Research Division
Federal Reserve Bank of St. Louis
Working Paper Series

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Working Paper 2009-058B
http://research.stlouisfed.org/wp/2009/2009-058.pdf

November 2009
Revised August 2010

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Where Does Noise Fall on People? Evidence from Atlanta Airport

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August 2010

Abstract: Spatial heterogeneity of the determinants of airport noise is explored using houses sold near the Atlanta airport. Ordered probit locally weighted regressions (OPLWR) produce results substantively different than those using standard ordered probit. We find notable differences in the signs and magnitudes of the parameter estimates for different individual observations using OPLWR. For example, using a standard ordered probit model, the coefficient estimate for the connection between the percentage of neighborhood households headed by a Hispanic and noise is double the average of the OPLWR estimates. Moreover, while the standard ordered probit point estimate is positive, 37 percent of the estimates using OPLWR are negative. Even in relatively small areas, the OPLWR results imply that the standard ordered probit model can generate biased estimates due to ignored heterogeneity among individual houses.

JEL classification: Q53, R41, C31

Keywords: airport noise, spatial heterogeneity, ordered probit, locally weighted regression

The authors thank Lesli Ott for excellent research assistance and the Atlanta Department of Aviation for noise contour data. We thank meeting participants at the Federal Reserve System Committee on Regional Economic Analysis, especially Anil Kumar, for their comments. We also benefitted from comments by participants at the Lincoln Institute of Land Policy Conference on Urban Economics and Public Finance in May 2010. Wim Vijverberg and Nancy Lozano-Gracia also provided helpful comments on earlier versions of the paper. The views expressed are those of the authors and do not necessarily reflect official positions of the Federal Reserve Bank of St. Louis, the Federal Reserve System, or the Board of Governors.

Introduction

Airport noise is an undesirable consequence of arriving and departing flights. Much research effort has focused on how such noise affects the prices of houses located nearby and consistently finds that more noise is associated with lower housing prices.[1] On the other hand, few studies have examined the determinants of airport noise.

Ogneva-Himmelberger and Cooperman (2010) and Sobotta, Campbell, and Owens (2007) are notable examples of studies focused on the determinants of airport noise. In the latter study, the authors 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.[2,3] One might wonder, however, whether a closer look might reveal some substantial differences across geographic locations. Such spatial heterogeneity could occur in the impacts of demographic variables, as well as other spatial variables including distance from the airport, on the probability of greater noise exposure.

The importance of addressing spatial effects has become clear in recent studies of airport noise (Cohen and Coughlin, 2008). In the present study, we focus on spatial heterogeneity in the

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[1] See Cohen and Coughlin (2008; 2009) for numerous references.

[2] This finding led them to conclude that those with Hispanic ethnicity incurred an environmental injustice. Environmental justice is not an issue that we can address effectively with our dataset. We lack sufficient data to assess whether a particular racial or ethnic group moved to a noisy neighborhood or airport noise encroached on a group to a disproportionate degree. Thus, we reach no conclusions as to whether some groups are affected unfairly by the decisions of others concerning airport noise.

[3] 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.

context of the determinants of the geographic distribution of airport noise. We postulate that there is substantial geographical variation in the determinants of airport noise, and that ignoring such heterogeneity can produce misleading views of where noise (from a geographic perspective) falls on different racial and ethnic groups.

Beyond incorporating spatial heterogeneity, our contribution includes several innovations directly relevant to the analysis by Sobotta, Campbell, and Owen (2007).[4] First, we order the dependent variable with three categories ranging from the least noisy to the greatest noisy area. The three categories, based on yearly day-night sound levels (DNL) are: 1) buffer zone – houses are located in a less the 65 DNL zone (i.e., less than 65 dB); 2) 65 DNL zone (i.e., 65 up to 70 dB); and 3) 70 DNL zone (i.e., 70 up to 75 dB).[5]

In addition to estimating a standard ordered probit model, following McMillen and McDonald (2004), we estimate ordered probit locally weighted regressions (OPLWR). This estimation approach allows us to explore the issue of spatial heterogeneity in the context of the determinants of airport noise, which to our knowledge has not been examined previously.[6]

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[4] In our study, we also considered confronting the possibility of simultaneity between housing prices and noise. In addition to the standard relationship of noise affecting housing prices, it is possible that housing prices affect noise. Airport authorities may choose to direct flights so as to distribute relatively more noise over relatively less expensive houses. This may be done for economic reasons, one of which is that compensation for harm might be less for lower-valued houses. Political reasons may also be operative as those living in less valuable houses may lack the political power to resist higher noise levels. We considered estimating an equation in which airport noise is a function of the instrumented housing prices, demographic variables, and other variables. This second equation would be estimated by ordered probit because airport noise is a qualitative dependent variable. But since the ordered probit is a nonlinear equation, we could not be sure that the parameters of the simultaneous system would be identified, so we opted to not pursue the simultaneous equations approach.

[5] The measure of noise, the yearly day-night sound level (DNL), is a standard measure of noise used by the Federal Aviation Administration. A DNL of 65 decibels is the Federal Aviation Administration's lower limit for defining a significant noise impact on people. At 65 decibels and above, individuals experience the disruption of normal activities, such as speaking, listening, learning, and sleeping. As a result, such noise levels are viewed as incompatible with residential housing.

[6] McMillen and Redfearn (2010) and Carruthers and Clark (forthcoming) estimate locally weighted regressions in the context of a hedonic housing price framework. However, we are unaware of any studies that attempt to implement locally weighted regressions to assess where noise falls on different groups of people.

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. One might anticipate that because our dataset is limited to those sales near the airport spatial heterogeneity is likely to be unimportant. Such an expectation is not supported by our results.

We find notable differences in parameter estimates for different houses in our sample with the OPLWR estimates. In particular, the sign on the coefficient for each explanatory variable contains some positive and some negative values. Also, the mean of the magnitudes of the coefficients for some of other explanatory variables are larger with the OPLWR model, while for other coefficients the mean is smaller. These differences between the OPLWR and the 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.

Prior to providing details on our equations and results, we provide an overview of our dataset. Next, we focus on the standard ordered probit model and the results. This is followed by details on the ordered probit locally weighted regressions. A discussion of our key findings completes the paper.

Data

We use data on airport noise levels surrounding the Atlanta airport in 2003. The airport noise contours were obtained from the Atlanta Department of Aviation, and are the same noise contours used by Cohen and Coughlin (2008). For 508 houses near the Atlanta airport that were sold in 2003, we purchased housing sales prices and characteristics data from First American

Real Estate. These data include house sale price as well as detailed housing characteristics such as the number of bedrooms, bathrooms, fireplaces, stories and the lot size.

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. 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" extending 0.5 miles outside of the 65 DNL zone. See Figure 1 for a plot of the locations of the houses that were sold in 2003 on the contour maps.

The houses are located in either Fulton County or Clayton County. In terms of cities, the houses are located in Atlanta, College Park, Conley, East Point, Forest Park, and Hapeville. The average house sold for approximately $128,400, contained about 3 bedrooms and 1.78 bathrooms, and was located on a lot of 0.37 acres. 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.

