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# DEMAND FOR ENVIRONMENTAL QUALITY: A SPATIAL HEDONIC ANALYSIS

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ABSTRACT

We first estimate the relationship between house prices and environmental disamenities using spatial statistics, confirming that nearby point-source pollutants depress house price. We then calculate implicit prices of environmental quality and related characteristics from the house price hedonics to estimate a demand curve for environmental quality, finding a price elasticity of demand of –0.12. We find evidence of significant spatial effects in both the hedonic and demand estimations. We find that environmental quality and school quality are purchased together (η=-0.80), environmental quality and house size are substitutes (η=0.91), and environmental quality and lot size are not related goods.

**Keywords:** Hedonic Prices, Spatial Statistics, Environmental Disamenities, Point-Source Pollution

**JEL Classification Codes:** R22, H40, Q21, C14

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## I. Introduction

A century of industrial activity has left the metropolitan areas of the United States pocked with abandoned factories, landfills, and other small but significant sources of air, water and ground pollution. The U.S. Environmental Protection Agency spent $7.8 billion in 2001 to combat and monitor pollution. The EPA's fiscal year 2001 budget includes $1.8 billion for the Brownfields National Partnership to redevelop contaminated land; it also includes $1.45 billion for proposed toxic waste site cleanup (U.S. Office of Management and Budget, 2001). Other agencies charged with environmental cleanup include the Departments of Defense, Transportation, Agriculture, and Energy, as well as various state government agencies. Since government resources are being used to clean up the environment, it is instructive to ask how consumer well being is affected by changes in environmental quality and what factors influence the demand for environmental quality in urban areas.

Demand curve estimation requires a set of demand shifters, a measure of quantity demanded, and the price of the good. Because no explicit price exists for a unit of environmental quality, researchers often use the housing market to derive its implicit price. Our study extends the literature in the following ways. First, the data set we use is large and unique, consisting of 44,255 houses in 5,051 census block groups (CBG), matched with local public goods and environmental hazards identified by the Ohio EPA. Second, we use spatial statistics to estimate hedonic house price equations, using the distance from each house to the nearest hazard as our measure of environmental quality. Spatial statistics represents a powerful, underutilized tool in urban and environmental economics, capable of addressing omitted variable bias. Our use of spatial statistics provides more efficient, consistent, and unbiased estimates for the relationship between house price and environmental quality than previous studies. Third, we estimate a demand curve for environmental quality using spatial statistics. Little attention has been given to the demand for freedom from point-source, land-based pollution in urban areas. Given the political importance of urban brownfields, this is an unfortunate deficit, which we attempt to begin to address with this study.

Significant spatial effects are found in all six hedonic house price estimations and the demand estimation, suggesting that in future hedonic studies, researchers should at least test their data for spatial effects. Proximity to an environmental hazard appears to have a small, but statistically significant relationship with constant-quality house price. At the mean, increasing the distance of a house from the nearest environmental hazard by ten percent is associated with a three percent rise in constant-quality house price.

The estimated own price elasticity of demand for environmental quality in urban areas is –0.12. A relatively inelastic demand curve may suggest that people are not very sensitive to changes in the price of environmental quality. Another interpretation is that individuals cannot easily respond to changes in environmental quality: they can only change environmental quality through collective action or moving. Cleanup is likely to require significant time to achieve, while moving presents a large fixed cost. Brownfields projects, toxic waste cleanup, and other programs to clean up point-source pollution seem to have support from homeowners.

The cross-price elasticity between environmental quality and school quality is -0.80, suggesting that school quality is complementary to environmental quality. People tend to purchase houses in good school districts in areas where relatively few point-source pollutants exist. On the other hand, house size is a substitute for environmental quality, implying that homeowners may trade off environmental quality to get a larger house. Next, one may expect that environmental quality and lot size would be purchased together, but our results suggest that the size of the lot and environmental quality are neither complements nor substitutes. Income levels are positively related to the demand for environmental quality, but the income elasticity of environmental quality is only 0.04. Higher-educated people and households with children tend to demand more environmental quality than less-educated people and households without children.

## II. Analytical Framework

Unlike the market for most tangible goods, the market for environmental quality does not yield an observable per unit price. Some researchers find the price of environmental quality by using direct elicitation of willingness to pay, travel costs, averting costs, direct monetary damages, the household production approach or some combination of the above (Cameron, 1992); others use the hedonic house price method. Previous studies have used the hedonic approach to estimate the relationship between house price and air pollution (Kiel and McClain, 1995; Chattopadhyay, 1999; Smith and Deyak, 1975; Beron, Murdoch and Thayer, 2001), water pollution (Hoehn, Berger and Blomquist, 1987), and hazardous waste sites (Kohlhase, 1991; Hite et al., 2001; Nelson, Genereux and Genereux, 1992).

**2.1 The Hedonic Method**

The formal theory of hedonic markets is generally credited to Sherwin Rosen (1974). Hedonic theory suggests that the price of a house represents the sum of expenditures on a number of bundled housing characteristics, each of which has its own implicit price. These housing characteristics include structural attributes such as the number of rooms and the square footage of the house and the yard. Expenditures on other less tangible characteristics, including local public goods and environmental quality, also contribute to house price.

The first stage hedonic estimates may be used to calculate the implicit price of housing characteristics. Rosen was the first to recommend using implicit prices to estimate a demand function in a second stage of analysis. Assuming that environmental quality increases directly with distance from a disamenity, we derive the implicit price of a unit of environmental quality from a series of house price hedonic estimations. In addition we estimate implicit prices for other related characteristics, such as house size, lot size, and the quality of local schools. We then use instrumented implicit prices along with exogenous shift variables to estimate the demand for environmental quality.

