to be associated with an increased probability of being in the buffer zone and a reduced probability of being located in the noisiest zone. Thus, the change from 2003 to 2012 in the estimated coefficients is favorable in terms of the noise faced by Hispanics.

Another perspective on the OPLWR results is provided by looking at the inequality of these coefficients across block groups for these minority populations. For 2003, Figure 3 shows a plot by block group of the rank of the coefficient estimates on the vertical axis against the cumulative percentage of the respective minority population in the block groups. The solid 45 degree line indicates that the rank of the coefficient estimate moves in lock-step with the minority's population share. In other words, the lowest 20 percent of the Hispanic estimates would be associated with 20 percent of the total Hispanic population in the block groups being examined. Comparing the plots for Hispanics and blacks, one sees that the inequality for blacks is less than that for Hispanics; in other words, the coefficient map for blacks is closer to the 45 degree line than for Hispanics. Figure 4 shows that a similar conclusion can be reached for 2012. What is different, however, is that the plots for both minority groups switch for being under the 45 degree line to above the 45 degree line. This means that a larger share of the cumulative population is associated with the higher coefficient estimates in 2012 than in 2003. This change is tempered by the fact that the coefficients tends to be smaller in 2012 than in 2003.

Figures 3 and 4 here.

In Figures 5 and 6, we provide spatial heat maps that look at the distributions of coefficients and how those compare to the minority household share of each block group. For 2003, Figure 5 demonstrates spatial clustering of coefficients, with many block groups having multiple contiguous block groups within the same coefficient bin. There is also a noticeable negative correlation between minority density and coefficient value for both the black and Hispanic populations; the correlation coefficients are -0.44 for both groups. For Hispanics, this correlation reiterates the finding in Figure 3 that the severe coefficients influence only a small portion of the Hispanic population living near the airport. For blacks, the correlation demonstrates that, while coefficient severity may be roughly equally distributed across the black population, blacks in areas of low black density tend to bear the larger coefficients.

Comparing the 2012 maps in Figure 6 with the 2003 maps shows another stark contrast between the two periods. There are still spatial clusters, but the correlation between coefficient severity and minority density is flipped: correlation coefficients of 0.55 for the black population and 0.73 for the Hispanic population. Looking at the Hispanic population maps specifically, the areas with the largest coefficients in 2003 tend to have the smallest in 2012, and vice versa. Overall, Figures 4, 7, and 8 demonstrate that in 2012 the black and Hispanic minority groups have the most severe coefficients in the block groups where their populations are the largest and the densest in the overall block group population.

Figures 5 and 6 here.

CONCLUSION

The findings of a vast degree of heterogeneity with the OPLWR approach contrast with those from the OP estimation, so it is clear that exploring heterogeneity in different neighborhoods generates additional insights in assessing where the noise falls that are masked in the OP model estimates.[14] One implication is that standard ordered probit in the present case generates misleading and biased estimates due to the ignored heterogeneity among individual houses. This implication arises despite the fact that our analysis is restricted to a relatively

[14] Due in part to this heterogeneity, we are unable to make any general statements about the presence of environmental justice (or injustice) with respect to airport noise in Atlanta. This is because the heterogeneity implies no clear pattern in the effects of demographics on noise levels, particularly for the Hispanic-related variable.

small geographic area near the Atlanta airport. One might reasonably expect spatial heterogeneity to become even more pronounced for larger geographic areas.

Specifically, we estimate how changes in the geographic concentrations of Hispanic and African-American populations are correlated with changes in probabilities of airport noise, in Atlanta, during the years 2003 and 2012. We estimate ordered probit and locally weighted ordered probit regressions for 3 different noise categories to determine the correlations between these two demographic groups and the aircraft noise levels experienced by people in individual houses that sold. Then we determine the average coefficient for all houses sold in each Census block group, and we plot each year's coefficients for each block group against the percentiles of the minority population to demonstrate the relationship between the distributions of the minority population in particular block groups and the average noise coefficients in each block. While the absolute level of noise has declined over the geographic area considered in 2012 compared with 2003, we find that the distribution of noise coefficients among blacks becomes more inequitable in 2012 compared with 2003. We find similar results for Hispanics.