Ordered Probit Model

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 – *BlkHH00*, 4) the percentage of houses in the neighborhood in which the house was sold with a Hispanic head of household – *HispHH00*, and 5) the median household income in the neighborhood in which the house was sold – *MedHHInc00*; and *u* is an error term with a normal distribution with zero mean and constant variance. The inclusion of variables is driven by our interest in both neighborhood characteristics – income levels as well as racial and ethnic characteristics – and house characteristics – location and age.[7]

Ordered Probit Results

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. The results in Table 3 must be transformed before interpreting them as marginal effects.[8] 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. 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.

[7] Upon first impression, the inclusion of age might be puzzling. It is an attempt to assess if newer or older houses are subjected to more noise. One possibility is that the construction of newer house would tend to take place where there is less noise. However, soundproofing might be more economical for new construction, so noise would be less of a nuisance for new construction. Thus, new construction might not necessarily avoid noisier areas.
[8] See Greene (2003).

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.

After transforming the results in Table 3, an examination of Table 4 reveals that the marginal effects are negative and significant in the buffer zone (noise less than 65 dB) for the black (*BlkHH00*), Hispanic (*HispHH00*), and income (*MedHHInc*) variables. Because of their positive coefficients in Table 3, increases in any of these three exogenous variables (i.e., larger neighborhood percentages of black and Hispanic heads of households and higher neighborhood median income) will shift the entire probability distribution to the right, which decreases the probability of being in the buffer zone.[9] Meanwhile, the variables for the age of the house (*AgeLog*) and distance from the airport (*DistanceLog*) are negative and statistically significant. Because of their negative coefficients in Table 3, the positive sign for the buffer zone partial derivatives in Table 4 reflects the fact that increases in these explanatory variables shift the buffer zone probability distribution to the left. Thus, higher values of these variables (i.e., older houses and houses farther from the airport) increase the probability of being in the buffer zone. For each explanatory variable, the signs of the marginal effects for the buffer zone and the most

[9] 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. Finally, they find a positive, statistically significant association between the percentage of households at or below the poverty rate in a neighborhood and more noise. Contrary to expectations, but somewhat similar to our results, they also found a positive association between the percentage of high-income households and more noise. However, this association was not statistically significant.

noisy (noise greater than 70 dB) part of the probability distribution are opposite each other, and the interpretations for houses in the most noisy zone follow accordingly.

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. A similar finding holds for median household income – for the average house in the 65 up to 70 dB zone, higher household income in the neighborhood leads to a higher probability of exposure to 65 up to 70 dB of noise. On the other hand, the age and distance marginal effects are negative and significant for the 65 up to 70 dB dependent variable. Larger values of either age of a house or distance from the airport lead to a lower probability that a house is exposed to 65 up to 70 dB of noise.

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. 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 and the demographic variables on the probability of greater noise.

McMillen and McDonald (2004) propose an estimation approach that allows for heterogeneity, which we call ordered probit locally weighted regressions (OPLWR).[10] They specify a "pseudo log-likelihood function" to estimate a separate set of parameters for each observation, and they call this a locally weighted ordinal probit pseudo log-likelihood function. For the case where there are 3 possible "regimes" in the ordered probit, the pseudo log-likelihood function is:

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

$$+ \, D_{2j} \log \Phi \, (-\mu_i + \beta_i' X_j)] \, , \qquad i,j = 1,2,\ldots,508, \qquad (2)$$

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 somewhat different than for typical spatial econometric weighting matrices. One possibility, which we use in our analysis, relies on the "Gaussian function", and is represented as:

$$w_{ij} = \phi \, (d_{ij}/(s_i b)) \qquad (3)$$

[10] See Fotheringham, et. al. (1998) and Fotheringham, et. al. (2002) for general background on locally weighted regressions.

where ϕ is the standard normal (Gaussian) density function; d_{ij} is distance (as the crow flies) between house i and house j; s_i is the standard deviation of the distances between house i and all other houses j; and b represents the "bandwidth".[11]

Many locally weighted regression applications have used the Gaussian function. The determination of the bandwidth tends to be more important than the choice of the weighting function. 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. In the present context, we estimated the pseudo-likelihood model for bandwidths of 0.4, 0.6, 0.8, and 1.0. Cross-validation implied that b = 0.4 was the preferred bandwidth.

Ordered Probit Locally Weighted Regressions: Results

Table 5 contains results for the OPLWR estimations, based on the preferred bandwidth of b = 0.4. Prior to examining the results for specific variables, we summarize some of our findings. While some similarity in terms of the signs (e.g., the matching of the signs using OP with the averages signs using OPLWR) and magnitudes of the estimated coefficients (e.g., the magnitude of the coefficient for distance using OP is roughly equal to the average of the coefficients using OPLWR) exists, most noteworthy is that substantial heterogeneity is found. For each variable, the estimated coefficients for the OPLWR model exhibit positive as well as

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

negative values. For every explanatory variable, there are at least some houses for which the estimated coefficients differ substantially between the OP and OPLWR models.

Turning to the results for specific variables, the mean estimate from the OPLWR for the household income (MedHHInc00) is roughly 4 times the magnitude of the coefficient estimate from the OP. While there are some negative values for some houses, the majority of the houses have positive income coefficients. Thus, the qualitative insights associated with this variable are similar across the two estimation procedures.

Results associated with the age explanatory variables suggest the additional insights and value provided by OPLWR. The mean OPLWR estimate for the age variable (*AgeLog*) is more than double the coefficient estimate of the OP. The range of estimates, which contains mostly negative values, is much larger than the distribution suggested by the OP results.

For the variable measuring the percentage of houses in the neighborhood in which a house was sold with a black head of household (*BlkHH00*), the mean from the OPLWR is roughly twice as large as the coefficient estimate of the OP. The range of the OPLWR results includes some negative values, but the vast majority of the houses have positive values.

The Hispanic variable (*HispHH00*) demonstrates a substantial amount of heterogeneity, with a notable mix of both positive and negative coefficients. The mean OPLWR is about half the magnitude, and the same sign as, the OP coefficient estimate. Thus, the OPLWR approach, compared with the OP estimates, adds explanatory power with respect to the Hispanic variable.

For the distance variable (*DistanceLog*), the mean OPLWR has the same sign but is about 8 times the magnitude of the coefficient estimate of the OP. Moreover, the range includes mostly negative but only a handful of positive values. In general, distances closer to the airport imply that houses are subjected to more rather than less noise.

Where Does the Noise Fall and Upon Whom? A Graphical View

The preceding discussion summarizes our results, but provides virtually no geographic perspective. Now we attempt to increase the insights relating to the effects of our independent variables by adding some geographic meat. Using a picture identifying the noise contours surrounding the Atlanta airport and the locations of houses in our sample, the estimates for each independent variable are presented in two ways. In the top panel of each figure, the locations of positive coefficients (in red) are distinguished from the negative coefficients (in black). In the bottom panel, the coefficients are grouped by quintiles with the first quintile containing the smallest estimates.

