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Abstract

Despite the refrain that housing prices are determined by “location, location, and location,” few studies of airport noise and housing prices have incorporated spatial econometric techniques. We compare various spatial econometric models and estimation methods in a hedonic price framework to examine the impact of noise on 2003 housing values near the Atlanta airport. Spatial effects are best captured by a model including both spatial autocorrelation and autoregressive parameters estimated by a generalized moments approach. In our preferred model, houses located in an area in which noise disrupts normal activities (defined by a day-night sound level of 70-75 decibels) sell for 20.8 percent less than houses located where noise does not disrupt normal activities (defined by a day-night sound level below 65 decibels). The inclusion of spatial effects magnifies the negative price impacts of airport noise. Finally, after controlling for noise, houses farther from the airport sell for less; the price elasticity with respect to distance is -0.15, implying that airport proximity is an amenity.

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Introduction

In a market whose prices are said to be determined by “location, location, and location,” a reasonable expectation is that spatial econometric techniques should prove valuable in an analysis of housing prices.¹ For example, spatial econometric techniques can prove useful in estimating a housing price model when the sales price of a specific house is similar to that of a nearby house for reasons not fully incorporated into the model. The exclusion of spatial considerations can cause biased estimates of parameters and their statistical significance as well as errors in interpreting standard regression diagnostic tests.² Published research using spatial econometrics in estimating hedonic housing price models dates back to articles in the late 1980s and early 1990s by Dubin (1988, 1992) and Can (1990, 1992). More recent studies include Bowen, Mikelbank, and Prestegaard (2001), which examines housing prices in Cuyahoga County, Ohio, and Kim, Phipps and Anselin (2003), which measures the benefits of improving air quality on housing prices in Seoul, Korea.³

No known published spatial hedonic study with an exclusive focus on airport noise has appeared in the literature.⁴ Using various spatial econometric models, estimation methods, and specification tests, we use hedonic price techniques to examine the impact of noise on housing values in the neighborhoods near Atlanta’s Hartsfield-Jackson

¹ See Bowen, Mikelbank, and Prestegaard (2001) for a discussion of theoretical issues regarding space in hedonic housing price studies.

² See Brasington and Hite (2005) for a discussion of ways to model the influence of different types of omitted variables in spatial models.

³ Many other hedonic studies that incorporate spatial effects, such as Dubin (1998), Dubin, Pace, and Thibodeau (1999), Irwin (2002), Munneke and Slawson (1999), Basu and Thibodeau (1998), and Gillen, Thibodeau, and Wachter (2001).

⁴ A working paper on the topic is Day, Bateman, and Lake (2004). One known piece incorporating spatial statistics that analyzes airports, trains, and automobiles is Theebe (2004).

International Airport, the world's busiest passenger airport. We also incorporate the notion of a spatial multiplier, which has not been used previously in the literature on the impact of airport noise on housing prices, and we use this multiplier to calculate a Marginal Willingness to Pay (MWTP) for noise reduction. The approach and findings discussed below can be useful for policymakers in Atlanta and elsewhere as they grapple with noise issues generally as well as those stemming from expansion.

Figure 1 provides some perspective on the location of the airport and the surrounding area. The airport is ten miles south of downtown Atlanta and, including the surrounding area under consideration covers parts of three counties—Fulton, Clayton, and DeKalb. The house sales in our sample occurred in Atlanta plus five other cities—College Park, Conley, East Point, Forest Park, and Hapeville.

In a survey of early work on airport-related noise and housing prices, Nelson (1980) noted that most studies had found a reduction in property values between 0.5 and 0.6 percent per decibel of additional noise. In a more recent survey, Nelson (2004) found a similar range—0.51 to 0.67 percent—for the reduction in property values per decibel of additional noise.⁵ For comparability purposes, the results of two recent studies of specific airports are especially relevant to our analysis. McMillen (2004) found that residential property values for houses subject to noise levels of 65 or more decibels near Chicago's O'Hare Airport were about nine percent lower than otherwise similar homes subject to less noise. Similarly, Espey and Lopez (2000) identified a significant decrease in the prices of homes subject to noise levels of at least 65 decibels. They found a \$2400 difference, which is slightly more than two percent, in the price of a

⁵ One of the studies in the survey, undertaken by O'Byrne, Nelson, and Seneca (1985), examined a residential area near the Atlanta airport for 1970-1972 and 1979-1980.

home in Reno-Sparks, Nevada, in areas where the noise level reaches at least 65 decibels.⁶

Aviation noise has potentially important distributional effects. A recent paper by Sobotta et al. (2007) examines who bears the cost of aviation noise. To the extent that a group appears to bear a disproportionate impact, an important question is why. Whether members of the affected group chose to locate near an environmental disamenity or, alternatively, the environmental disamenity was located near large numbers of the affected group is important in reaching a conclusion about discrimination. Local communities make decisions on the location of runways, which is effectively a decision on where to locate noise. Sobotta et al. find support for the hypothesis that discrimination can be an important factor in where to locate aviation noise. They find that being Hispanic was a key predictor of exposure to airport noise in Phoenix. Our paper does not address distributional issues from the perspective of specific racial and ethnic groups, but rather attempts to assess the costs of aviation noise that are capitalized into housing prices for different areas near the airport.

Coinciding with our focus on the connection between noise and housing prices is the simultaneous consideration of proximity. Tomkins, Topham, Twomey and Ward (1998) and McMillen (2004) have found that, *ceteris paribus*, proximity to the airports in Manchester, England, and Chicago, respectively, had a positive effect on housing prices. Access to airport-related jobs and air transportation services can be capitalized into the value of a house. Ignoring the value of accessibility in the present context may lead to

⁶ Kaufman, Espey and Englin (1998) find that there was a 3 percent fall in housing values for a 10 decibel increase in airport noise in the Reno-Sparks area.

biased estimates of the impact of noise.⁷ On the other hand, traffic congestion on nearby roads may be associated with proximity to the airport, so proximity to the airport need not be positively related to housing prices.