There are at least two potential mechanisms behind these correlations. One possibility is that more noise may cause minorities to concentrate in certain neighborhoods, due to preferences for spending different income shares on certain types of housing. Or, perhaps noisier flight paths are imposed upon higher minority neighborhoods as a result of discrimination. Given that some of the demographic data was from earlier years than the noise data (2000 demographic data for 2003 noise; 2009-2011 demographic data for 2012 noise), it may be less plausible that the underlying mechanism for these correlations consists of higher noise leading to locational sorting into those neighborhoods by larger numbers of minorities.

Our results may be generalizable to other cities, however, we expect a substantial degree of heterogeneity in the correlations both within and across different cities and over time. Our findings also contribute to the broader literature on environmental justice, despite the fact that we cannot definitively infer the direction of the causality.

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Table 1

Variable Definitions

Name	Definition
Noise	Ordered categorical variable with three noise levels for houses in the buffer zone (least noise), 65 decibel day-night sound level noise contour, and 70 decibel day-night sound level noise contour.
DistanceLog	Distance in miles from house to airport (in natural logs).
AgeLog	Age of house (in natural logs).
B1kHH00	Percentage of houses in the neighborhood in which a house was sold with a black head of household.
HispHH00	Percentage of houses in the neighborhood in which a house was sold with a Hispanic head of household.
MedHHInc00	Median household income in the neighborhood in which a house was sold.
PriceLog	Sale price (in natural logs).

Table 2: Summary Statistics				
	Count:2003	**Percentage:2003**	**Count:2012**	**Percentage:2012**
House Sales in the buffer zone	343	67.5	175	87.9
House Sales in 65 db zone	146	28.7	20	10.1
House Sales in 70 db zone	19	3.7	4	2.0
Total House Sales	508	100	199	100
	Mean	**Range**	**Mean**	**Range**
Price (dollars)	128,442.4	32,378-460,500	116,875.8	6,000-4,192,000
Distance (miles)	3.29	1.06-6.02	3.34	1.38-5.15
Age (years)	40.85	1-101	37.05	3-113
B1kHH (percent)	56.92	0-96.38	70.67	12.96-97.81
HispHH (percent)	8.74	0-31.03	9.98	0.82-33.70
MedHHInc (hundreds of dollars)	319.37	116.67-606.25	319.95	116.67-704.25

TABLE 3: Estimation Results (1) – Ordered Probit

Variable	2003	2012
AgeLog	-0.249*	0.121
	(-4.86)	(0.99)
DistanceLog	-0.624*	-0.195
	(-3.29)	(-0.46)
B1kHH	0.030*	0.025*
	(8.28)	(1.80)
HispHH	0.032*	0.060*
	(2.89)	(1.87)
MedHHInc	0.00003*	0.000
	(4.22)	(0.16)
PriceLog	-0.499*	0.332*
	(-3.13)	(2.94)
Log likelihood	-310.22	-76.54
LR χ^2 (6)	137.94	15.06
Prob > χ^2	0.00	0.02
Pseudo R^2	0.18	0.09
Observations	508	199

*Denotes significance at the 10 percent (two-tailed) level.

Notes: Z-statistics are in parentheses. Dependent variable is an ordered, categorical noise variable with three noise levels starting from least noise (lowest level).