<u>2.1.1 Segmentation and Identification</u> The main shortcoming of Rosen's second stage demand estimation is that the estimated implicit price may not contain any information beyond what the first stage hedonic provides. The only new information is the functional form restriction placed on the demand equation. If there is no new information, the estimated demand equation simply reproduces the results of the hedonic regression from which it was produced initially (Tinbergen, 1956; Brown and H. Rosen, 1982); that is, the demand cannot be identified from the hedonic. There are other ways to

deal with the identification problem (e.g., Quigley, 1982; Chattopadhyay, 1999), but the most widely accepted solution found in the literature is the use of segmented markets (Brown and H. Rosen, 1982; Palmquist, 1984; Zabel and Kiel, 2000; Brasington, 2000, 2003).[1] A separate hedonic house price function is estimated for each market segment. In our case, market segments consist of the six major metropolitan areas in Ohio: Akron, Cincinnati, Cleveland, Columbus, Dayton, and Toledo. Estimating hedonic functions for the six metro areas separately generates six different parameter estimates for the relationship between environmental quality and house price, from which the implicit prices are calculated. The implicit prices are then instrumented and pooled to estimate the demand equation. Use of segmented markets combined with the pooled demand estimation addresses the identification problem.[2]

How can a researcher theoretically justify using a separate hedonic for each metropolitan area? Palmquist (1984) assumes there is no segmentation within a metro area but there is between them because of moving costs; however, moving between suburbs of a single metro area costs nearly as much as moving between metro areas. So instead we reason that market segmentation arises between metro areas but not within a metro area because of different construction costs and job availability. It is relatively easy to commute to the workplace from anywhere in the same MSA. It becomes more difficult to commute to the workplace from a different MSA. It is even more difficult and costly in the short run to find a job in a new metro area and move to that new area, than to move or find a new job in the same metro area.

Most previous papers that use market segmentation to address identification simply assume their data constitutes segmented markets. The current study goes a step further by running a series of Chow tests of the form described in Kennedy (1992, p.108). The Chow tests support the assertion that each of the six Ohio MSAs represents a different segmented market. Consequently, a separate hedonic is estimated for each metropolitan area.[3]

## 2.2 First Stage Hedonic Analysis

An important estimation problem that we address in the first stage hedonic is spatial dependence in the data. One example of spatial dependence is when a given house affects the price of neighboring houses (LeSage, 1997). Ordinary least squares does not account for the interplay between spatially close observations, which may lead to biased, inefficient and inconsistent parameter estimates (Anselin, 1988, p.58-59; LeSage, 2001). A study by He and Winder (1999) demonstrates bi-directional price causality between three adjacent housing markets in Virginia, suggesting that there may indeed be spatial effects in housing markets. An instrumental variables technique may be used, but most attempts to adjust for spatial effects have been based on maximum likelihood (Anselin and Hudak, 1992). Using maximum likelihood in the manner that follows not only addresses spatial effects but may also help with identification above and beyond the use of segmented markets (Epple, 1987).

The traditional house price hedonic takes the following form:

$$v = \beta x + \varepsilon, \tag{1}$$

where $v$ represents the average value of a house in a CBG, $x$ is a vector of explanatory variables and $\varepsilon$ is the error term. Rather than using the traditional hedonic model of Equation (1), we use a spatial Durbin model to address the problem of spatial dependence

(Pace and Barry, 1997a).[4] The spatial Durbin model includes a spatial lag of the dependent variable as well as spatial lags of the explanatory variables, as in Equation (2):

$$v = \rho Wv + X\beta + W\underline{X}\alpha + \varepsilon,\ \varepsilon \sim N(0, \sigma^2 I_n) \tag{2}$$

In Equation (2) the scalar term $\rho$ is the spatial autoregressive parameter to be estimated. It measures the degree of spatial dependence between the values of nearby houses in the sample. The $W$ term is an n by n spatial weight matrix. It has non-zero entries in the i,jth position, reflecting CBGs that are nearest neighbors to each of the i block groups in the sample. In this manner the spatial weight matrix $W$ summarizes the spatial configuration of the sample. Next, $\underline{X}$ is the explanatory variable matrix $X$ with the intercept excluded, and $\alpha$ is the parameter associated with the spatial lag of the explanatory variables.

The $Wv$ term in (2) captures the extent to which house prices in one area are affected by the price of houses in neighboring areas. Such spatial interplay is appropriate because, among other reasons, when a house is put on the market, the offer price is often set with the knowledge of the selling price of similar houses in the neighborhood. Multiple listing services publish offer prices and newspapers in Ohio publish sale prices, so typically offers and bids on houses will be influenced by offers and bids on nearby houses.

The $W\underline{X}\alpha$ term in (2) allows the structural characteristics of neighboring houses to influence the price of each house. A common saying in real estate is to never own the largest (or the smallest) house on the block: the market will force such a house to sell at a discount, an example of the type of impact captured by $W\underline{X}\alpha$. The $W\underline{X}\alpha$ term also allows other structural characteristics of neighboring houses to affect the sale price of houses. Glower, et al. (1998) find that the degree to which a house is atypical influences its time on the market and sale price, so it may be important to incorporate the structural characteristics of neighboring houses into the house price hedonic.