Let's start by examining the estimates for the distance variable (*DistanceLog*). For the model with the b = 0.4 bandwidth, the 505 houses with negative coefficients on the distance variable are plotted in black in Figure 2a, while the three houses with positive coefficients for the distance variable are in red. For the "red" houses, moving closer to the airport (i.e., the value of the distance variable declines) increases the probability of those houses being in the buffer zone. While there are few red houses, their sign may be a result of the fact that just to the north of the airport, the 65 and 70 DNL zones are very thin. For the houses shaded in "black", moving closer to the airport lowers the probability of those houses being in the buffer zone. Also, for houses not located directly east or west of the airport, moving closer to the airport may or may not lead to higher noise levels. For example, for the "red" shaded houses located north of the airport in the buffer zone, moving further from the airport in the southeasterly direction can put them in the 65 DNL zone and, thus, subjected to more noise.

Overall, however, the negative relationship between the estimated coefficients and distance (in logs) is strong. Generally speaking, the farther the house from the airport, the more likely the house is in the buffer zone (is subjected to the lowest noise level).[12] This statement is corroborated by Figure 2b. The smallest coefficient estimates (i.e., houses identified by white dots) tend to be farthest from the airport, while the largest coefficient estimates (i.e., houses identified by red dots) tend to be nearest the airport.

The results for the variable measuring the percentage of houses in the neighborhood in which a house was sold with a Hispanic head of household (*HispHH00*) exhibit much heterogeneity. While the majority of estimates are positive (319 or 63 percent), a substantial number (189 or 37 percent) of the estimates are negative. The positive and negative values in Figure 3a do cluster. Generally speaking, as shown in Figure 3b, the smallest values are located west of the airport, while the largest values are located southeast of the airport. When we calculate the correlation between the coefficient estimates and *HispHH00*, we find a positive association.[13] This means that for these largest values an increase in the Hispanic percentage tends to be associated with a reduced probability of being in the buffer (i.e., more likely to be subjected to a noisier area).

We also find heterogeneity in the parameter estimates for the variable measuring the percentage of houses in the neighborhood in which a house was sold with a black head of household (*BlkHH00*). However, the vast majority of estimates are positive (463 or 91 percent).

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[12] The Pearson coefficient is -0.80 and the Spearman rank-order coefficient is -0.84.
[13] The Pearson coefficient is 0.44 and the Spearman rank-order coefficient is 0.56.

The few negative values (45 or 9 percent) are clustered and dominate the southwest portion of our map in Figure 4a. Because the majority of estimated coefficients are positive, an increase in the level of this variable is generally associated with a reduced probability of remaining in the buffer zone.

Also, contrary to the findings for our Hispanic-related variable, the correlation between the coefficient estimates and *BlkHH00* is negative.[14] Thus, the very largest percentages of this variable tend to be associated with the smallest (i.e., negative) coefficients. This means that for these largest values an increase in the black percentage tends to be associated with an increased probability of being in the buffer (i.e., less likely to be subjected to a noisier area).

Turning attention to the income variable, the 36 negative values are clustered slightly northeast of the airport in Figure 5a. Nearly all the negative values are in the buffer zone. The majority (472 or 93 percent) of estimated coefficients are positive. Thus, somewhat surprisingly, an increase in income is generally associated with a reduced probability of remaining in the buffer zone. The correlation between the coefficient estimates and income levels is, at most, weakly positive.[15] Still, we find that for these highest income levels, an increase in income is associated with a reduced probability of being in the buffer zone.

Finally, the clustering of positive values of the age variable occurs northeast of the airport in Figure 6a. The vast majority (457 or 90 percent) of the estimated coefficients are negative. Thus, an increase in age is generally associated with an increased probability of being in the buffer zone. This result is consistent with the possibility that modern soundproofing can

[14] The Pearson coefficient is -0.43 and the Spearman rank-order coefficient is -0.32.
[15] The Pearson coefficient is 0.002 and the Spearman rank-order coefficient is 0.14.

increase the attractiveness of building a new house in a noisier area. There is, however, no obvious relationship between the estimated coefficients and house age.[16]

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 are masked in the OP model estimates.[17] One implication is that standard ordered probit in the present case generates misleading and biased estimates due to the ignored heterogeneity among individual houses. Thus, generalizations concerning the relationship between racial or ethnic groups and airport noise are quite likely inaccurate and inappropriate. This implication arises despite the fact that our analysis is restricted to a relatively small geographic area near the Atlanta airport. One might reasonably expect spatial heterogeneity to become even more pronounced for larger geographic areas.

The Hispanic population variable exhibits a notable amount of heterogeneity in the sign of the coefficients. The impact of Hispanic population on airport noise varies in sign depending on geographic location. For the preferred bandwidth of 0.4, the estimated coefficient tends to be negative for the majority of the houses located west of the airport and positive for most houses east of the airport.

[16] The correlation coefficients are absolutely small and possess opposite signs – the Pearson coefficient is -0.12, while the Spearman rank-order coefficient is 0.12

[17] 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.

We find heterogeneity depending on the composition of neighborhoods. The use of OPLWR is especially well-suited to identify such heterogeneity. In contrast, it is not possible to generate such detailed insights in an ordered probit model, so the OPLWR model enhances the interpretative potential by generating different parameter estimates for each house in our sample. By providing detailed geographic content, the OPLWR approach allows a more thorough and nuanced understanding of how location, neighborhood, and house characteristics relate to airport noise. Our OPLWR results lead us to conclude that there are differences in where and to what extent noise falls on different groups of people. Such understanding provides important background for designing and assessing the wisdom of policies to address noise pollution and environmental justice issues.

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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.

Table 2: Summary Statistics -- 508 Observations		
	Count	**Percentage**
House Sales in the buffer zone – 2003 contours	343	67.5
House Sales in 65 db zone -- 2003 contours	146	28.7
House Sales in 70 db zone -- 2003 contours	19	3.7
House Sales in Atlanta	49	9.6
House Sales in College Park	147	28.9
House Sales in Conley	60	11.8
House Sales in East Point	66	13.0
House Sales in Forest Park	136	26.8
House Sales in Hapeville	50	9.8
1 story	425	83.7
2 or more stories	83	16.3
2 or less bedrooms	138	27.2
3 bedrooms	258	50.8
4 bedrooms	99	19.5
5 or more bedrooms	13	2.6
1 bathroom	246	48.4
2 bathrooms	151	29.7
3 or more bathrooms	111	21.9
0 or 1 fireplace	494	97.2
2 or more fireplaces	14	2.8
	Mean	**Range**
Price (dollars)	128,442	32,378-460,500
Distance (miles)	3.29	1.06-6.06
Acres	0.37	0.03-3.88
Age (years)	39.85	0-100
B1kHH00 (percent)	56.96	0-97.5
HispHH00 (percent)	8.64	0-30.1
MedHHInc (hundreds of dollars)	319.4	116.7-606.3