The effects of airport noise and proximity on housing prices in the Atlanta area were addressed by Lipscomb (2003).⁸ Lipscomb examined housing prices in a small city, College Park, which is located near the Atlanta airport. Among other things, he found that, *ceteris paribus*, houses closer to the airport tended to sell for higher prices; however, airport-related noise did not have a statistically significant effect on housing prices. In contrast to our study, he did not incorporate spatial econometric techniques.

An important feature of our analysis addresses the best way to incorporate spatial effects —via spatial lagging of the dependent variable (i.e., spatial autoregression), spatial lagging of the error term (i.e., spatial autocorrelation), or a combination of both (general spatial model). Using the first approach requires the assumption, based on proximity, that the weighted average of housing prices affects the price of each house. Such indirect impacts are in addition to the direct effects associated with the standard explanatory variables that capture the structural features of the housing units, neighborhood characteristics, and attributes of the social and natural environment. In contrast, the use of a spatial error model does not include indirect effects, but rather incorporates spatial considerations via a spatially weighted error term. In this case, it is assumed that there is, at least, one omitted variable and that the omitted variable varies

⁷ Pace, Barry, and Sirmans (1998) show that using spatial econometrics is preferable to including a long list of proximity variables for different amenities, so we chose to include an amenity variable only for the distance from the airport as well as explore various forms of spatial dependence in our analysis.

⁸ A referee pointed out that there may not be sufficient variation in Lipscomb's study because of the small size of the city in his sample.

spatially, or that sets of regression variables are measured at different geographic levels and are thus subject to measurement error.

Obviously, the combined model contains spatial autoregressive and spatial error features. After determining which approach is more appropriate, we estimate a hedonic price model that corrects for the identified spatial dependence and compare these results with estimates that do not use spatial econometric techniques.

Prior to discussing our models and data, we preview our results and compare them to prior research. Our preferred model is the general spatial model, and our noise discount is larger than those of McMillen (2004) and Espey and Lopez (2000). After accounting for feedback effects in the general spatial model, the noise discount is magnified further, and this is one way in which our noise discount may be larger than that of previous studies. From spatial econometric theory we know that ignoring a spatially lagged dependent variable can lead to biased parameter estimates. These potential biases can lead to the noise discount estimated using ordinary least squares (OLS) being different (either larger or smaller) from the general spatial model noise discount. We show that the OLS noise discount is higher than the general spatial model noise discount (before incorporating multiplier effects), and we attribute this result to the fact that our statistical tests show that the general spatial model is preferred over the OLS model. Finally, our model allows for nonlinearities in the noise discount, by setting up two separate “noisy” zones (65 decibels to 70 decibels, and 70 decibels and higher). The McMillen (2004) and Espey and Lopez (2000) studies only incorporate one noisy zone (65 decibels and higher), so we would expect there to be some differences in the

noise discounts in their studies. We present our models in more detail after describing our data.

Standard Model and Data

Our analysis uses a hedonic price model. With such a model the price of a house is a function of its attributes. These attributes are the individual characteristics of the housing unit and its location characteristics.

Two data sources are used to construct our dataset. One key piece of information is a noise contour map for the neighborhoods surrounding Atlanta's Hartsfield-Jackson International Airport. The noise contour map for 2003 is from the City of Atlanta Department of Aviation and is in a format that can be read into ArcView GIS software. The map is based on a standard measure of noise used by the Federal Aviation Administration and other federal agencies. This measure, the yearly day-night sound level (DNL), is measured in decibels. 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.⁹

Despite the fact that the extent of noise is a major issue for those purchasing property near airports, we are not suggesting that the details of these noise contour maps are well known. These maps must be viewed as different from the boundaries that

⁹ A referee suggested that the *U.S. Federal Interagency Committee on Noise* (1992a,b) reports are the best sources for this standard. This standard is not without controversy. Sobotta et al. (2007) state that the Environmental Protection Agency and the World Health Organization consider 65 DNL unacceptably high.

differentiate school attendance zones. The lack of precision is a common issue for many environmental disamenities. In the case of noise, a potential buyer can acquire information about noise in ways other than via the noise contours. A buyer's visits to the property in noise-affected areas plus visits to other properties subject to less noise will provide information about noise. The buyer of a house can use this imperfect information in assessing what he or she is willing to pay.

Houses near a noise contour boundary but on different sides might sell for similar prices, *ceteris paribus*. An alternative possibility, however, is that there is a discontinuity at the boundary and that housing price differences are relatively large on different sides of the boundary. By using dummy variables we generate estimates of the average price difference in houses subject to some noise levels, say 70 to 75 decibels, versus those subject to other noise levels, say between 65 and 70 decibels. Thus, our estimate is an average of the impact of differing noise on housing prices comparing two areas. To the extent that there is a discontinuity in the impact of noise, our dummy variable approach may or may not handle the situation. If any discontinuity occurs near the boundary, then our approach is on solid ground. Given the FAA's judgment that houses subject to noise levels of 65 or more decibels are in areas not suitable for residential housing, it is quite possible that such a discontinuity occurs at 65 decibels.

The second piece of information, purchased from First American Real Estate Services, includes single family dwelling sale price data for the year 2003 for houses in and near the 65 DNL and 70 DNL boundaries.^{10,11} These data include house sale price

¹⁰ For comparability with the information on the airport noise contour maps, the Census demographic were categorized by block group and placed onto maps for the neighborhoods surrounding the Atlanta airport using ArcView software. Thus, the ArcView GIS software was valuable in modeling the relationships between the housing and the demographic data.

as well as detailed housing characteristics such as the number of bedrooms, bathrooms, fireplaces, and 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 data from the year 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 2 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.