The $W\underline{X}\alpha$ term also captures how the price of houses in one area depends on the characteristics of neighboring areas. For example, school quality differs across space. The $W\underline{X}\alpha$ term allows the quality of neighboring schools to spill over--possibly through peer group effects--and influence the price of houses in the original school district. Poverty may impose negative externalities and therefore spill over across CBG boundaries. In addition, the tax competition literature suggests that the tax rate charged by a neighboring taxing jurisdiction will affect the tax rate chosen by the home jurisdiction, which may in turn affect house prices. The $W\underline{X}\alpha$ term allows for these types of spillovers.

There are few published environmental economics studies that use spatial statistics. Geoghegan, Wainger and Bockstael (1997) employ spatially-explicit indices. Gawande and Jenkins-Smith (2001) estimate a house price hedonic using a simple spatial autoregressive model. Leggett and Bockstael (2000) and Bockstael and Bell (1998) use a simple spatial error model. But the spatial technique we adopt allows for spatial dependence through both the prices of nearby properties and through the x-characteristics of nearby properties. It is a more general model than the spatial autoregressive model and the spatial error model, capable of capturing spatial dependence from more sources than the models of Gawande and Jenkins-Smith (2001), Bockstael and Bell (1998), or Leggett and Bockstael (2000). In fact, imposing restrictions on the spatial Durbin model can yield both the spatial error model and the spatial autoregressive model.

The log-likelihood for the spatial Durbin model in Equation (2)--concentrated with respect to the parameters $\beta$ and $\sigma$--takes the following form (Anselin, 1988, p. 181; Pace and Barry, 1997a):

$$ln\ L = C + ln\ |I_n - \rho W|\ -(n/2)ln(e'e) \tag{3}$$

where

$e = e_o - \rho e_d$

$e_o = v - Z\beta_o$

$e_d = Wv - Z\beta_d$

$\beta_o = (Z'Z)^{-1}Z'v$

$\beta_d = (Z'Z)^{-1}Z'Wv$

$Z = [X\ WXI]$

and $C$ is a constant term that does not involve the parameters.

The need to compute the log-determinant of the $n$ by $n$ matrix $(I_n - \rho W)$ makes it computationally difficult to solve the maximum likelihood problem in Equation (3). But the sparsity of $W$ may be exploited (Pace, 1997; Pace and Barry, 1997a) so that a personal computer can handle the large data set estimations with computational ease. The Cholesky decomposition is used in Barry and Pace's (1999) Monte Carlo estimator to compute the log-determinant over a grid of values for $\rho$ restricted to the interval [0,1]. This estimator allows larger problems to be tackled without the memory requirements or sensitivity to orderings associated with the direct sparse matrix approach.

<u>2.2.1 Omitted Variable Bias</u> The sparse spatial Durbin procedure has been demonstrated to greatly improve cross-sectional regression estimates that are spatial in nature (Pace, 1998a, 1998b; Pace and Barry, 1997b). Part of the improvement stems

from incorporating the influence of omitted variables (Anselin, 1988, p.103; Pace, Barry and Sirmans, 1998). Traditional hedonic estimation does not address omitted variable bias. Attempts to circumvent the problem include focusing on narrow geographic areas where many influences are already controlled for (e.g., Brasington, 2003), or including vast numbers of explanatory variables to capture every influence which diligent data collection can offer. Still, studies with limited geographic coverage have limited appeal, and structural characteristics may be similar within small areas so that multicollinearity problems are exacerbated. In fact, in most papers it is precisely the variation across markets that enables identification in the Rosen two-stage hedonic demand estimation. Furthermore, the presence of omitted variables is a primary source of identification difficulties. By addressing omitted variable bias, spatial statistics may also help with identification.

Similar to the way a time lag of the dependent variable picks up unobserved autoregressive influences, the spatial lag term $Wv$ picks up unobserved influences that affect house value (Bolduc et al., 1995; Griffith, 1988, p.82-83). But while a lagged dependent variable in time series regressions relies on observations nearby in time, the spatial lag relies on a linear combination of house values nearby in space. Unmeasured influences help determine the value of neighboring houses and, as explained earlier, the value of neighboring houses is related to the value of our own house. So our own house value is affected by the unmeasured influences of neighboring observations. And the unmeasured influences of neighboring houses are similar to the unmeasured influences for our house because our neighbors are close: the same things that affect our neighbors should affect us, too. So the $Wv$ term in Equation (2) incorporates the influence of omitted variables on the value of our own house. In a similar manner, the *WX* term also helps capture the influence of omitted variables whose effects would otherwise be subsumed in the error term.

The spatial Durbin model thus captures the influence of air pollution, the presence of shopping centers, interstate highways, lakes, hospitals, multiple environmental disamenities, and all other omitted variables that vary across space. In the presence of omitted variable bias, least squares estimates are plagued by a multitude of econometric sins. A detailed proof of how spatial statistics achieves consistent and unbiased parameter estimates, unbiased estimates of the standard errors, and efficient parameter estimates where least squares may not, is available in Griffith (1988, p. 94-107).

<u>2.2.2 Choice of Hedonic Variables</u> The hedonic variables include structural house characteristics and neighborhood characteristics. We aggregate our housing transactions to the CBG level. The following CBG averages for house characteristics are used in the hedonics: lot size in square feet, age of the house, size of the house in square feet, the number of full and partial bathrooms, and the number of detached structures on the lot. Also included is the proportion of houses in each CBG that have garages, fireplaces, porches, patios, decks, pools and central air conditioning. The squares of lot size, house size, and age are included because these variables may influence a house's value in a nonlinear fashion.