TABLE 3: Estimation Results (1')

Variable	Ordered Probit
AgeLog	-0.178*
	(-4.43)
DistanceLog	-0.548*
	(-2.89)
B1kHH00	0.029*
	(8.07)
HispHH00	0.034*
	(3.16)
MedHHInc	0.003*
	(3.92)
μ	1.7
Const	-2.14
Log likelihood	-312.46
LR χ^2 (5)	133.47
Prob > χ^2	0.00
Pseudo R^2	0.18
Observations	508

*Denotes significance at the 5 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

Variable	Buffer Zone	65DB	70DB
AgeLog	0.062*	-0.056*	-0.006*
	(4.40)	(-4.26)	(-2.97)
DistanceLog	0.189*	-0.171*	-0.018*
	(2.90)	(-2.87)	(-2.31)
B1kHH00	-0.010*	0.009*	0.001*
	(-8.19)	(7.52)	(3.46)
HispHH00	-0.012*	0.010*	0.001*
	(-3.18)	(3.14)	(2.43)
MedHHInc	-0.001*	0.001*	0.00009*
	(-3.91)	(3.83)	(2.75)

TABLE 5: Ordered Probit Models for Aviation Noise

Variable	Standard Ordered Probit[1]	Locally Weighted Ordered Probit[2]
AgeLog	-0.178 (-4.43)	-0.422 (0.299) [-1.613, 0.233]
DistanceLog	-0.548 (-2.89)	-4.460 (2.420) [-9.600, 0.109]
B1kHH00	0.029 (8.07)	0.056 (0.039) [-0.129, 0.104]
HispHH00	0.034 (3.16)	0.017 (0.056) [-0.239, 0.122]
MedHHInc	0.003 (3.92)	0.013 (0.014) [-0.003, 0.042]
μ	1.7	2.78 (1.00) [1.27, 5.37]
Const	2.14	-0.981 (5.234) [-6.802, 27.489]
Log likelihood	-312.46	-6855.42
Observations	508	508

[1] Parameter estimates with z-statistics in parenthesis.

[2] The average of the 508 parameter estimates 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. The log-likelihood value is the sum of the log likelihoods for the 508 regressions. Bandwidth = 0.4.

Figure 1

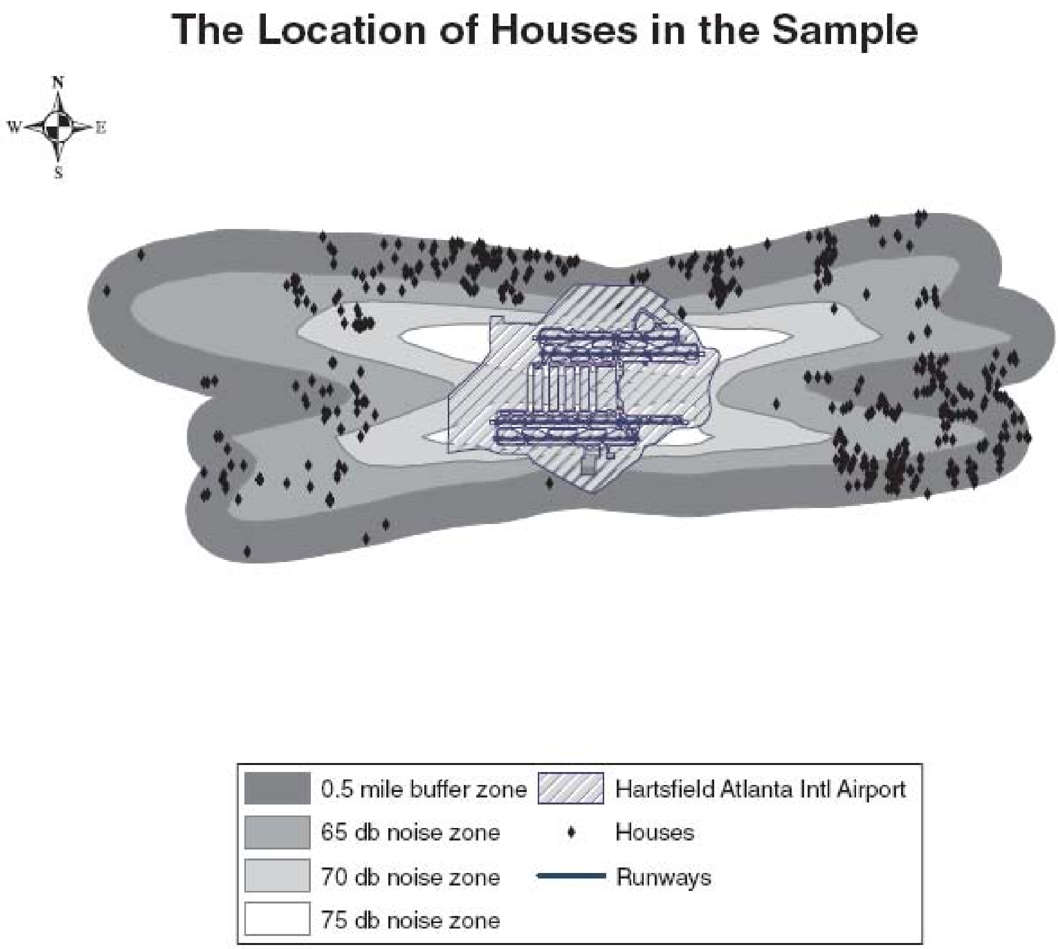
The Location of Houses in the Sample
N
W
E
S
0.5 mile buffer zone
65 db noise zone
70 db noise zone
75 db noise zone
Hartsfield Atlanta Intl Airport
Houses
Runways