TABLE 4: Partial Derivatives (z-statistics) – Ordered Probit

	2003			2012		
Variable	Buffer Zone	65DB	70DB	Buffer Zone	65DB	70DB
AgeLog	0.086*	-0.078*	-0.008*	-0.022	0.018	0.004
	(4.85)	(-4.68)	(-2.99)	(-0.98)	(0.97)	(0.89)
DistanceLog	0.215*	-0.196*	-0.019*	0.035	-0.029	-0.006
	(3.30)	(-3.25)	(-2.46)	(0.46)	(-0.46)	(-0.45)
B1kHH	-0.010*	0.009*	0.0009*	-0.004*	0.004*	0.001
	(-8.37)	(7.65)	(3.40)	(-1.86)	(1.79)	(1.43)
HispHH	-0.011*	0.010*	0.001*	-0.011*	0.009*	0.002
	(-2.90)	(2.87)	(2.28)	(-1.94)	(1.87)	(1.45)
MedHHInc	-0.00001*	0.000009*	0.0000009*	-0.000	0.000	0.000
	(-4.22)	(4.11)	(2.80)	(-0.16)	(0.16)	(0.16)
PriceLog	0.172*	-0.157*	-0.015*	-0.060*	0.050*	0.010*
	(3.14)	(-3.10)	(-2.41)	(-2.84)	(2.64)	(1.72)

TABLE 5: Locally Weighted Ordered Probit Models

Variable	2003	2012
AgeLog	-0.794	-0.0004
	(0.957)	(0.084)
	[-7.451, 0.036]	[-0.493, 0.061]
DistanceLog	0.370	-0.730
	(0.887)	(0.811)
	[-0.855, 2.551]	[-6.093, -0.329]
B1kHH	0.051	0.020
	(0.006)	(0.003)
	[0.036, 0.061]	[0.010, 0.022]
HispHH	0.023	-0.010
	(0.067)	(0.054)
	[-0.050, 0.263]	[-0.210, 0.051]
MedHHInc	0.00003	0.000003
	(0.00002)	(0.000005)
	[0.00001, 0.00008]	[-0.00002, 0.000]
PriceLog	-0.495	-0.246
	(0.005)	(0.214)
	[-0.512, -0.485]	[-0.578, 0.332]
Observations	508	199

Notes: The average of the parameter estimates (508 for 2003 and 199 for 2012) for the variable is listed on the first of the three lines, the standard deviation in parenthesis is on the middle line, and the range of parameter estimates in brackets is provided on the third line. Bandwidth = 1.5 for 2003 and 1.0 for 2012.

Figure 1

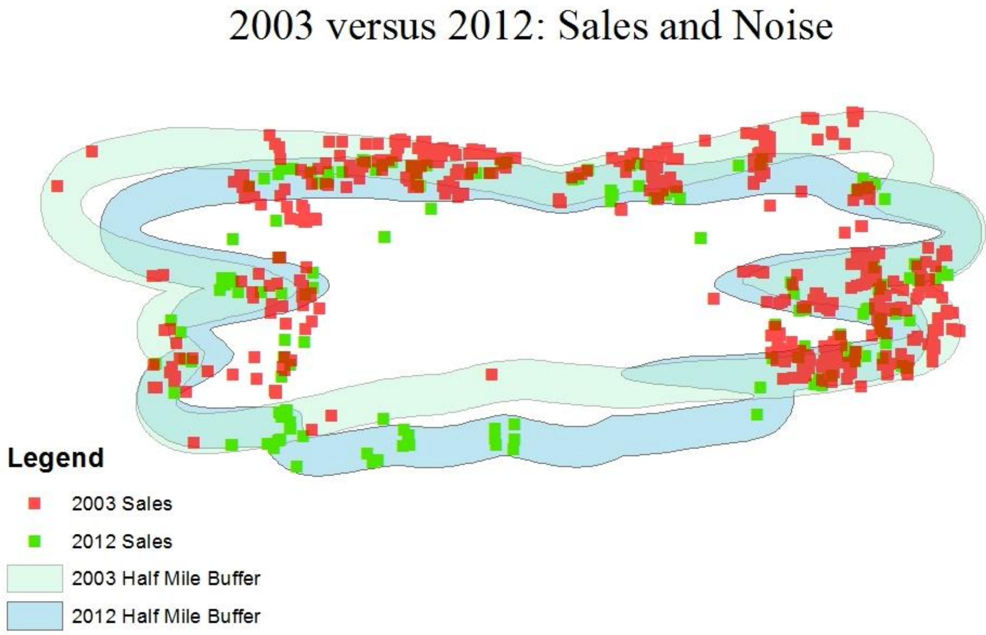
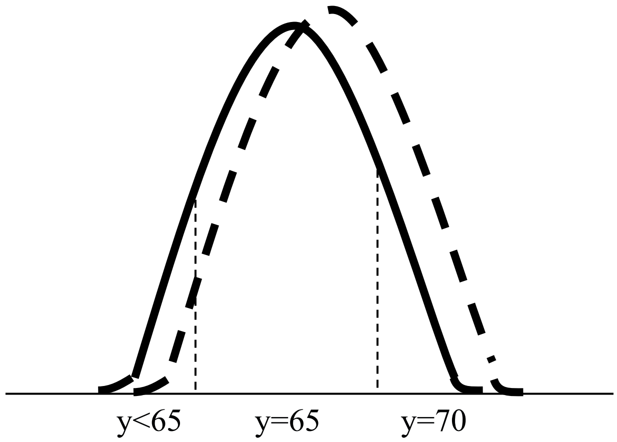