In addition to structural house characteristics, many neighborhood characteristics may affect house value. Standard urban economic theory suggests that distance from the central business district affects house price. The central business district is the primary employment center and therefore many individuals want to live close in order to reduce commuting costs. The house price appreciation literature suggests that community population growth may raise house prices (Archer, Gatzlaff and Ling, 1996). The amenity literature suggests that neighborhood racial composition, education levels, income levels, and poverty rates also affect house prices.

Local public economic theory suggests that house value may depend on taxes and school quality. To avoid possible assessor bias, the local property tax rate is used as a long-run estimate of tax price (Brasington, 2000). Public school quality is an important local public service that affects house prices (Goodman and Thibodeau, 1998; Haurin and Brasington, 1996). Proficiency test scores appear to be one of the most consistent measures of public school quality used in house price hedonics (Brasington, 1999a). All else constant, higher tax rates in a CBG are expected to lower average house value while improved school quality is expected to increase average house value.

The focus variable is a measure of environmental quality. We have data on the location of point-specific pollution sites in Ohio's six major urban areas. Such sites are of interest to policy makers because they are urban sites that may qualify as brownfield sites, or may be slated for future cleanup under Superfund. Data on the polluting sites comes from the Ohio Environmental Protection Agency (OEPA). The OEPA maintains a Master Sites List that documents sites in Ohio "where there is evidence of, or it is suspected that waste management has resulted in the contamination of air, water, or soil and there is a confirmed or potential threat to human health or the environment. These sites may be operating or abandoned industrial facilities, contaminated or potentially contaminated public water supplies with the source of contamination undiscovered, or other locations where the environmental media is contaminated through a variety of waste management activities" (OEPA, 1997).

We call the waste management contamination sites *hazards*. Some of these hazards are Superfund sites. Example of hazards include the following: Twinsburg Township landfill; Republic Steel Corporation Niles Plant; Kimble Coal Co.; Reilly Tar & Chemical Corp.; Goodyear Tire & Rubber Blue Pond; Miami county incinerator; Emery Transportation tanker spill; Mayer China (dumping into Tinker's Creek); Milford wellfield / unknown source; and U.S. Steel Central Furnaces.

Being near a hazard should be associated with depressed house prices. Therefore, all else constant, the greater the average distance to the nearest hazard, the higher the average house price is expected to be. DISTANCE TO HAZARD is constructed by taking each house and finding the distance from the house to the nearest hazard. This distance is averaged over all the houses in the CBG, resulting in an observationally weighted distance measure. The mean distance to the nearest hazard for houses in a CBG is 1.28 miles. The minimum is 0.0125, and the maximum is 10.9, with 1.08 miles as the median. The 25$^{th}$ percentile is 0.68 miles, and the 75$^{th}$ percentile is 1.63 miles. Distance to the nearest hazard may be nonlinearly related to house price, so a natural log transformation of distance to the nearest hazard is included in the hedonic regressions (Hite, 1998; Nelson, Genereux and Genereux, 1992).

Our measure of pollution does not account for the presence of multiple sources of pollution. But previous studies measure pollution imperfectly as well. Studies that measure proximity to a single well-known polluting source (e.g., Nelson, Genereux and Genereux, 1992) ignore the presence of other sources of pollution that may in fact be closer. Studies that measure the number of polluting sources in a county or census tract (e.g., Hoehn, Berger and Blomquist, 1987) fail to note how close or far the pollution sources are, and if there are none in the county, how close the nearest source is.[5] Suppose a house is on the edge of a county which has no polluting sources, but there are two polluting sources directly across the county line. Using numbers of hazards per county as a measurement rule would record zero polluting sources when in fact there are two nearby.

Using distance to the nearest hazard helps get around these sources of measurement error. And even though distance to the nearest hazard does not account for the possibility that there could be more than one hazard nearby, this may not pose a major problem: the influence of hazards on property values is known to drop off quickly with distance (e.g., Nelson, Genereux and Genereux, 1992; Hite, et al., 2001), so most of the effect is attributable to the nearest hazard.[6] So, although using distance from the nearest hazard is not a perfect way to measure pollution, it has certain advantages over other methods, and it is a reasonable way to measure pollution with precedent in the literature (e.g. Kohlhase, 1991; Thayer, et al., 1992).

Variable definitions and sources are shown in Table 1; the means of the hedonic variables are shown in Table 2. We expect high correlations between the non-housing explanatory variables, but most are 0.31 or less in absolute value. The highest correlations are between SCHOOL QUALITY and GROWTH RATE (0.57), SCHOOL QUALITY and POVERTY (-0.49), POVERTY and INCOME (-0.46), and POVERTY and %WHITE (-0.40).

(Insert Table 1)

(Insert Table 2)

The hazards come from a 1994 listing, while the housing transactions come from 1991. In most cases we expect this to cause no problems, but there are circumstances under which it might matter. If there are hazards in 1991 that affect house price but are not listed in the Master Sites List, DISTANCE TO HAZARD is overstated. On the other hand, if the hazard is still on the list, but it is no longer a source of pollution, it might no longer affect house price. In this case our DISTANCE TO HAZARD variable is probably understated. The Master Sites List records 1,192 sites in Ohio in the year of our sample: 16 were delisted (1.3%), while 18 (1.5%) were added during our sample year. Therefore the vast majority of sites listed in 1994 were probably also listed in 1991, the year of our housing sample.