Figure 2a
Distance Coefficients and Location of Houses

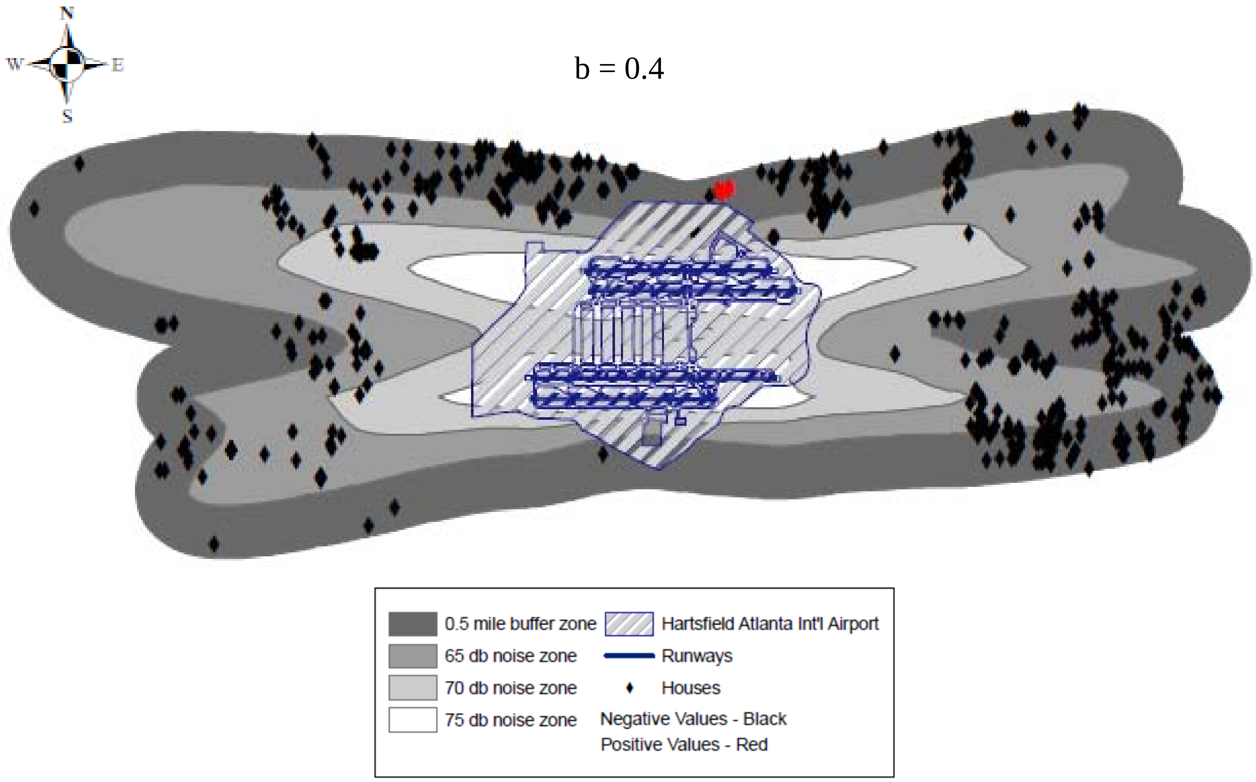

Figure 2b
Distance Coefficient Quintiles and Location of Houses

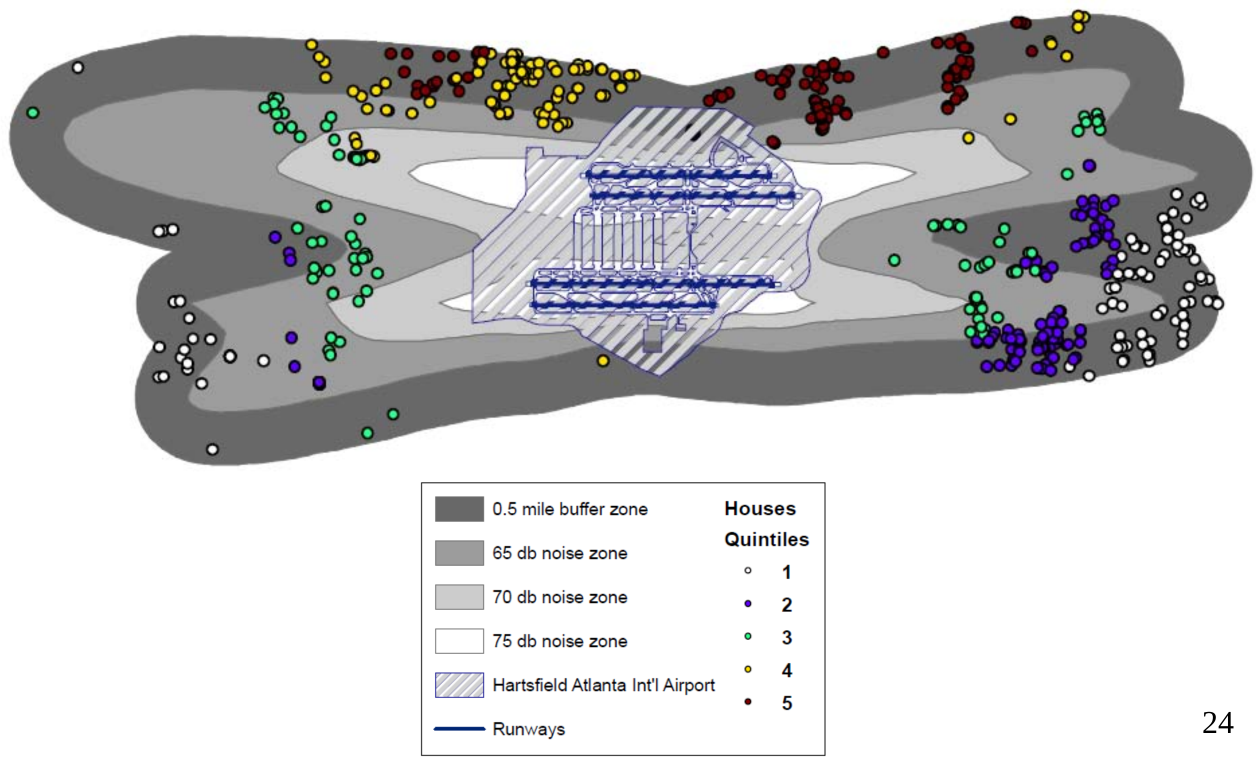

Figure 3a
Hispanic Coefficients and Location of Houses