2003 versus 2012: Sales and Noise
Legend
2003 Sales
2012 Sales
2003 Half Mile Buffer
2012 Half Mile Buffer

Figure 2

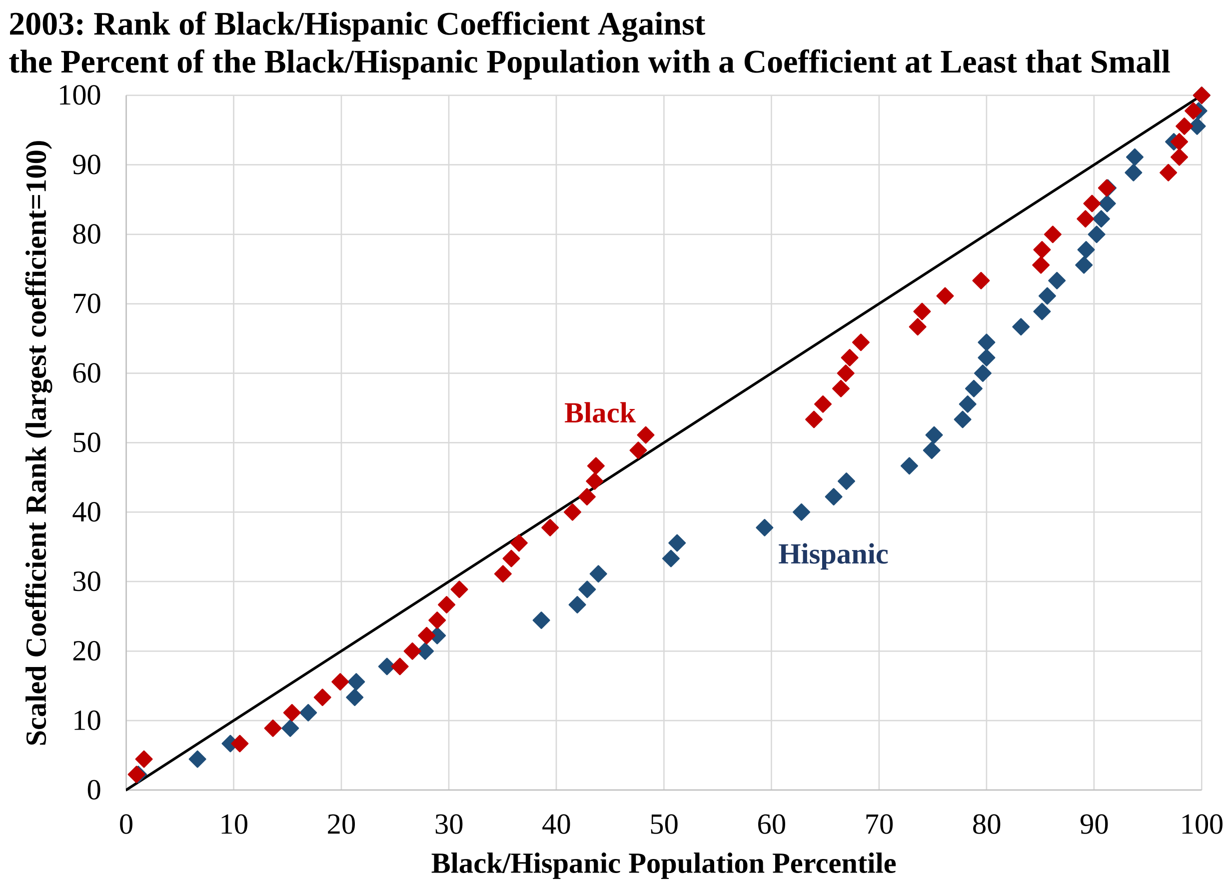


When an X increases, two possible outcomes:

1) (+) distribution shifts right prob(y<65) falls, prob(y=70) rises
2) (-) distribution shifts left prob(y<65) rises, prob(y=70) falls

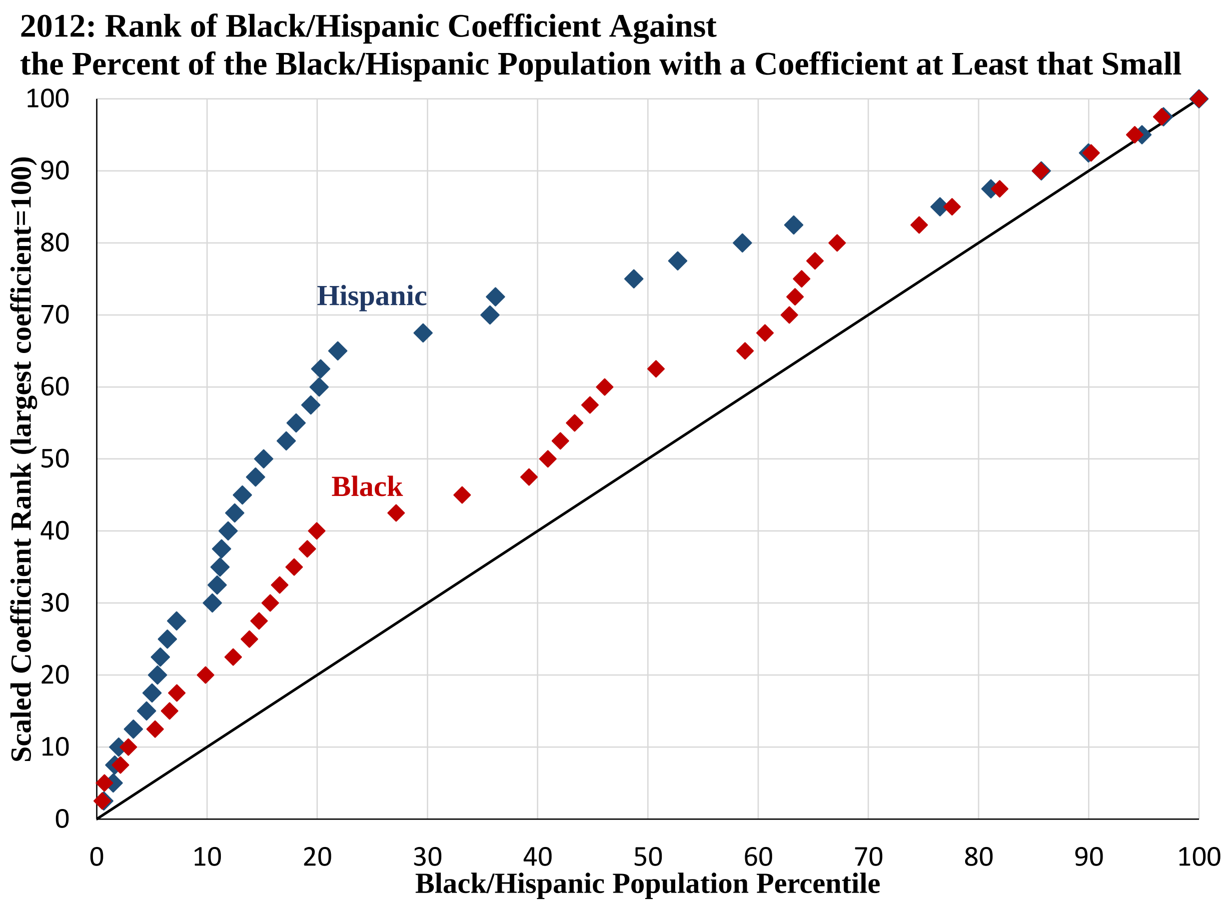
In both cases, effect on prob(y=65) is ambiguous but will be determined by the model.

