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Spatial Heterogeneity and the Geographic Distribution of Airport Noise

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Abstract: One might expect that houses closer to an airport and those in higher minority population neighborhoods experience more airport noise. We find evidence supporting these conjectures when estimating a standard ordered probit model for houses sold near the Atlanta airport. However, because the various neighborhood demographics surrounding the airport can be heterogeneous, and the noise contours are not necessarily correlated with distance in certain neighborhoods, we hypothesize that the impacts of explanatory variables on the probability of greater noise vary across space. We explore spatial heterogeneity by estimating ordered probit locally weighted regressions (OPLWR). These results differ from those using a standard ordered probit model. Moreover, we find notable differences in parameter estimates for different observations (i.e., houses). Even in relatively small areas, our results imply that the standard ordered probit model can generate biased estimates.

JEL classification: Q53, R41, C31

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

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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.

Sobotta, Campbell, and Owens (2007) is a notable example of a study focused on the determinants of airport noise. They regress airport noise, 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] 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 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

[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.

such heterogeneity can lead to a misstatement of the true effects of demographic and other variables on the probability of a given level of noise exposure.

Beyond incorporating spatial heterogeneity, our contribution includes several innovations directly relevant to the analysis by Sobotta, Campbell, and Owen (2007). In our study, we also confront 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.

To address the issue of simultaneity, we use instrumental variables techniques to generate fitted values for housing prices by estimating an equation with housing prices as a function of housing characteristics. Next, we estimate an equation in which airport noise is a function of the instrumented housing prices, demographic variables, and other variables. This second equation, which is of primary interest, is estimated by ordered probit because airport noise is a qualitative dependent variable. The dependent variable is ordered 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).[3]

[3] 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

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. 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 argue 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, for the majority of the observations the sign on the coefficient for the Hispanic explanatory variable differs from the sign for the ordered probit model. Also, the mean of the magnitudes of the coefficients for some of the 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.

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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.

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.[4] 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 the locations on the contour maps of the houses in our sample.

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 roughly $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 2000 while the noise levels were based on 2003 estimates, we postulate that previous demographics influenced 2003 noise levels.

Ordered Probit Model

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

[4] While Table 2 presents the descriptive statistics for the sale price in 2003 dollars, in our regressions we use the log of the adjusted sale price, which is adjusted for the increase in average housing prices in Atlanta (1995=100).

Noise = f(*X*, *Z*, *u*)   (1)

where *Noise* is a categorical variable for a house sold in one of three noise level groupings 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*; *Z* is the log of the adjusted sales price of the house; and *u* is an error term with a normal distribution with zero mean and constant variance. In studies focused on the determinants of housing prices, such as Cohen and Coughlin (2008), *Z* is the dependent variable. In the current study, *Z* is an endogenous variable. Thus, we use an instrumental variables approach to obtain a fitted value for *Z.*

In our quest for the appropriate instruments for Z, we started with a subset of the independent variables used in Cohen and Coughlin. Because we desire instruments that are correlated with the price but uncorrelated with the error term in equation (1), we chose as instruments the variables in the Cohen and Coughlin regression equation that were both significant and not included in equation (1) of the present study. After running some preliminary regressions of the log of price against characteristics that were not included as explanatory variables in the model of our equation (1), we eliminated those variables that were not statistically significant. Ultimately, the remaining instruments for log of price were dummies for 2 baths (*Baths2d*) and 3 baths (*Baths3d*), 2 or more fireplaces (*Fire2d*), the log of acres of land (*AcresLog*), and a constant. We took the fitted value for the log of price based on these regressors, Z*, and used this fitted value in place of Z in equation (1).[5] We denote this estimated equation as (1').

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 except the fitted price (*PriceLog-fitted*) are statistically significant. The lone exception may be attributable to multicollinearity: the correlation coefficient between log age and log of fitted price is -0.7. Another possible explanation for the insignificant fitted price parameter estimate is that there may be spatial autocorrelation unaccounted for in our model. Because ignoring significant spatial autocorrelation can lead to inefficient parameter estimates, this could be a source of the insignificant parameter estimates in our models.

The results in Table 3 must be transformed before interpreting them as marginal effects.[6] 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.