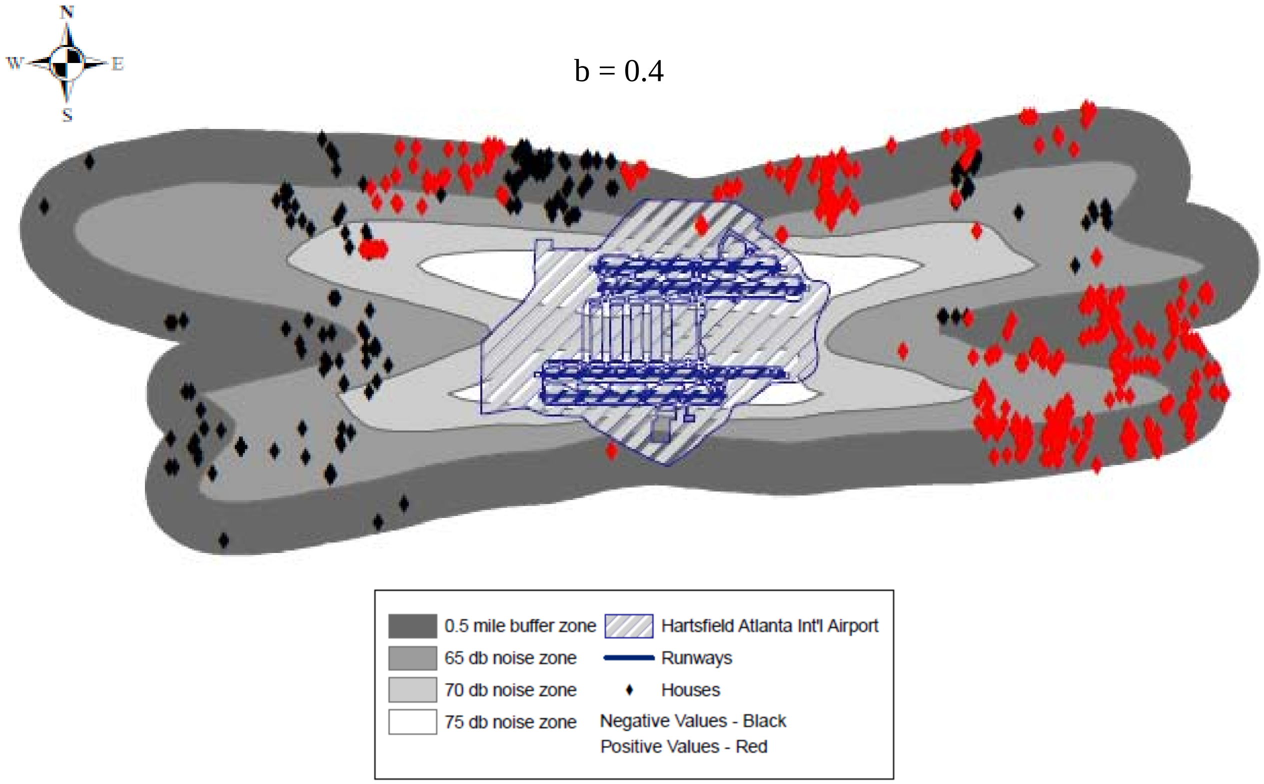

Figure 3b
Hispanic Coefficient Quintiles and Location of Houses

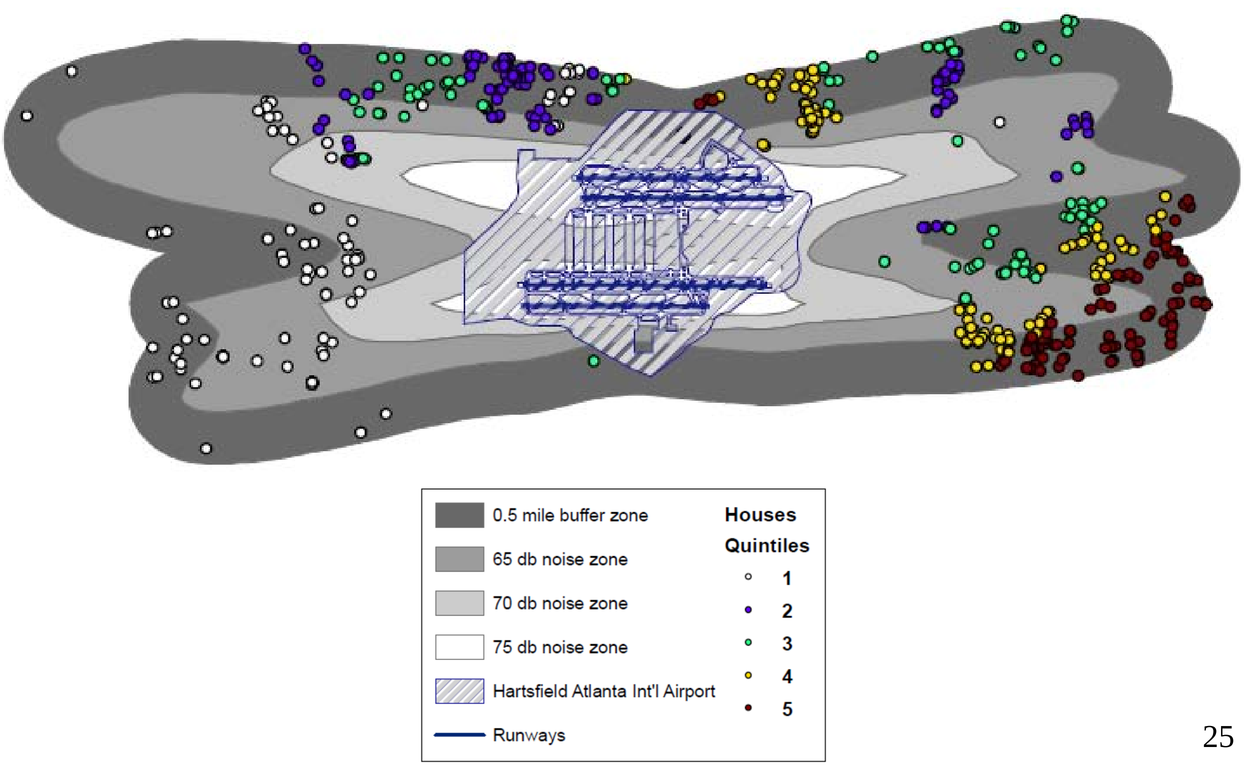

Figure 4a
Black Coefficients and Location of Houses