Our standard hedonic model regresses the natural log of housing sale price (Y) against a variety of characteristics (X 's), such as dummy variables for the number of bedrooms, bathrooms, fireplaces, and stories; log of lot size in acres; log of distance in miles from the airport;¹¹ dummy variables for the cities of College Park, Conley, East Point, Forest Park, and Hapeville (where Atlanta is the base city); and dummy variables to distinguish dwellings that fall in the 65 DNL and 70 DNL noise contours from the buffer zone. The standard model can be written as:

$$(1) Y = X\beta + \varepsilon,$$

¹¹ Houses in the buffer zone were exposed to less than 65 decibels of noise. Houses within the 65 DNL contour but outside of the 70 DNL contour were exposed to at least 65 decibels of noise, but less than 70 decibels. Houses inside of the 70 DNL contour but outside of the 75 DNL contour were exposed to at least 70 decibels of noise, but less than 75 decibels. There were no houses in our sample that were within the 75 DNL contour.

¹² We would like to stress that by including the distance variable that we are not testing whether there is a tradeoff between noise and distance from the airport. Instead, we are testing whether distance affects price, holding noise (and all other housing characteristics) constant.

where ε is assumed to be normally distributed with zero mean and constant variance.

Standard Hedonic Price Results

The column labeled OLS (Ordinary Least Squares) in Table 3 contains results similar to those presented in many other studies. Overall, the estimated model explains roughly 50 percent of the variation in the log of housing prices, *PriceLog*. Nearly every individual variable performed as expected. For example, most of the dummy variables for the numbers of bedrooms (except for 4 bedrooms), bathrooms, fireplaces, and stories, are positive, statistically significant (at the 5 percent level) determinants of housing sale price. Lot size is positively and significantly related to housing sale prices. In addition, possibly reflecting that the benefits and costs of publicly-provided services differ across cities, whether a house is located in College Park or East Point (versus Atlanta) appears to affect its price. Relative to Atlanta, the location of houses in Conley, Forest Park, and Hapeville does not appear to affect housing prices.

Turning to the results directly related to the airport, we find that the 65 DNL dummy (*DB65_2003*) is negative but is not statistically significant, while the 70 DNL dummy (*DB70_2003*) is negative and statistically significant. Despite the lack of statistical significance of the 65 DNL dummy variable, a test of the joint significance of the noise variables indicated that they were jointly significant at the five percent level. These results are consistent with results reported by Cohen and Coughlin (2006) for the effects of Atlanta airport-related noise covering 1995-2002. Holding noise and other determinants constant, the results for *DistanceLog* indicate that houses closer to the

airport sold for higher prices, a result that falls just short of significance at the 5 percent level.¹³

Incorporating Spatial Effects

As noted previously, we examine a sample of house sales during the year 2003. Restriction of the sample to a single year cross section for the purpose of a spatial econometric analysis follows the approach of Kim, Phipps and Anselin (2003) and of Bowen, Mikelbank, and Prestegaard (2001). Also, it allows for a direct correspondence of our house sale price and characteristics data with the 2003 noise contour data, as we do not have annual data for noise contours, nor do we have sale price data for the same units in multiple years.

Our analysis of spatial effects addresses three questions. First, are spatial effects present? To answer this question, we compare a model that includes spatial effects to one without spatial effects.¹⁴ If evidence of spatial autocorrelation and/or spatial (autoregressive) dependence is found, the relationships between housing sale price and housing and location characteristics will need to be modeled through the use of spatial statistics (e.g., see Cliff and Ord (1981)). For example, spatial autocorrelation may exist when omitted unobservable characteristics, such as sound-proofing, are correlated across households.¹⁵ Also, because the price of a particular home may depend on the prices and characteristics of nearby homes, we will need to incorporate and test for the

¹³ Because the noise contours are elongated, with takeoffs and landings occurring either to the east or west, the correlation between noise and distance is close to zero. For our sample, houses located farther from the airport are subjected to less noise, but a Spearman rank correlation shows only a value of -0.1. As a result, multicollinearity between distance and noise is not a problem.

¹⁴ Bowen, Mikelbank, and Prestegaard (2001) found that the explicit modeling of space was not always justified.

¹⁵ Despite our attempts to find information on specific homes that were soundproofed, we were unable to obtain these data.

significance of a spatially lagged dependent variable. Such a conceptualization corresponds with a standard description of how the housing market operates. Offer prices of houses are set based on the price history of nearby houses, especially those of so-called comparable houses.

In light of evidence that spatial effects exist, then we attempt to answer a second question. What is the preferred estimation model? To answer this question, we make a series of pairwise comparisons between different spatial effects models. Finally, because we find evidence of spatial autocorrelation, we must also answer the following question: Which estimation approach—maximum likelihood or generalized moments—is more appropriate? The existence of spatial autocorrelation increases the possibility that the errors will not be distributed normally. Maximum likelihood estimation of the spatial autocorrelation coefficient depends on the assumption of normality of the regression error terms, while the generalized moments approach does not.

A general spatial econometric model can be written by incorporating a spatial error process as well as a spatially lagged dependent variable, modifying equation (1) as follows:

$$(2) \quad Y = \rho WY + X\beta + \varepsilon,$$

$$\varepsilon = \lambda W\varepsilon + \mu,$$

where μ is distributed normal with zero mean and constant variance, and W is an N by N weight matrix.¹⁶ The number of observations, N , is equal to 508, the number of sale

¹⁶ Kelejian and Prucha (forthcoming) show that both λ and ρ are under “reasonable conditions, clearly identified.”

price observations for houses in the neighborhoods near the Atlanta airport. In scalar notation, the weight that an individual house (j) has on house i's sale price is equal to

$$w_{i,j} = 1/d_{i,j}, \quad i,j=1,2,\dots,508.$$

$$= 0, \quad i=j,$$

where $d_{i,j}$ is the Euclidean distance between house i and j.¹⁷ These weights are “row normalized” so that

$$\sum_j w_{i,j} = 1, \quad i,j=1,2,\dots,508.$$

When λ and ρ are equal to zero, what remains is the standard model of equation (1) that we estimated by ordinary least squares (see the first column of table 2).