Our level of observation is the CBG; thus, it should be noted that all inferences from the models are based on a 'representative' CBG transaction, similar to models using representative households as the unit of analysis. The data consists of 550 census block groups in the Akron metropolitan area, 911 in Cincinnati, 1,580 in Cleveland, 872 in Columbus, 524 in Dayton, and 611 in Toledo. These census block groups represent 5,018, 7,148, 13,723, 7,680, 6,779, and 3,907 housing transactions, respectively. The housing transactions are a cross section of arm's length sales of single-family detached houses sold in 1991. With 44,255 housing transactions in 5,051 census block groups, on average there are about 10 houses sold in each census block group.

We have additional data on 2,004 census block groups in the relevant counties in which no housing transactions are recorded. These census block groups are in rural school districts.[7] It is possible that our analysis might suffer from sample selection bias, but experimentation shows that the inverse Mills ratio is not statistically significant in any of the six hedonic regressions, suggesting that sample selection bias is not an issue in our estimation situation.[8] Still, our selection experiment may not have captured the relationship between frequency of sales and DISTANCE TO HAZARD accurately. When we omit all houses within 0.68 miles of a hazard, two parameter estimates lose statistical significance. So *if* houses near hazards sell less often, our hedonics probably understate the discount from being near a hazard.

Another potential estimation problem is endogeneity. Jud (1985) pointed out that school quality may be endogenous to house prices, but he concluded that proper instruments are hard to find. It has remained an open problem in the literature. However, endogeneity is a problem of contemporaneous correlation between a regressor and the error term. The error term consists in part of omitted variables. When these omitted variables are correlated with included regressors, the regressors are endogenous, and yield biased and inconsistent parameter estimates. Spatial statistics helps control for the influence of omitted variables, thus alleviating the need to instrument for endogenous variables (Brasington, 2001).

### 2.3 Second Stage Hedonic Analysis: The Demand Model

The demand analysis that we present follows 2SLS methodology in that we use instrumental variables for the prices that are included as explanatory variables. However, analogous to the first stage hedonic estimates, our estimation technique specifically accounts for spatial dependence and omitted variable bias. The form of the demand model is given by

$$Q = \rho WQ + D\gamma + WD\alpha + \varepsilon, \tag{4}$$

where $Q$ is the quantity of environmental quality available to residents of the census block group, as measured by proximity to a hazard. $D$ represents a vector of implicit prices and demand shift variables. The error structure is analogous to that in Equation (3).

2.3.1 Demand Variables We include the implicit price of environmental quality in the demand equation, as well as the implicit prices for three related goods: school quality, house size and lot size. Implicit prices are calculated from the partial derivative of HOUSE PRICE with respect to DISTANCE TO HAZARD, SCHOOL QUALITY, HOUSE SIZE, and LOT SIZE. The implicit prices are calculated for each of the 5,051 census block groups and pooled across metropolitan areas in order to estimate a single environmental quality demand curve, in accordance with the traditional two-stage hedonic demand literature.

The price of the good is an element of every demand function. The implicit prices of environmental quality, school quality, house size and lot size are endogenous, and therefore instruments must be found that are uncorrelated with distance to the nearest environmental hazard. The instruments chosen are ARTS (correlation 0.085), ACCESSIBILITY (0.205), MSA GROWTH (-0.069), and COMMUTE TIME (0.024). Definitions and sources of the instrumental variables are found in Table 1. In addition to being uncorrelated with the dependent variable, the instruments should be sufficiently related to the variable for which they serve as instruments. The instruments pass the Nelson and Startz (1990) test for irrelevant instruments.[9,10]

Other variables are included in the demand equation as shift variables. If environmental quality is a normal good, higher community income may be related to increased demand for environmental quality. In addition, people in cities with a pleasant climate may go outside to enjoy the weather more. Thus, better environmental quality may be demanded the more temperate the climate. Enjoyment of the weather is expected to diminish the closer a person is to an environmental disamenity.

%GRADUATE DEGREE is also included as a shift variable. People with high educational attainment may be more aware of the harmful effects of pollution and may therefore demand more environmental quality than people with lower levels of education.[11] Finally, having children may affect a household's demand for environmental quality. Children tend to play in drainage ditches and abandoned landfills more than adults, so parents with children are probably more fervent about demanding locations far from environmental hazards than households without children. We therefore expect %WITH CHILDREN to be a positive demand shifter. Having discussed the empirical model, the estimation results are now presented.

## III. RESULTS

### 3.1 Hedonic Regression Results

The results of the six spatial hedonic regressions for Akron, Cincinnati, Cleveland, Columbus, Dayton and Toledo are shown in Table 3.

(Insert Table 3)

Before specific regression results are discussed, notice that the optimal spatial lag coefficient ranges from 0.18 to 0.42. Given the number of explanatory variables included, the optimal spatial lag coefficient is moderately large. Because the spatial model is more complex than ordinary least squares, it is appropriate to test whether the incorporation of spatial dependence adds to the analysis. It appears that it does: a likelihood ratio test for overall spatial effects rejects the null hypothesis of no spatial effects at the 0.01 significance level for all six hedonics.[12]

The hedonic results generally conform to expectations. Having a large proportion of houses with pools within a census block group seems to make no difference to average house price in Ohio; having a deck, patio, porch, outbuildings and additional bathrooms also generally fails to attain statistical significance. But having a larger proportion of houses with garages raises average house price, and so does being in a census block group with larger houses, larger lots, and more houses with fireplaces. In addition, block groups with older houses generally suffer price discounts. There are a few neighborhood variables that do not completely follow expectations. Distance to the central business district (CBD) is related to average house price in less than half the regressions; the increasingly dispersed nature of employment centers may be the driving force behind the less consistent capitalization of the downtown access variable (Mieszkowski and Mills, 1993). Contrary to the house price appreciation literature, population GROWTH RATE is not related to average house price and neither is the tax rate. On the other hand, school quality, the proportion of white residents, high average education and income levels generally are positively related to average house prices, and poverty is negatively related to average house prices. The regressions explain between 85% and 97% of the variation in house prices.