[5] The results of this estimation are not reported, but will be provided upon request.
[6] 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 will shift the entire probability distribution to the right, which decreases the probability of being in the buffer zone.[7] The marginal effects for the exogenous variables of age of the house (*AgeLog*), distance from the airport (*DistanceLog*), and the fitted value for price (*PriceLog-fitted*) are all positive, but only the first two are 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 increase the probability of being in the buffer zone. For all six of our explanatory variables, the signs of the marginal effects for the buffer zone and the

[7] 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.

most 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. Finally, the fitted price marginal effect is negative; however, recall that this variable 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. 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).[8] 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:

$$\Sigma_j \, w_{ij} \, [\, D_{0j} \log \Phi\,(-\, \beta_i{'}X_j) + D_{1j} \log \Phi\,(y_i - \beta_i{'}X_j) + D_{2j} \log \Phi\,(-y_i + \beta_i{'}X_j)] \,, \quad (2)$$

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; y_i is the value of the dependent variable 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:

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

[8] See Fotheringham, Brunsdon, and Charlton (1998; 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".[9]

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. Most noteworthy is that significant heterogeneity is found. For some of our explanatory variables, the estimated coefficients differ substantially between the OP and OPLWR models. Moreover, in some cases, the estimated coefficients for the OPLWR model exhibit both positive and negative values. For some of our explanatory variables, the estimated coefficients are similar in sign and magnitude in the OP and OPLWR models. Even with this similarity, the range of estimated coefficients for some variables exhibits much diversity.

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

Turning to the results for specific variables, the mean estimate from the OPLWR for the household income (MedHHInc00) is roughly the same as the coefficient estimate from the OP. The range seems reasonable and does not seem especially large. Thus, the insights associated with this variable are similar across the two estimation procedures.

The mean OPLWR estimate is virtually identical to that of the OP for the fitted price variable (*PriceLog-fitted*). The range of the estimates for the OPLWR suggests a tight fit. Once again, the insights associated with this variable are similar across the two estimation procedures.

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

The results for the three remaining variables exhibit much heterogeneity. 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 the same as the coefficient estimate of the OP. The range of the OPLWR results includes a value of -0.094, but this is clearly an outlier as it is the only negative value. The next smallest value is 0.022. A closer look at the results for this variable indicates the estimated coefficient tends to increase with the value of *BlkHH00*. Using a ranking from lowest (1) to highest (508) of both the estimated coefficient and the level of BlkHH00, the rank correlation is 0.35, which is statistically significant at the one percent level.[10] Combining this positive correlation with the positive parameter estimates suggests that houses sold in neighborhoods with higher percentages of households headed by a black are less likely to be in the buffer zone and more likely to be subjected to the highest noise level.

For the distance variable (*DistanceLog*), the mean OPLWR has a different sign and a different magnitude than the coefficient estimate of the OP. Moreover, the range includes negative (207) and positive (301) values. The shape of the noise contours, in conjunction with the location of the houses that were sold, provides some information for understanding these results. Given the location of some of the houses in our sample and the weights function, distances closer to the airport can mean that houses are subjected to less rather than more noise.

For the model with the b = 0.4 bandwidth, the houses with negative coefficients on the distance variable are plotted in black in the top panel of Figure 2, while the 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. For the black houses, moving closer to the airport lowers the probability of those houses being in the buffer zone.

In Figure 2, the red houses are almost exclusively on the east side of the airport, while the black houses are almost exclusively on the west side of the airport. This split, however, might not hold the key to understanding our results. Comparing the houses in red with the houses in black, one observes relatively more red houses directly east of the airport than black

[10] A rank correlation coefficient is a non-parametric measure of correlation indicating the strength between two variables of a monotonic function. The Spearman rank correlation (ρ) is: $\rho = 1 - (6\Sigma d_i^2 / (n(n^2 - 1)))$ where d_i is the difference between the ranks of the two variables and n is the number of observations of each variable.

houses directly west of the airport. Moving directly toward the airport from these red houses and these black houses, noise tends to increase. This effect is more pronounced for the red houses overall because of the relatively higher number of these red houses than the corresponding number of black houses. 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 houses located northwest of the airport in the 65 DNL, moving closer to the airport in the northeasterly direction puts one in the buffer zone and, thus, subjected to less noise.

This observation is reinforced by the lower panel in Figure 2, which is calculated using a bandwidth of 0.8. Recall that relative to the bandwidth of 0.4, a bandwidth of 0.8 causes the weights to decline more slowly as distance from a given house increases. In this panel, the houses with positive coefficients are primarily clustered in the southeast corner of the map, with a smaller number of houses scattered in the northeast part of the map. Note that the houses with negative coefficients are primarily clustered directly to the north of the airport, while there are a smaller number of houses scattered to the southwest of the airport. Comparing the two panels, the use of the b = 0.8 bandwidth causes the number of negative parameter estimates to increase, with the increase occurring for houses immediately northeast of the airport.