To see if spatial effects are present, we first compare the model in equation (1) with the following model:

$$(3) \quad Y = X\beta + \varepsilon,$$

$$\varepsilon = \lambda W\varepsilon + \mu$$

where μ is an error term that is distributed normal with zero mean and constant variance, and W is as described above. Specifically, we test for the presence of spatial autocorrelation in this model (i.e., the significance of λ) with the Moran I test, the Likelihood Ratio (LR) test, and the Wald test.¹⁸ We find that the Moran I equals 0.029, and the Moran I statistic equals approximately 3.89, which is statistically significant at

¹⁷ We experimented with a variety of other spatial weights specifications, including a quadratic distance penalty. These alternatives produced results similar to our reported results.

¹⁸ See Greene (2003) for a description of the LR, and Wald tests, and Anselin and Kelejian (1997) for a description of the Moran I test.

the 5% level (P-value = 0.0001).¹⁹ The LR statistic is 357.56, which is statistically significant at the 5% level. Finally, the Wald statistic is 268.63, which is also statistically significant at the 5% level.²⁰ Thus, there is strong evidence of spatial autocorrelation using these tests.

Next, we proceed to test the significance of including the spatial autoregressive parameter ρ in this spatial error model. In other words, we test model (3) against model (2) as described above. We would expect that higher “average” sale prices would result in a higher sale price of a nearby home, *ceteris paribus*.²¹ Thus, we would expect the sign of the coefficient on the spatially lagged dependent variable (ρ) to be positive. This implies the presence of positive adjacency effects – when houses in an area as a whole become more valuable, the price of an individual home increases. Thus, another objective of this study is to test for the sign and magnitude of such adjacency effects through the spatial autoregressive parameter, ρ .

Using the spatial error model as a baseline, we test whether we can reject the hypothesis that this baseline is the “true” model, in favor of the alternative of the spatial autoregressive model with spatial errors. Based on the LR test (where the LR statistic is 561.74 while the $\chi^2_{(1, .95)} = 3.84$), we reject the null hypothesis of the spatial error model being the true model, and the alternative with spatial errors along with the spatially lagged dependent variable is preferred. Also, with the Wald test (i.e., testing the one restriction that the spatial autoregressive parameter equals zero) we reject the null

¹⁹ The Moran I statistic has a normal distribution. See Anselin and Kelejian (1997) for more details on the Moran I test.

²⁰ In the present context, the LR and Wald statistics all have Chi-squared distributions with one degree of freedom (since there is one restriction when comparing the Spatial Errors model with the Ordinary Least Squares estimation). In the present context, $\chi^2_{(1, .95)} = 3.84$.

²¹ See Can (1990) for details on how a positive value is consistent with the actual workings of housing markets.

hypothesis that the spatial error model is the “true” model, where the alternative is that the spatial error model with the spatial autoregressive structure is the “true” model (the Wald statistic is 84.64 and $\chi^2_{(1, .95)} = 3.84$).

Finally, we conducted a Jarque-Bera test for normality of the residuals resulting from the maximum likelihood estimation of the General Spatial Model because the maximum likelihood estimation of the General Spatial Model assumes normality of the errors while the generalized moments technique does not. In this case, the test statistic was 74.52, while the critical value (5% significance) was 5.99. Thus, the null hypothesis of normal residuals was rejected and we conclude that the generalized moments estimation procedure should be followed here. Consequently, we focus our attention for the next section of the analysis on the General Spatial Model that is estimated with the generalized moments technique using two-stage least squares, although results for a variety of different combinations of models are presented in Table 3.

Spatial Econometric Results

The results of the generalized moments General Spatial Model estimation are presented in the column labeled “GSM/GM” of Table 3.²² For most variables, the parameter estimates and statistical significance are very similar between the GSM/GM and OLS estimates. For the GSM/GM estimates, the 65 DNL dummy is negative but insignificant, while the parameter estimate for the 70 DNL dummy is negative and significant with a coefficient value of -0.23. Similar to the results reported earlier using ordinary least squares, the noise variables are jointly significant at the five percent level.

²² We used James LeSage’s Spatial Econometrics Toolbox in MATLAB software to estimate the spatially lagged dependent variable model with the presence of spatially autocorrelated error terms for the maximum likelihood as well as the generalized moments procedures.

In percentage terms, the impact of additional noise on housing prices equals $(e^{\beta} - 1) \times 100$, where e is the base of the natural exponential function and β is the parameter relating noise to housing price (see Halvorsen and Palmquist, 1980). With $\beta = -0.23$, this implies that houses in the 70 DNL zone sold for about 20.8 percent less than houses in the buffer zone (an area of 0.5 miles wide surrounding the 65 DNL zone), *ceteris paribus*.²³ In other words, the noise discount was 20.8 percent.