The focus variable in the hedonic estimations is DISTANCE TO HAZARD. The parameter estimates for this variable are always positive and are statistically significant in five of the six MSAs. The parameter estimate is insignificant for Toledo, the urban area with the highest average value of DISTANCE TO HAZARD.[13] Still, Smolen et al. (1992) find significant results for Toledo even for houses 2.6 to 5.75 miles from a landfill, which is much farther out than our 75th percentile distance of 1.63 miles.

Because both the dependent variable and DISTANCE TO HAZARD are logged, the parameter estimates are elasticities. The elasticities are small, ranging from 0.004 to 0.063. The results confirm prior studies' findings that environmental quality has a small, statistically significant relationship with house prices. At the mean, all else constant, increasing the average distance of a house from the nearest environmental hazard by one percent is associated with a 0.029 percent rise in the price of the average house.

Previous studies have investigated the relationship between property values and environmental quality, but the measure of environmental quality varies greatly (Jackson, 2001; Boyle and Kiel, 2001). Hoehn, Berger and Blomquist (1987) use suspended particulates, the number of superfund sites, the number of hazardous waste facilities, and the number of water pollution discharges in a county. Leggett and Bockstael (2000) use fecal coliform concentration and distance from a sewage treatment facility. Zabel and Kiel (2000) use four air quality measures, and Smith and Deyak (1975) and Jackson (1979) use suspended particulates. Kohlhase (1991) uses distance from the nearest toxic waste dump. None of these articles finds a consistent relationship between house prices and environmental quality.

Other studies, like ours, find a consistent relationship between house prices and environmental quality. Again, the measure of environmental quality varies. Beron, Murdoch and Thayer (2001) find elasticities of house price with respect to ozone, particulates, and visibility of –0.30, -0.41, and 1.04. Smolen et al. (1992) find that for houses within 2.6 miles of a hazardous waste landfill, each extra mile from the landfill is worth between $9,000 and $14,000. Folland and Hough (2000) find that land price consistently suffers a 6% discount if it is near a nuclear reactor.[14] This 6% discount is similar to the 5.5% discount Reichert, et al. (1992) find for houses affected by a nearby landfill. Nelson, Genereux and Genereux (1992) find the elasticity of house price with respect to distance from a landfill is 0.094. Our 0.029 mean elasticity is most similar to that of Gawande and Jenkins-Smith (2001), who use a similar statistical technique to find a house price elasticity with respect to distance from a spent nuclear fuel shipment route of 0.032.

### 3.2 Demand for Environmental Quality

Our demand analysis is based on 5,051 observations at the census block group level. Like Beron, et al. (2001), we find that aggregating from individual house prices does not substantially change the results. Theory provides little guidance for choosing the shape of the demand curve. A series of Davidson and MacKinnon (1981) tests for functional form suggests that the log-linear functional form is best for our data. Including the implicit prices in the demand estimation creates a generated regressor problem; therefore, the demand estimation is weighted by a combination of the estimated variance of the error terms from the hedonic regressions and the demand estimations, as detailed in Brasington (2002).[15] We estimate the demand curve using a number of statistical techniques, including 2SLS, LIML, and the same spatial Durbin technique used for the house price hedonics.

It should be noted that the all the models we estimate are based on the standard assumptions widely held in the literature. That is, segmented markets give rise to differences in underlying implicit prices because of variations in local cost functions for housing, while consumer preferences for housing are more or less homogeneous. Thus, individual hedonics price functions are estimated for each market segment, while the parameters of the demand function are constrained to be equal across all market segments.

Rosen (1974) suggested that second-stage hedonic demand regressions be performed using two-stage least squares (2SLS), and much of the ensuing literature has done so. We believe that using 2SLS, because it does not address omitted variable bias, may result in biased parameter estimates with invalid hypothesis testing. Still, we perform 2SLS to compare it to the estimates achieved using spatial statistics. The results are found in the 2SLS column of Table 4. Own price is positive and statistically insignificant, but most of the other parameter estimates appear plausible. But as we shall see, the results change when other estimation techniques are adopted. The fit of the model is poor, the explanatory variables explaining only three percent of the variation in the dependent variable.

The next column of results in Table 4 is LIML, a model using limited-information maximum likelihood. Like 2SLS, LIML does not address omitted variable bias, but unlike 2SLS, the LIML model is based on the maximum likelihood approach, as is the spatial model. Compared to the 2SLS model, the LIML model shows a downward-sloping demand curve. Using LIML also inverts the relationships between environmental quality and house size, and environmental quality and climate. Adjusted R-squared has risen from 0.03 to 0.25.

(Insert Table 4)

Some researchers have used fixed effects models to address the influence of omitted variables within a spatial context (Deaton, 1988; Beron, et al., 2001). The Fixed Effect column in Table 4 reports results of a fixed effects model that uses metropolitan area dummy variables to capture spatial effects.[16] The INCOME and %GRADUATE DEGREE estimates are halved, and the presence of children no longer influences the demand for environmental quality. The parameter estimates of own price, price of house size and climate double. Adjusted R-squared rises from 0.25 in the standard LIML model to 0.85 in the Fixed Effect model.