In the lower panel, it appears as if many of the red houses in the southeast would actually be exposed to less noise if they were to move closer to the airport, given the shapes of the noise contours in that region. Also, for the black houses that are concentrated to the north of the airport, it appears as if these houses would be exposed to more noise if they were to move closer to the airport, given the shapes of the noise contours directly to the north of the airport. Thus, in this figure the shapes of the different parts of the noise contours, and the concentrations of the majority of each type of house (those with positive and negative distance coefficients), are consistent with each other in terms of the likely potential noise outcome if houses were to move closer to the airport. Overall, the results for distance demonstrate the heterogeneity among the houses in different neighborhoods surrounding 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*) also exhibit heterogeneity. The mean from the OPLWR has a different sign and a far different magnitude than the positive estimate based on OP. In fact, 439 of the coefficient estimates from the OPLWR are negative, while only 69 are positive. The locations of these houses are shown in Figure 3. Clearly this demonstrates spatial heterogeneity, even though this variable is statistically significant for the OP.

For the houses with negative coefficients on the Hispanic variable, this negative sign implies that an increase in the Hispanic population leads to a higher probability of a house being in the buffer zone. In the lower panel of Figure 3, for the houses in relatively low Hispanic population neighborhoods, it appears that on average they would likely end up exposed to less than 65 dB of noise if they were to move closer to houses in higher Hispanic population neighborhoods. The higher Hispanic population neighborhoods are identified by the dots that have shaded colors. For those houses with positive coefficients on the Hispanic variable, greater Hispanic population in their neighborhood decreases the probability of a house being in the buffer zone. The data appear to confirm this empirical result, as the white dots in the upper panel of Figure 3 are nearly all in the buffer zone, but if they were to move to the locations of houses in higher Hispanic population neighborhoods those houses (on average) would be exposed to greater noise levels.

Note also, as can be seen in Figure 3, that for neighborhoods with relatively low percentages of households headed by a Hispanic, positive as well as negative values are generated using OPLWR. These findings contrast with those from the OP estimation, so it is clear that exploring heterogeneity in different neighborhoods generates additional insights that are masked in the OP model estimates.[11]

Conclusion

Using OPLWR, we find noteworthy spatial heterogeneity in the determinants of the geographic distribution of airport noise. 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 small geographic area near the Atlanta airport. One might reasonably expect spatial heterogeneity to become even more pronounced for larger geographic areas.

The impact of distance from the airport on airport noise varies in sign depending on geographic location. The use of OPLWR is especially well-suited to identify such heterogeneity. For the preferred bandwidth of 0.4, the estimated coefficient tends to be negative for houses located west of the airport and positive for houses east of the airport.

[11] 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.

We also find heterogeneity depending on the composition of neighborhoods. Specifically, we find, for a given neighborhood, that the higher the percentage of households headed by a black, the higher the estimated coefficient. We also find, for a given neighborhood, that the percentage of households headed by a Hispanic appears to matter for the estimated coefficient to varying degrees. The coefficient is more likely to be negative when the percentage of Hispanic heads of households in a neighborhood is relatively large, but appears to be of little importance for relatively low percentages. 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.

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Table 1

Variables in Regressions

Name	Definition
PriceLog	Adjusted house sales price in dollars (in natural logs) – adjusted by average housing prices in Atlanta (1995=100).
PriceLog-fitted	Estimate of adjusted house sales price in dollars (in natural logs)
Baths2d	Dummy variable equal to one for houses with two bathrooms; zero otherwise.
Baths3d	Dummy variable equal to one for houses with three or more bathrooms; zero otherwise.
Fire2d	Dummy variable equal to one for house with two or more fireplaces; zero otherwise.
AcresLog	Lot size in acres (in natural logs).
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	-0.236*
	(-4.15)
DistanceLog	-0.564*
	(-2.96)
PriceLog-fitted	-0.421
	(-1.44)
B1kHH00	0.030*
	(8.14)
HispHH00	0.034*
	(3.20)
MedHHInc	0.003*
	(4.15)
Log likelihood	-311.40
LR χ^2 (6)	135.58
Prob > χ^2	0.00
Pseudo R^2	0.18
Observations	508

*Denotes significance at the 5 percent (two-tailed) level.