Other variables in the model that were positive and statistically significant included dummy variables for the number of bathrooms, bedrooms (except for 4 bedrooms), and stories (two or more), and the log of the lot size in acres. Contrary to the OLS results, the dummy for fireplaces (two or more) was not statistically significant. The estimated coefficient for this variable, however, is virtually the same in the two models. A similar comment applies to the estimated coefficient for the log of distance to the airport, which is another variable whose statistical significance differs between the OLS and the GSM/GM estimations. For the latter estimation, the log of the distance from the airport was negative and significant, with a coefficient of -0.15, indicating that a 1 percent increase in the distance from the airport leads to a fall in the sale price of housing by 0.15 percent, *ceteris paribus*. This implies that access to the airport enhances housing prices, after accounting for the additional noise that accompanies proximity to the airport, as well as the other housing price determinants. Finally, the results for the city dummies differ between the GSM/GM and OLS estimates. For the GSM/GM estimation, none of the city dummies are significant, while for the OLS estimation, the dummy variables for College Park and East Point are significant.

²³ For the GSM/GM model, “*ceteris paribus*” includes adjustments for spatial autocorrelation and spatial dependence, as well as the other variables in the regression, including other housing characteristics.

Next, we examine the estimates for the spatial parameters. The spatial autocorrelation parameter λ is negative, and the specification tests above indicate that the GSM/GM results, with both the spatially lagged dependent variable and spatial errors, is our preferred model.²⁴ Since the generalized moments estimation of λ does not depend on the assumption of normally distributed error terms, it is not possible to conduct a t-test of the significance of this coefficient. Thus, we include “n/a” in place of the t-statistics for λ in Table 3, and rely on the results of the specification tests discussed earlier for evidence of the presence of spatial autocorrelation in our model. The significance of incorporating the spatial errors is consistent with the notion that some unobserved variables, such as soundproofing that has been undertaken in the Atlanta area, varies across houses.

The spatially lagged dependent variable is positive and significant in the GSM/GM estimation, with a parameter estimate of 0.536. This implies that if the weighted average of all other house sale prices increases 1 percent, the sale price of an individual house on average will increase by 0.54 percent, *ceteris paribus*.²⁵ As Kim, Phipps and Anselin (2003) and Beron et al (2004) mention, this is consistent with the notion that often comparable prices of recently sold homes are used in determining an individual price, with higher prices of comparable homes leading to a higher price of the particular home.

²⁴ See Kelejian and Prucha (1998) for details of the generalized moments estimation technique.

²⁵ Our results for the spatial autoregressive parameter for housing prices near the Atlanta airport are similar to those of Kim, Phipps, and Anselin (2003) for housing prices in Seoul, Korea. Their estimate of 0.55 suggests that an increase in “neighboring” house price sales will cause the sale price of an individual house to increase 0.55 percent. A referee pointed out that a working paper by Pace and LeSage (2006) also incorporates a spatial multiplier approach.

To focus attention on some additional issues pertaining to interpretation, we follow the approach of Kim, Phipps and Anselin (2003) to analyze the impact of a spatial multiplier on marginal benefits of less noise. First, we re-write the estimation equation (i.e., equation (2)) in an analogous form to equation (3) in Kim, Phipps and Anselin as:

$$(4) \quad Y = [I - \rho W]^{-1} X\beta + \phi ,$$

where $\phi \equiv [I - \rho W]^{-1} \varepsilon$

or, in scalar notation,

$$(4') \quad Y_i = [1/(1 - \rho \sum_j w_{i,j})] \sum_k \beta_k X_{k,i} + \phi_i,$$

where $i,j=1,2,\dots,508$; $k=1,2,\dots,17$ (the number of explanatory variables including a column of ones), and

$$\phi_i \equiv [1/(1 - \rho \sum_j w_{i,j})] \varepsilon_i.$$

Since the rows of W sum to 1, equation (4') can be re-written as:

$$(5) \quad Y_i = [1/(1 - \rho)] \sum_k \beta_k X_{k,i} + \phi_i,$$

where $\phi_i \equiv [1/(1 - \rho)] \varepsilon_i$.

Thus, $[1/(1 - \rho)]$ can be thought of as a spatial multiplier that describes the impact on Y_i if a unit change were induced at every location. These effects are considered to be induced because in the context of our paper, a change in airport noise in the 70 DNL zone, for instance, leads to a change in a particular home's sale price in that area, which in turn impacts sale prices of other homes, and these additionally impact the original home's sale price, and so on. In addition to the noise variable, a similar induced effect

can pertain to every independent variable. However, because the focus of the present study is primarily on airport noise, the analysis below describes the induced impacts of airport noise on housing prices.

In the context of describing how the multiplier effect impacts the marginal benefits of lower air pollution, Kim, Phipps and Anselin (2003) present an analysis that can be applied to analyzing the induced impacts of airport noise. Alternatively, we could use the terminology of Beron et al (2004) of “marginal willingness to pay (MWTP)” for less noise. As Kim, Phipps, and Anselin (2003) note for their pollution problem, it is important here to keep in mind that the inclusion of the multiplier effect only holds for a small change in noise and “that would not be expected to hold for a non-marginal change” in noise. In the context of our airport noise problem, first, we define a "marginal change" in noise as going from the 70 DNL noise contour to the 65 DNL noise contour.²⁶ As a result, the difference between the impacts of the coefficients on the 70 DNL and 65 DNL dummy variables measure the impact of a "marginal change". Kim, Phipps and Anselin (2003) say that for their application, a marginal change results in a 4 percent change in air quality. In our case, a marginal change is an approximately a 7 percent decline in the decibel level (the percentage change in going from 70 DNL to 65 DNL). Next, Kim, Phipps and Anselin (2003) focus on measuring what we will call the mean marginal willingness to pay (MWTP) for better air quality (they may call it the marginal benefit of better air quality, but Beron (2004) uses MWTP). The mean MWTP (per household), for the 19 households in the 70 DNL contour, can be written as:

²⁶ Even though the 65 DNL dummy was individually insignificant based on a t-test, both the 65 DNL and 70 DNL contour dummies were jointly significant. For this reason we have chosen to define a marginal change as going from the 70 DNL to 65 DNL.