But second-stage demand estimations achieve identification by constraining all parameter estimates to equality, following standard practice (e.g., Brown and Rosen, 1982). By including fixed effect MSA dummies that allow the intercept to vary we may undermine the identification of the demand equation achieved by the method of Brown and Rosen. However, there is another way to capture omitted spatial effects: by using spatial statistics. Use of spatial statistics allows us to capture omitted effects that vary across space while retaining identification. In addition, spatial statistics allows us to capture omitted effects at a more localized level than by including fixed effect MSA dummy variables.

Leggett and Bockstael (2000), Geoghegan, et al. (1997), Bockstael and Bell (1998), and Gawande and Jenkins-Smith (2001) use spatial models to estimate the relationship between house prices and environmental quality. But our study seems to be the first to use spatial statistics to estimate a demand curve of environmental quality. Because of the negative externalities of polluting sites, the demand for environmental quality by one household is probably related to its neighbor's demand for environmental quality. Spatial statistics can address the interrelations; it can also pick up the influence of omitted variables, suggesting that the use of spatial statistics is a potentially important advance in the urban and environmental economics literatures. The results of the spatial demand estimation are shown in the Spatial column of Table 4.

As with the hedonic regressions, significant spatial effects are found at the 0.01 level of significance.[17] The spatial lag coefficient is 0.77, which is high; explanatory power is higher for the spatial estimation than for all previous demand estimations. The large $\rho$ estimate is at least partly a result of the way the environmental variable is constructed, because average distance to the nearest hazard should be similar for nearby block groups. But we propose that the spatial technique may be capturing more influence of omitted variables than the previous models. Our proposal rests not only on the large estimate of $\rho$ but also on the fact that many of the parameter estimates change markedly when using the spatial model.

Both PRICE OF HOUSE SIZE and PRICE OF LOT SIZE have positive parameter estimates, which would suggest that house size and lot size are substitutes for environmental quality. However, the parameter estimate for lot size is statistically insignificant. Therefore, lot size, which 2SLS found to be a substitute for environmental quality, appears to be unrelated to environmental quality.[18] If one were to calculate the economic effect, one would find a cross-price elasticity between lot size and environmental quality of only 0.02. So when lots become more expensive, it appears that home buyers do not make any tradeoff in the amount of environmental quality that they purchase.

House size, on the other hand, seems to be a substitute for environmental quality. The cross-price elasticity is 0.91, almost unit elastic. Thus when the price of larger houses rises by ten percent, people purchase nine percent more environmental quality. In contrast, the 2SLS model showed house size to be a weak complement to environmental quality. And while the LIML model showed house size to be a substitute, the cross-price elasticity was paltry: 0.000067.

The 2SLS model showed no relationship between the price of school quality and environmental quality. The LIML models showed school quality and environmental quality to be substitutes. In contrast, the results of the spatial model suggest instead that people who purchase high-quality schools also tend to purchase high levels of environmental quality. The cross-price elasticity is –0.80, which is not trivial. All else constant, if school quality were to become ten percent cheaper, households would purchase eight percent more environmental quality.

Among the demand shift variables, higher income is statistically significantly related to higher demand for environmental quality. The non-spatial models achieved the same result, but suggested a stronger effect than the spatial model. The estimated income elasticity of demand for the spatial model is 0.044. The result suggests that people do not purchase much more environmental quality when their incomes rise. The 2SLS model suggested that a better climate resulted in reduced purchases of environmental quality. The LIML models suggested the more intuitively appealing, opposite conclusion. But the spatial model suggests that there is no significant relationship between climate and environmental quality. Because the climate differs little across Ohio's urban areas, such a result is reasonable. The statistical insignificance of the spatial model may illustrate how spatial statistics achieves less biased estimates of the standard errors of parameter estimates. The spatial statistics model suggests that households with children and households with the highest education levels purchase more environmental quality; both of these outcomes are consistent with expectations.

Perhaps the most compelling reason for using the spatial model is in estimating welfare impacts that are relevant to policy decisions. The estimate of the own price elasticity of demand for environmental quality in the spatial model is –0.12, suggesting an even more inelastic demand curve than given by the LIML or Fixed Effects models.[19] This finding has significance in that it suggests that changes in environmental quality may result in larger changes in consumer welfare than would be the case if spatial effects are not accounted for. To illustrate, we compare the per household consumer surplus change of a move from the sample median distance to hazard (1.08 miles) to a distance ½ mile closer to a hazard (i.e. 0.58 miles), using our LIML and spatial models. Consumer surplus estimated from the LIML model without spatial effects suggest a $2,276 per household one-time loss of surplus while the spatial model estimates a one-time consumer surplus loss of $3,278.[20] Given the even higher elasticity for the Fixed Effects model, we would expect that it would generate even greater bias in the welfare estimates than does the LIML model.

Our estimated own-price elasticity of demand of –0.12 may be compared to the results of other studies, none of which use spatial statistics, all of which include only air pollution, and some of which are not identified. Zabel and Kiel (2000) find a price elasticity of –0.479 for ozone and –0.128 for particulates. Bender, et al. (1980) find an air quality price elasticity that ranges from –0.503 to –0.262. Beron, et al. (2001) report a visibility elasticity of –0.0024, and Nelson's (1978) particulates demand elasticity ranges from –1.2 to –1.4.

## IV. Conclusion

Using an extensive data set, we have investigated the relationship between polluted sites and house price, and we have estimated the demand for environmental quality in urban areas. Both the hedonics and the demand estimation use spatial statistics to address omitted variable bias and spatial effects in the data.