Figure 3



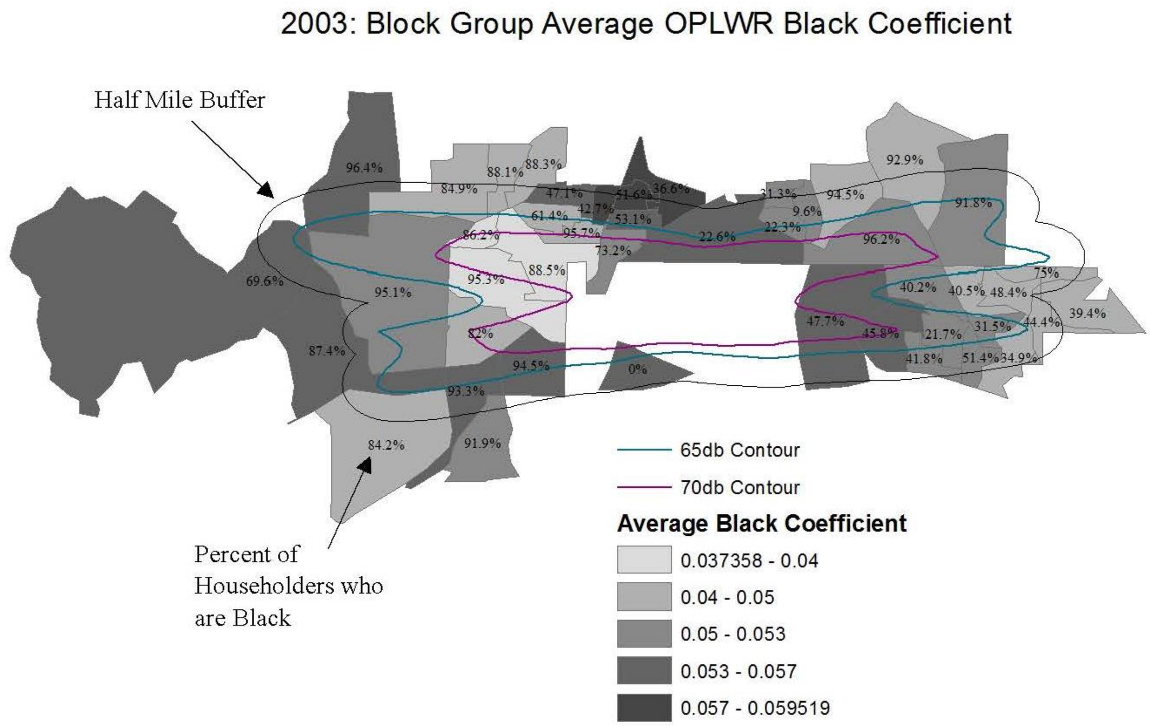
Notes: Coefficient ranks are based on the average coefficient in a Census block group. Points moving up along the 45 degree line would indicate an equal dispersion of coefficient severity across the population. For the black population, there is a roughly equal dispersion of severity. The Hispanic population demonstrates a more unequal distribution. However, only about 25 percent of the Hispanic population is subjected to the more severe half of the coefficients, compared to roughly 50 percent of the black population.