Notes: t-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 (t-statistics) – Ordered Probit

Variable	Buffer Zone	65DB	70DB
AgeLog	0.081*	-0.074*	-0.008*
	(4.13)	(-4.01)	(-2.86)
DistanceLog	0.195*	-0.177*	-0.018*
	(2.98)	(-2.94)	(-2.34)
PriceLog-fitted	0.145	-0.132	-0.014
	(1.44)	(-1.43)	(-1.35)
B1kHH00	-0.010*	0.010*	0.001*
	(-8.26)	(7.58)	(3.44)
HispHH00	-0.012*	0.011*	0.001*
	(-3.22)	(3.18)	(2.44)
MedHHInc	-0.001*	0.001*	0.00009*
	(-4.15)	(4.05)	(2.81)

TABLE 5: Ordered Probit Models for Noise

Variable	Standard Ordered Probit[1]	Locally Weighted Ordered Probit[2]
AgeLog	-0.236 (-4.15)	-0.401 (0.192) [-1.187, -0.179]
DistanceLog	-0.564 (-2.96)	0.291 (0.665) [-0.873, 2.036]
PriceLog-fitted	-0.421 (-1.44)	-0.415 (0.008) [-0.436, -0.386]
B1kHH00	0.030 (8.14)	0.039 (0.010) [-0.094, 0.058]
HispHH00	0.034 (3.20)	-4.928 (13.920) [-117.043, 0.112]
MedHHInc	0.003 (4.15)	0.002 (0.001) [0.000, 0.008]
Log likelihood	-311.40	-1539.52
Observations	508	508

[1] Parameter estimates with t-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