$$\text{Mean MWTP} = [(b_{70} - b_{65})/(1-\rho)] * [\sum P_i] / 19$$

$i=1,2,\dots,19,$

where b_{70} and b_{65} are the results of adjusting the 70 DNL and 65 DNL dummy coefficient estimates a la Halvorsen and Palmquest (1980), P_i is the individual sale price of house i in the 70 DNL zone, ρ is the coefficient on the spatially lagged dependent variable, and 19 is the number of homes in the 70 DNL noise contour for our sample. This implies that an average home buyer would be willing to pay \$33,228 more to live in the 65 DNL zone instead of the 70 DNL zone, holding all else constant.²⁷

Given that houses exposed to noise between 65 and 74 decibels are incompatible with residential use, people may be willing to give up a substantial amount of money to have a livable house with a more tolerable level of noise by moving from the 70 DNL to the 65 DNL contour, where they can sleep and concentrate better. As discussed below, the Atlanta airport's noise mitigation program has undertaken efforts costing hundreds of millions of dollars to assist residents in mitigating noise exposure since the 1980's.

Conclusion and Discussion

The impact of noise on housing prices has been an important public policy issue for many years. Various policies and programs have been proposed and pursued over the years. One approach has been for the local government authorities to assist the affected homeowners take defensive actions against the noise through soundproofing or relocating. According to the website of Hartsfield's Noise Mitigation Program, since the

²⁷ At the suggestion of a referee, we also computed the marginal willingness to pay when the spatial effects (both the multiplier and spatial autocorrelation) are not present – that is, when $\rho=\lambda=0$. In this case, the average individual who purchases a home in the 70 DNL zone would be willing to pay only \$18,847 to move to the 65 DNL zone, ceteris paribus. Thus, it appears as if incorporating spatial effects has a large impact on the marginal willingness to pay for noise reduction.

1980's they already have undertaken "sound insulation of approximately 10,150 structures at a cost of about \$174.5 million" as well as "relocation of residents, including the acquisition of over 2,720 structures at a cost of about \$171 million."²⁸

Another option is for airport authorities to impose a tax on aircraft based on the amount of noise that they emit. This way, airlines may alter their flight paths so as to choose the number and location of flights where the marginal benefits equal the social marginal costs, instead of equating the marginal benefits to the private marginal costs. A third possibility would be for local government to impose quantity controls on the level of noise and flight paths, so that the marginal benefits of flights would equal the marginal social costs. These options for addressing the potential noise externality are consistent with those outlined by Baumol and Oates (1988) for environmental externalities.²⁹

A key piece of information in determining policies and assessing the cost-effectiveness of programs is the impact of noise on housing prices. Our goal is to provide insights concerning the usefulness of spatial econometric models and estimation methods in pinning down the impact of noise on housing prices. In summary, we conduct a series of specification tests in order to choose among a variety of hedonic models of the housing price impacts of airport noise. Our preferred specification is a spatial error model with a spatially lagged dependent variable estimated by the generalized moments approach of Kelejian and Prucha (1998). Similar to the conclusion one would reach using a model without spatial effects, we conclude that houses located

²⁸ www.atlanta-airport.com/fifth/pdfs/noms.pdf

²⁹ Another alternative would be for airlines to negotiate with homeowners directly to choose the socially optimal amount of airport-related noise. This alternative is feasible only if negotiation costs are sufficiently small.

in the 70 DNL noise contour have significantly lower prices, *ceteris paribus*.³⁰ Also, we conclude that greater airport noise leads to lower housing prices after reaching a certain noise threshold (that is, 70 DNL). In comparison with other studies, McMillen (2004) uses OLS and finds a 9.2% (statistically significant) noise discount in moving from outside the 65 DNL contour to inside the contour. In the present study, we find that moving from the buffer zone to inside the 65 DNL zone (but outside the 70 DNL zone) has no statistically significant impact on house prices, *ceteris paribus*. Espey and Lopez (2000) estimate the model using a variety of specifications, including a semi-log (OLS) and a Box-Cox specification, assuming that a noise dummy variable takes the value of 1 if a home is inside the 65 DNL noise contour, and zero otherwise. Thus, they find about a 2% noise discount (which is statistically significant in some specifications). This difference in findings may arise due to the fact that McMillen's and Espey and Lopez's samples include only one noise contour – 65 DNL and above, so their analyses include the impact of houses in the 70 DNL zone as well. Their lumping together of all homes in the noise affected areas could explain why their 65 dB dummy was significant (while ours was not), but their noise impact estimate (based on both 65 and 70 dB noise exposure) was lower than our estimates based strictly on 70 dB and above.^{31,32}

³⁰ While the insignificance of the coefficient on the 65 dB dummy is quite robust, previous soundproofing and/or relocation efforts may help explain this consistent insignificance.

³¹ As suggested by a referee, another possible explanation for the differences in results is that we only have 19 observations in the 70 DNL zone. Although Espey and Lopez also have a small number of observations in the 70 DNL zone, their analysis does not distinguish between houses within both the 65 DNL and 70 DNL, and those above 70 DNL.

³² A referee noted that the McMillen and Espey/Lopez studies imply per-decibel noise discounts of 0.92% and 0.28%, respectively. In our paper, the per-decibel noise discounts would be about 3.3% for the GSM/GM model (and about 7.2% after accounting for the spatial multiplier). Our estimates may have been higher than previous studies due to differences in the ways “noisy” areas are chosen (moving from below 65 dB to 65 dB and above for the previous mentioned studies, while moving from 65 dB to 70 dB, and 70 dB or higher, in our study). Since noise measurement in decibels is logarithmic opposed to linear, it does not necessarily follow that the relationship between noise and the magnitude of the discount should be linear as well,

The use of our spatial model generates additional insights because these negative housing price effects are magnified by the presence of a spatial multiplier effect. The spatial multiplier arises due to feedbacks from the spatially lagged housing price variable. This spatially lagged dependent variable is positive and significant in our preferred specification. The findings of this study imply that by ignoring spatial autocorrelation and spatially lagged dependent variables in estimation of hedonic housing price models of airport noise, serious econometric problems may arise that can affect the policy implications of the model's parameter estimates.