Figure 4



Notes: Coefficient ranks are based on the average coefficient in a Census block group. While points moving up along the 45 degree line would indicate an equal dispersion of coefficient severity across the population, only 15 percent of the Hispanic population and 40 percent of the black population are in block groups with the lower half of the average coefficients.

Figure 5


2003: Block Group Average OPLWR Black Coefficient
Half Mile Buffer
Percent of Householders who are Black
65db Contour
70db Contour
Average Black Coefficient
0.037358 - 0.04
0.04 - 0.05
0.05 - 0.053
0.053 - 0.057
0.057 - 0.059519

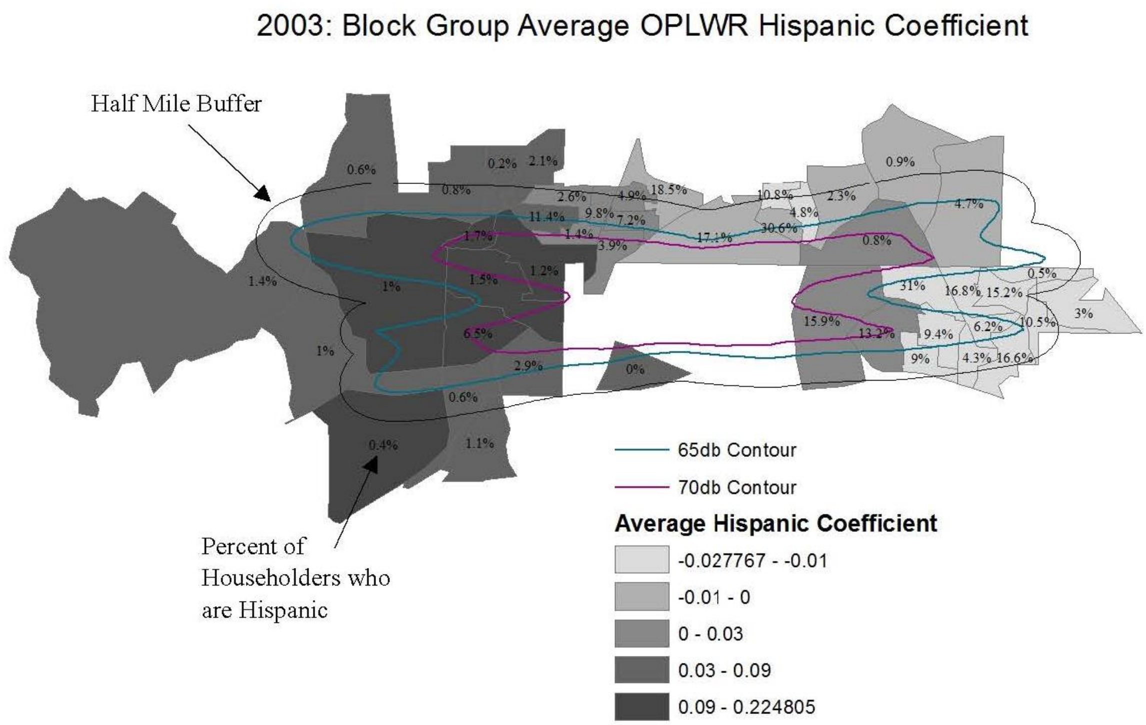
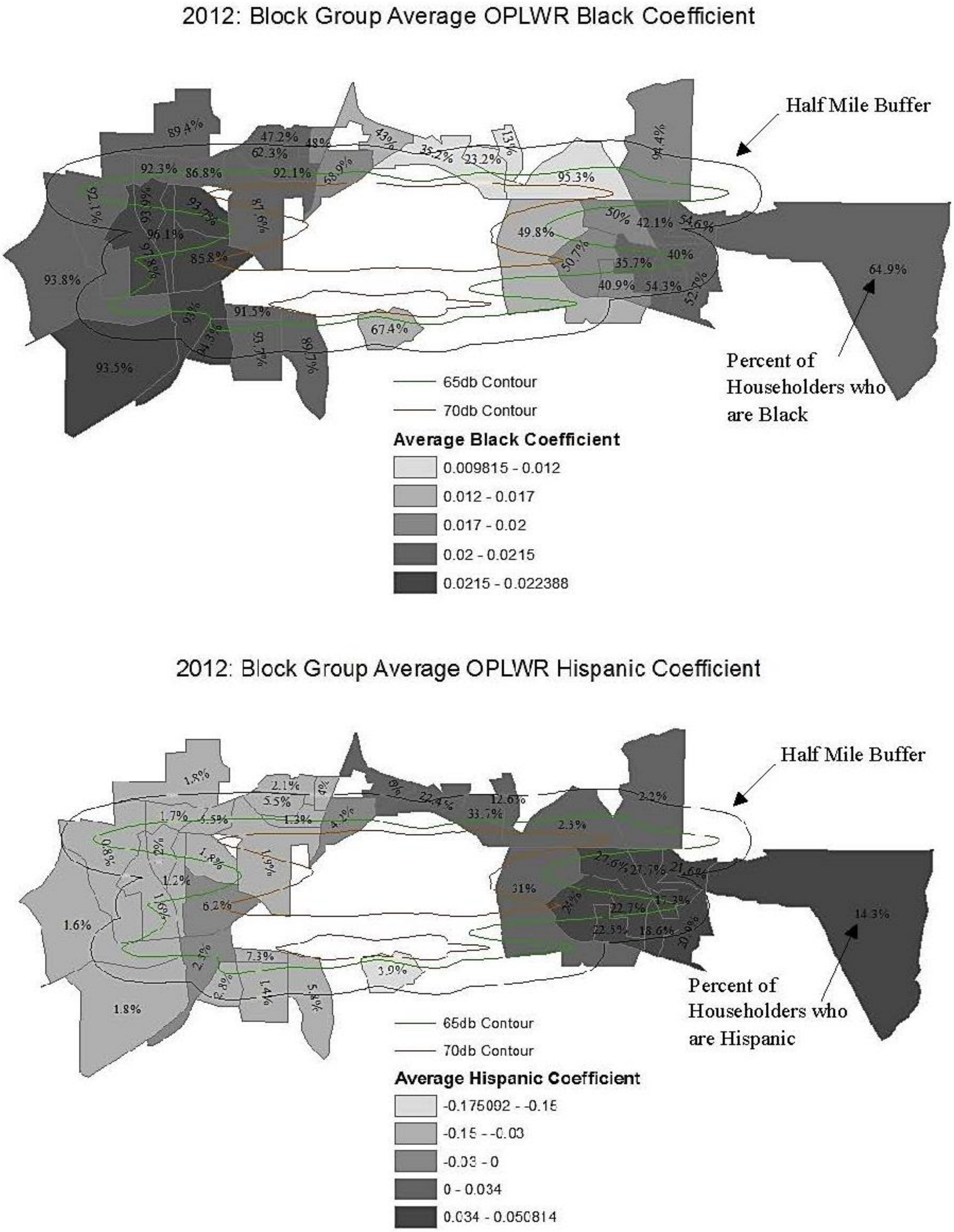

2003: Block Group Average OPLWR Hispanic Coefficient
Half Mile Buffer
Percent of Householders who are Hispanic
65db Contour
70db Contour
Average Hispanic Coefficient
-0.027767 - -0.01
-0.01 - 0
0 - 0.03
0.03 - 0.09
0.09 - 0.224805

Figure 6


2012: Block Group Average OPLWR Black Coefficient
Half Mile Buffer
Percent of Householders who are Black
65db Contour
70db Contour
Average Black Coefficient
0.009815 - 0.012
0.012 - 0.017
0.017 - 0.02
0.02 - 0.0215
0.0215 - 0.022388
2012: Block Group Average OPLWR Hispanic Coefficient
Half Mile Buffer
Percent of Householders who are Hispanic
65db Contour
70db Contour
Average Hispanic Coefficient
-0.175092 - -0.15
-0.15 - -0.03
-0.03 - 0
0 - 0.034
0.034 - 0.050814