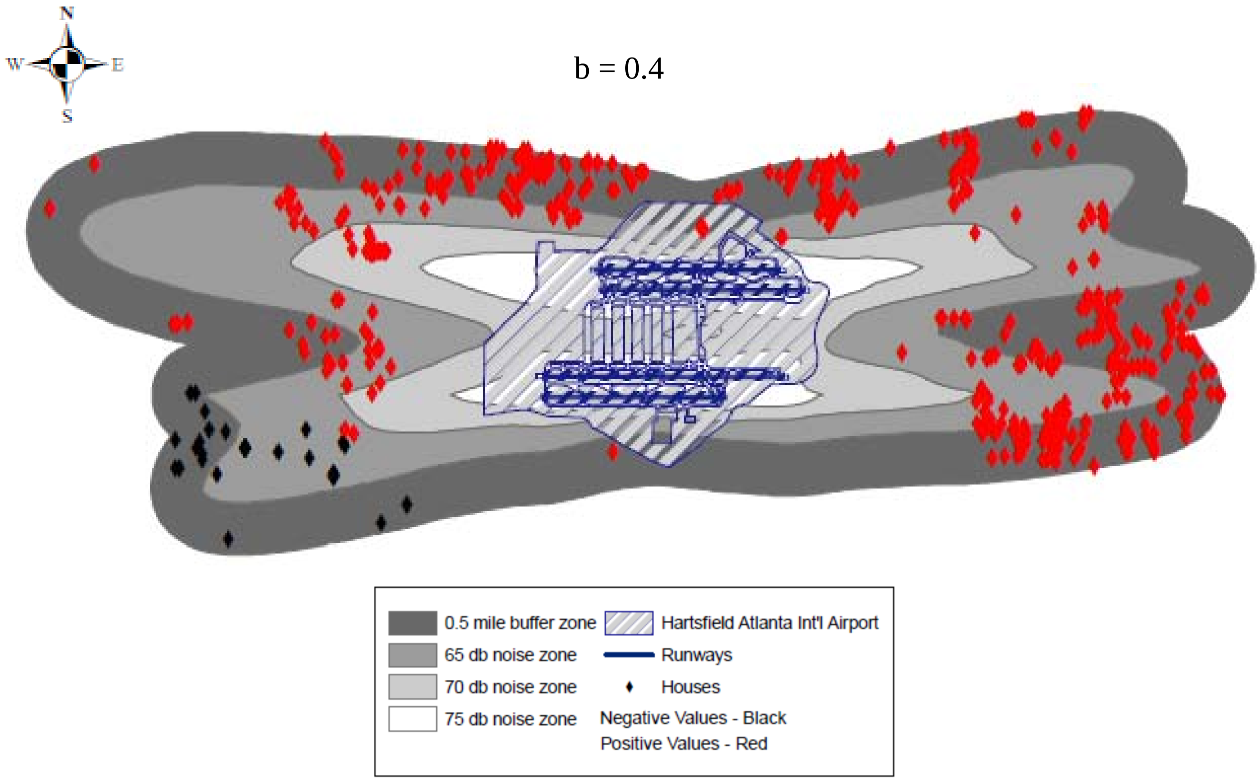

Figure 4b
Black Coefficient Quintiles and Location of Houses

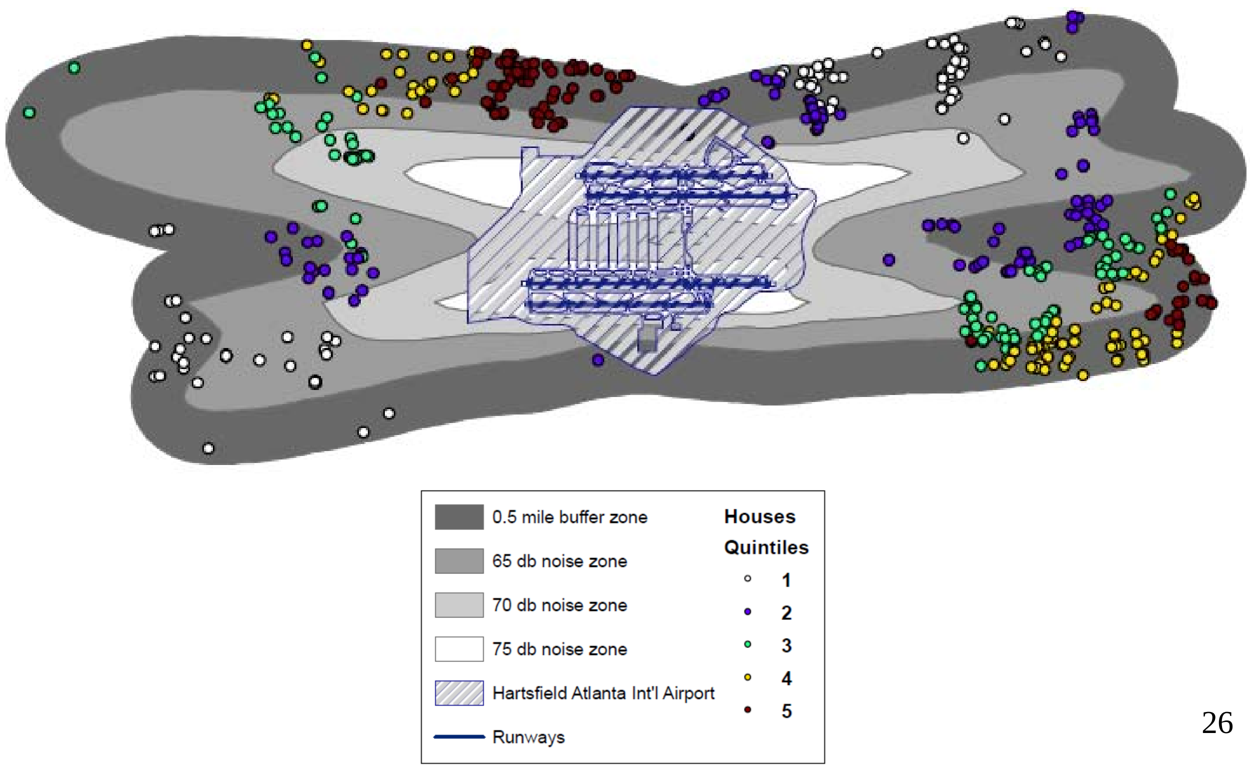

Figure 5a
Income Coefficients and Location of Houses

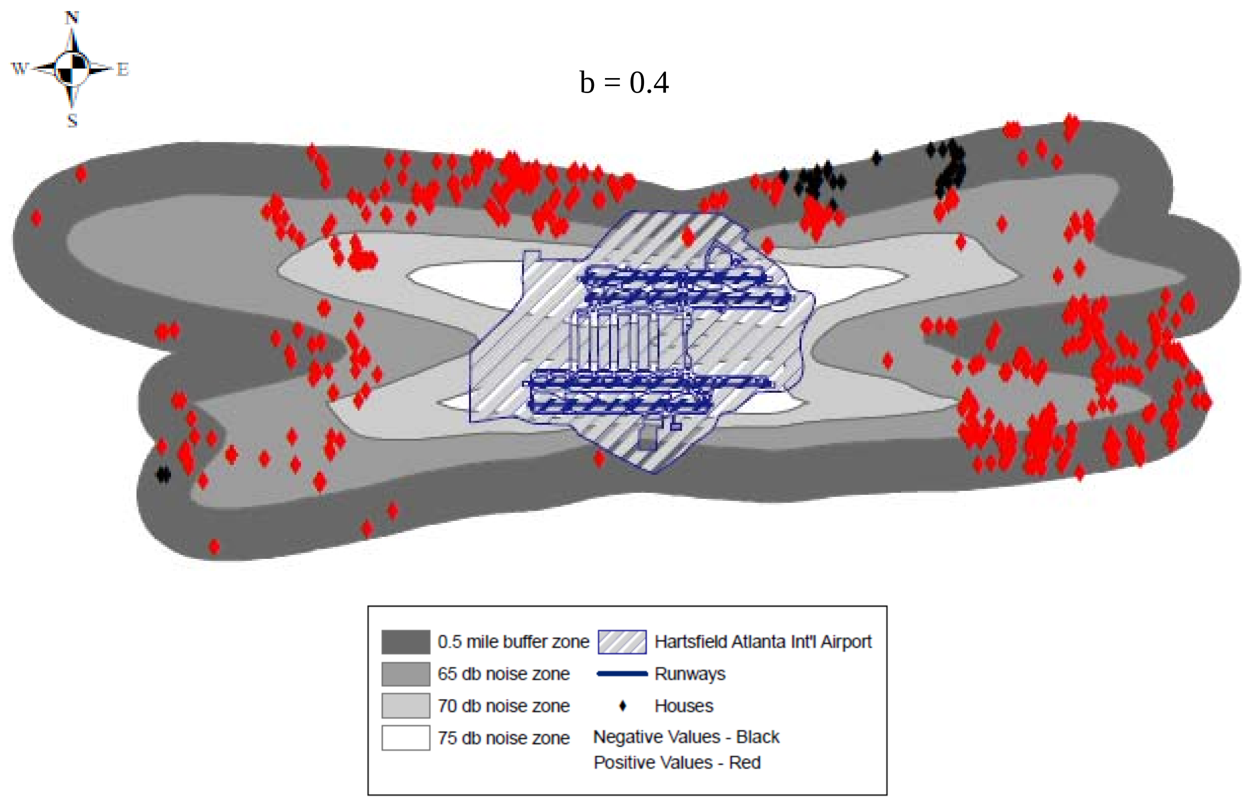

Figure 5b