One possible topic for future research would be to estimate a demand curve for noise reduction, along the lines of Zabel and Kiel (2000) or Brasington and Hite (2005). Although it is not clear to us at this time how one might approach this task given discontinuities in the noise contours, it may be possible to use the MWTP results to estimate such a demand curve, given more detailed noise contours.

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| Table 1 | |
|---|---|
| Variables in Hedonic Regressions | |
| Name | Definition |
| <i>PriceLog</i> | House sales price in dollars (in natural logs). This is our dependent variable. |
| <i>DB65_2003</i> | Dummy variable equal to one for houses within the 65 decibel day-night sound level 2003 noise contour; zero otherwise. |
| <i>DB70_2003</i> | Dummy variable equal to one for houses within the 70 decibel day-night sound level 2003 noise contour; zero otherwise. |
| <i>Beds3d</i> | Dummy variable equal to one for houses with three bedrooms; zero otherwise. |
| <i>Beds4d</i> | Dummy variable equal to one for houses with four bedrooms; zero otherwise. |
| <i>Beds5d</i> | Dummy variable equal to one for houses with five or more bedrooms; zero otherwise. |
| <i>Baths2d</i> | Dummy variable equal to one for houses with two bathrooms; zero otherwise. |
| <i>Baths3d</i> | Dummy variable equal to one for houses with three or more bathrooms; zero otherwise. |
| <i>Fire2d</i> | Dummy variable equal to one for house with two or more fireplaces; zero otherwise. |
| <i>Storiesd</i> | Dummy variable equal to one for houses with more than one story; zero otherwise. |
| <i>AcresLog</i> | Lot size in acres (in natural logs). |
| <i>DistanceLog</i> | Distance in miles from house to airport (in natural logs). |
| <i>City#d</i> | Series of dummy variables: <i>City2d</i> for College Park, <i>City3d</i> for Conley, <i>City4d</i> for East Point, <i>City5d</i> for Forest Park, and <i>City6d</i> for Hapeville, using Atlanta as the base city. Thus, for houses sold in College Park <i>dCity2d</i> is set equal to one and all other city dummies are set equal to zero. |

| 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 |
| <i>Price</i> | 128,442 | 32,378-460,500 |
| <i>Distance</i> | 3.29 | 1.06-6.06 |
| <i>Acres</i> | 0.37 | 0.02-3.88 |

Table 3 – Estimation Results

| Variable | OLS | SEM | SAR | GSM | SEM/GM | GSM/GM |
|-----------------------|-------------------|---------------------|-------------------|--------------------|-------------------|-------------------|
| <i>Constant</i> | 11.61* (95.44) | 11.60* (1034.58) | 8.62* (277.77) | 10.23* (665.01) | 11.60* (85.89) | 5.94* (3.13) |
| <i>DB65_2003</i> | -0.04 (-1.16) | -0.04 (-1.19) | -0.04 (-1.24) | -0.04 (-1.19) | -0.04 (-1.18) | -0.04 (-1.31) |
| <i>DB70_2003</i> | -0.28* (-3.24) | -0.25* (-2.62) | -0.25* (-3.05) | -0.25* (-2.75) | -0.24* (-2.54) | -0.23* (-2.80) |
| <i>Beds3d</i> | 0.10* (2.48) | 0.10* (2.64) | 0.10* (2.47) | 0.10* (2.54) | 0.10* (2.59) | 0.09* (2.33) |
| <i>Beds4d</i> | 0.10 (1.45) | 0.11 (1.54) | 0.09 (1.33) | 0.10 (1.46) | 0.11 (1.54) | 0.08 (1.10) |
| <i>Beds5d</i> | 0.31* (2.70) | 0.30* (2.74) | 0.29* (2.57) | 0.30* (2.65) | 0.30* (2.70) | 0.26* (2.30) |
| <i>Baths2d</i> | 0.13* (3.13) | 0.13* (3.27) | 0.12* (3.11) | 0.13* (3.21) | 0.13* (3.28) | 0.12* (2.93) |
| <i>Baths3d</i> | 0.40* (5.95) | 0.41* (6.20) | 0.38* (5.84) | 0.40* (6.06) | 0.41* (6.21) | 0.36* (5.38) |
| <i>Fire2d</i> | 0.19* (2.02) | 0.15 (1.65) | 0.17 (1.89) | 0.16 (1.71) | 0.15 (1.62) | 0.17 (1.77) |
| <i>Storiesd</i> | 0.24* (3.60) | 0.24* (3.61) | 0.23* (3.48) | 0.23* (3.56) | 0.23* (3.60) | 0.21* (3.16) |
| <i>AcresLog</i> | 0.10* (2.85) | 0.09* (3.14) | 0.09* (2.81) | 0.09* (2.66) | 0.09* (2.62) | 0.09* (2.67) |
| <i>DistanceLog</i> | -0.14 (-1.92) | -0.14* (-2.95) | -0.15* (-2.06) | -0.14 (-1.80) | -0.14 (-1.71) | -0.15* (-2.21) |
| <i>City2d</i> | 0.22* (3.43) | 0.22* (4.22) | 0.14* (2.17) | 0.19* (2.64) | 0.23* (3.11) | 0.06 (0.76) |
| <i>City3d</i> | 0.02 (0.24) | 0.02 (0.23) | 0.03 (0.52) | 0.03 (0.35) | 0.02 (0.23) | 0.05 (0.79) |
| <i>City4d</i> | 0.19* (2.83) | 0.20* (2.99) | 0.13* (1.98) | 0.17* (2.37) | 0.20* (2.74) | 0.07 (0.96) |
| <i>City5d</i> | -0.05 (-0.84) | -0.04 (-0.69) | -0.02 (-0.34) | -0.03 (-0.51) | -0.04 (-0.64) | 0.01 (0.18) |
| <i>City6d</i> | 0.05 (0.63) | 0.05 (0.69) | 0.02 (0.29) | 0.04 (0.41) | 0.05 (0.51) | -0.01 (-0.09) |
| <i>W*PriceLog (ρ)</i> | | | 0.26* (17.36) | -0.12* (9.20) | | 0.54* (3.55) |