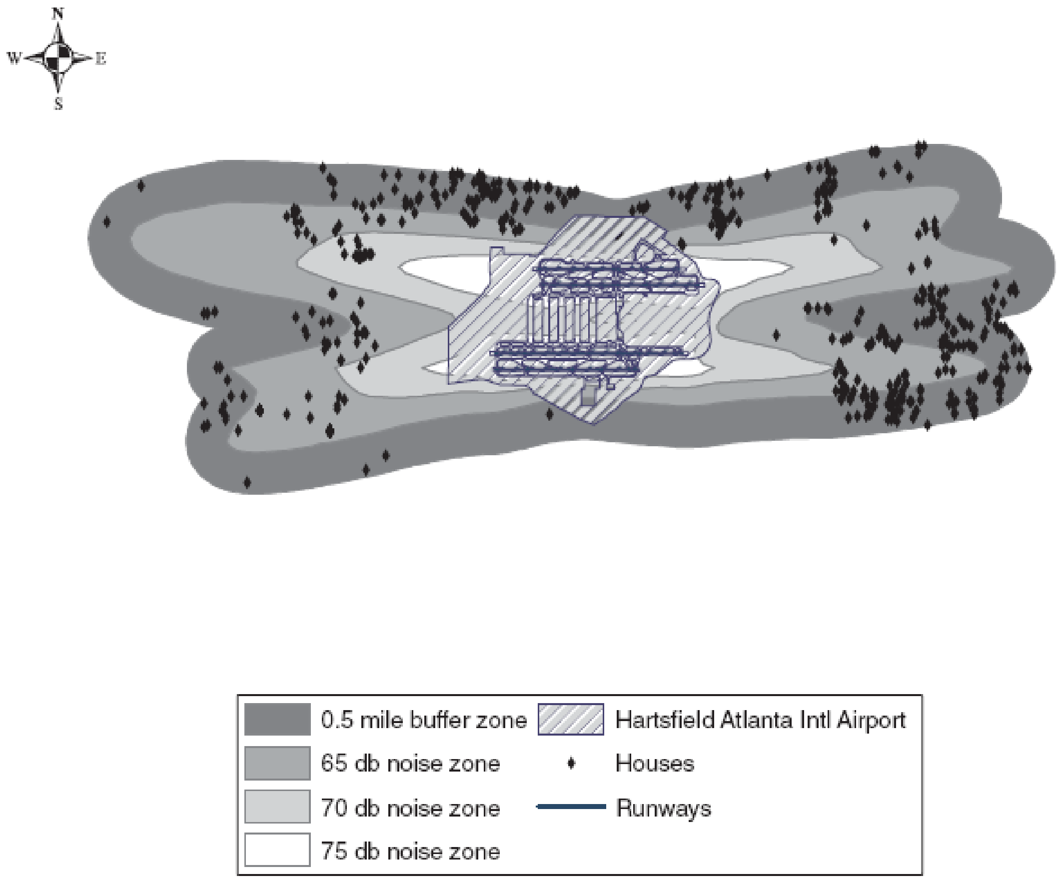

Figure 2
Distance Coefficients and Location of Houses

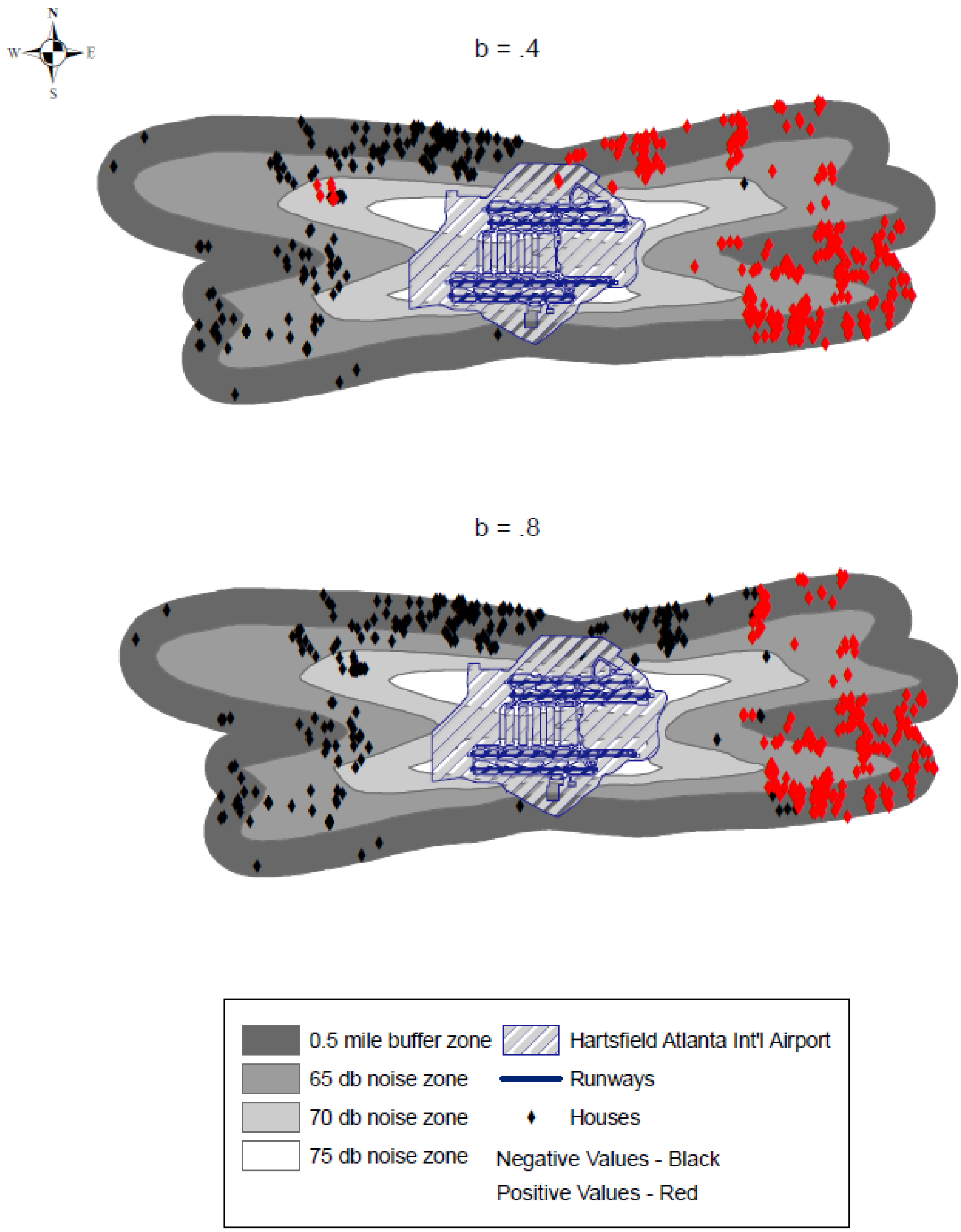

Figure 3
Hispanic Coefficients and Location of Houses