Income Coefficient Quintiles and Location of Houses

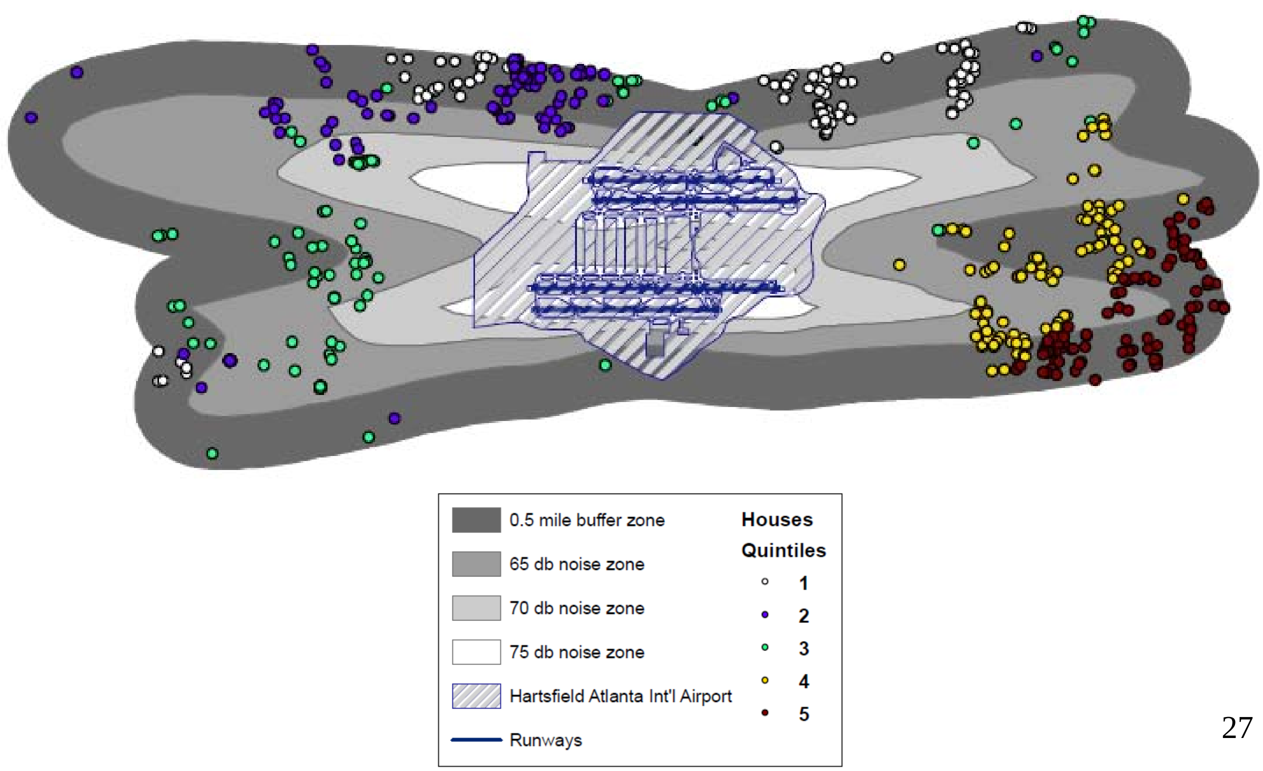

Figure 6a
Age Coefficients and Location of Houses

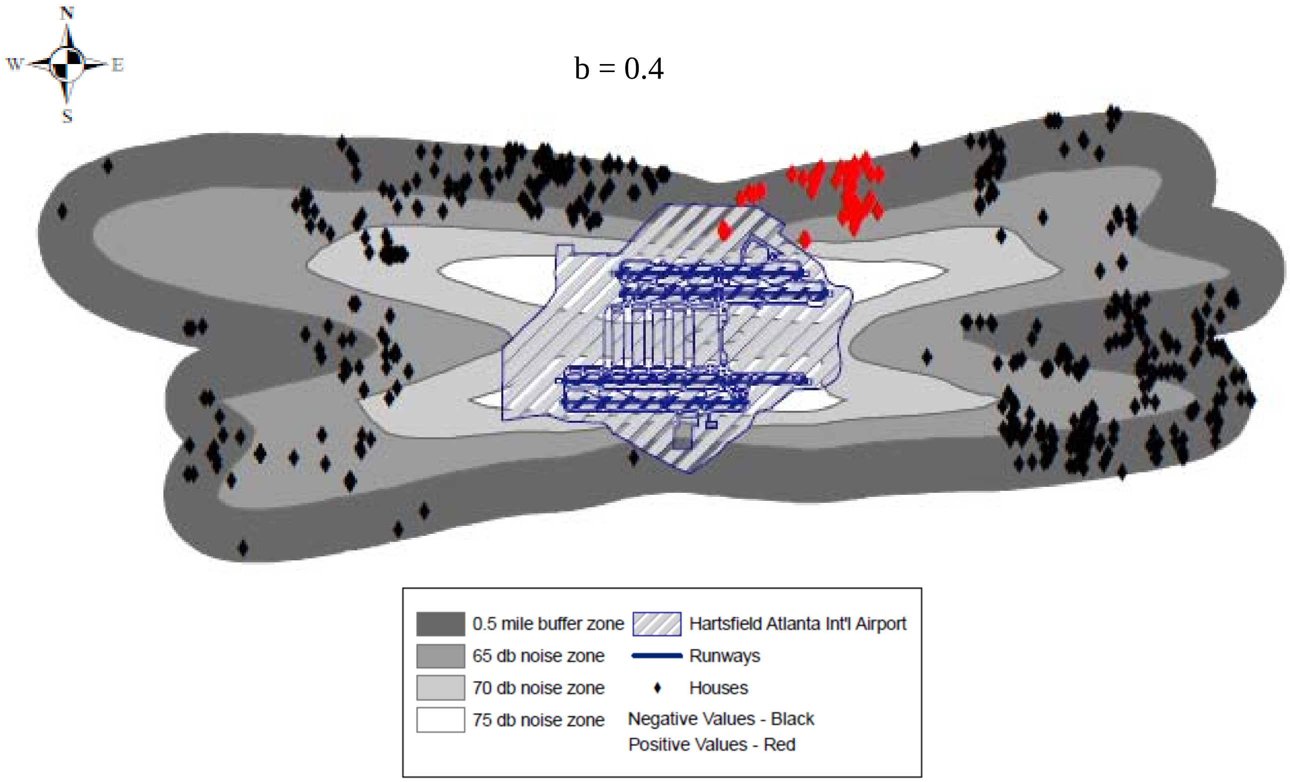

Figure 6b
Age Coefficient Quintiles and Location of Houses