| | | | | | | |
|-----------------------------|---------|---------|-------|--------|------|-------|
| $W^* \varepsilon (\lambda)$ | | 0.33* | | 0.22* | 0.36 | -0.09 |
| | | (16.39) | | (9.11) | n/a | n/a |
| R^2 | 0.51 | 0.52 | 0.51 | 0.52 | 0.52 | 0.52 |
| \bar{R}^2 | 0.49 | 0.50 | 0.49 | 0.50 | 0.50 | 0.50 |
| GM σ^2 | | | | | 0.11 | 0.11 |
| σ^2 | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 |
| Log-Likelihood | -155.69 | 23.09 | 22.88 | 313.96 | | |

* denotes significance at the 5% (two-tailed) level

t-statistics are in parentheses

Dependent Variable: *PriceLog*

Key to abbreviations:

OLS – Ordinary Least Squares

SEM – Spatial Error Model

SAR – Spatial Autoregressive Model

GSM – General Spatial Model

SEM/GM – Spatial Error Model, Generalized Moments

GSM/GM – General Spatial Model, Generalized Moments

Figure 1
The Location of Hartsfield–Jackson
Atlanta International Airport

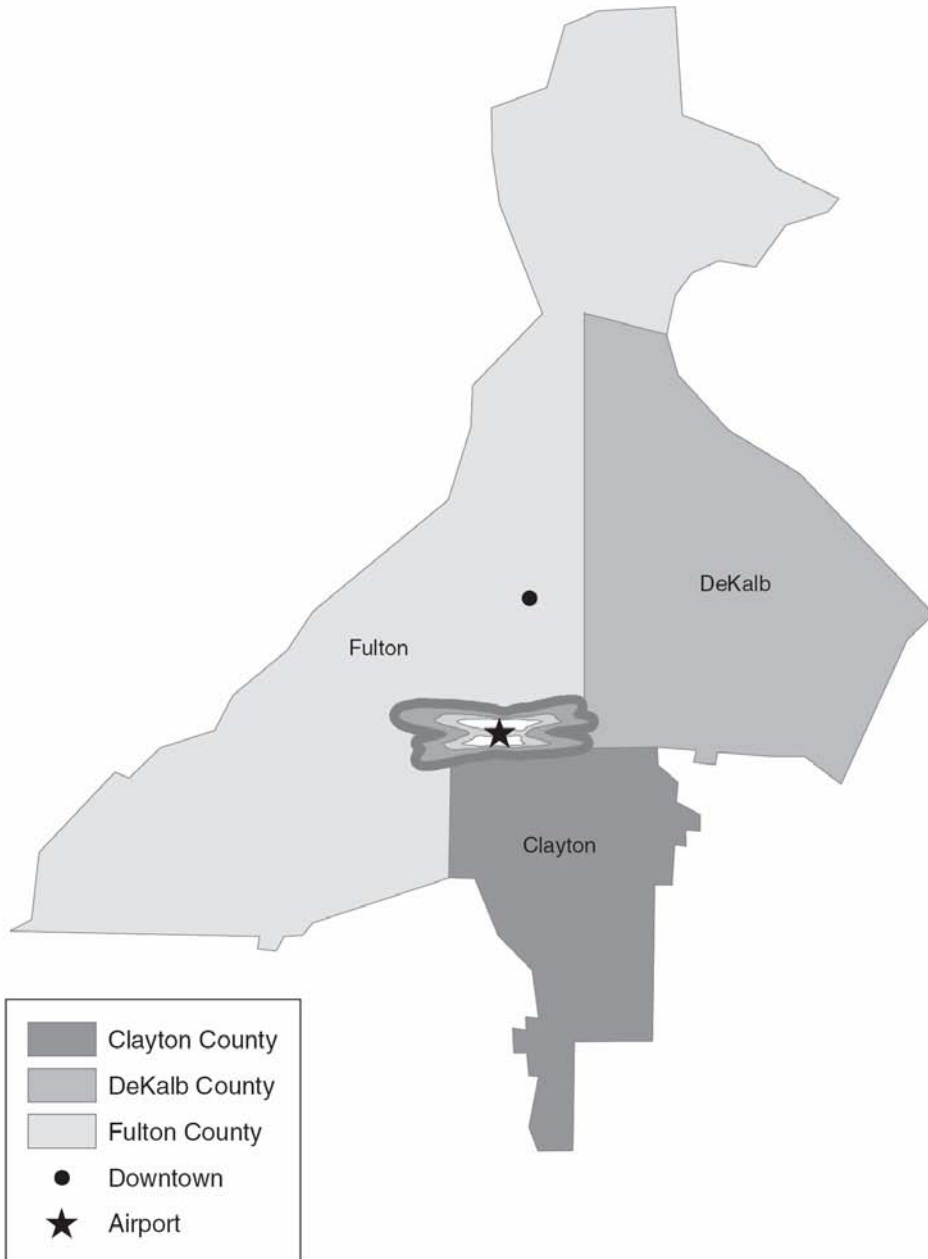


Figure 2
The Location of Houses in the Sample