The hedonic regressions suggest that environmental hazards have a small, statistically significant relationship with average constant-quality house price. At the mean, moving ten percent closer to the nearest hazard is expected to decrease average house price by three-tenths of one percent.

The demand regression suggests that people with higher incomes, higher education levels, and people with children demand more environmental quality. The implicit price of environmental quality is negatively related to quantity demanded; the price elasticity of demand of –0.12 suggests a relatively inelastic demand curve. School quality and environmental quality tend to be purchased together. But larger houses and environmental quality seem to be substitutes: when large houses become more expensive, people purchase smaller houses farther from polluting sources.[21] When large houses become less costly, people buy larger houses and less environmental quality. On the other hand, lot size seems to be neither a complement nor a substitute for environmental quality.

The presence of significant spatial effects in both the hedonic regressions and the demand regression suggests that researchers should account for spatial effects in future work. The spatial effects may capture spillovers, omitted variables, or other forms of spatial dependence. Whatever the cause of the spatial effects, spatial statistical methods should be used to increase efficiency and consistency and reduce the bias of parameter estimates.

The governmental units of the United States are devoting considerable resources to cleaning up the environment. The current study traces out a demand for environmental quality curve for residents of urban areas in Ohio. If our estimates are accurate, then taking a house that is slightly further than one mile from a hazard and moving it one half a mile closer would result in a mean welfare loss (lost consumer surplus) of $3,278. This represents about 6% of the value of the average house. Looking at the Cincinnati sample, we find 1451 houses that are about one mile from a hazard. Moving these houses half a mile away from the hazard would increase consumer surplus by nearly $4.8 million dollars[22]—more if the hazard were removed altogether. The $4.8 million grossly underestimates the change in property values, though, because the 1451 houses are only those between 1.1 and 0.6 miles from a hazard. Our estimate excludes houses closer to a hazard, and it excludes houses that are not part of our sample: our sample only includes those houses that sold during 1991. In addition, it is noteworthy that the LIML model estimates just $3.3 million in total consumer surplus for these houses. This type of welfare loss estimate can provide the basis for establishing priorities for cleanup of polluted urban sites, as well as providing input for siting and compensation schemes for new disamenities.

Future research should use the same statistical technique to see to what extent residents of other urban areas value environmental quality. Another important, but difficult area of investigation would be to compare the demand for environmental quality of urban residents to that of rural residents.

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Table 1
Variable Definitions And Source

| Variable Name | Definition (Source) |
|---|---|
| HOUSE PRICE | Mean house transaction price for 1991 sales in census block group, deflated by MSA and logged (1) |
| AIR CONDITIONING | Proportion of houses in census block group that have central air conditioning (1) |
| FIREPLACE | Proportion of houses in census block group that have a fireplace (1) |
| OUTBUILDINGS | Average number of detached structures on lot for houses in census block group (1) |
| LOT SIZE | Mean size of lot in tens of thousands of square feet in census block group (1) |
| AGE | Mean age of house per census block group in hundreds of years (1) |
| HOUSE SIZE | Average size of house in census block group in thousands of square feet (1) |
| GARAGE | Proportion of houses in census block group that have a garage (1) |
| FULL BATHROOMS | Mean number of full bathrooms in house in census block group (1) |
| PART BATHROOMS | Mean number of partial bathrooms in house in census block group (1) |
| PORCH | Proportion of houses in census block group that have a porch (1) |
| PATIO | Proportion of houses in census block group that have a patio (1) |
| DECK | Proportion of houses in census block group that have a deck (1) |
| POOL | Proportion of houses in census block group that have a pool (1) |
| %WHITE | Proportion of census block group residents who are white (5) |
| %POVERTY | Proportion of persons living under official 1989 poverty income in census block group (5) |
| TAX RATE | Property tax rate in mills; property tax collections from school taxes on all real Class 1 (residential) properties divided by 1000, divided by total real Class 1 property valuation, after tax reduction factors are accounted for (2) |
| SCHOOL QUALITY | Percentage of students passing the Ohio 9th grade proficiency test in 1990; average passage rate of math, reading, writing, and citizenship sections (2) |
| DISTANCE TO CBD | Distance from centroid of census block group to central business district, in miles |
| DISTANCE TO HAZARD | Average distance from house to nearest environmental hazard in census block group, in miles, logged (4) |
| GROWTH RATE | Rate of change in school district population from 1980 to 1990 (3) |
| PRICE OF ENV QUALITY | Log price of a unit of environmental quality derived from hedonic regressions |
| PRICE OF SCHOOL | Price of a unit of public school quality derived from hedonic |

| | |
|---|---|
| QUALITY | regressions |
| PRICE OF HOUSE SIZE | Price of an extra 10,000 square feet of house size derived from hedonic regressions |
| PRICE OF LOT SIZE | Price of an extra thousand square feet of lot size derived from hedonic regressions |
| CLIMATE | Mildness of the climate in the MSA; beginning with 1000 points, points are subtracted for the number of very hot and very cold months, the degree of seasonal temperature variation, the number of heating and cooling degree days, and the number of freezing, zero-degree, and 90-degree days (6) |
| INCOME | Average income in census block group in tens of thousands of dollars, deflated by MSA (5) |
| %GRADUATE DEGREE | Proportion of persons in census block group who have a master's degree or doctorate (5) |
| %WITH CHILDREN | Proportion of households in census block group that have children under 18 years of age (5) |
| ARTS | A measure of the number of arts performances, museums, and library holdings in the MSA (6) |
| ACCESSIBILITY | A measure of the MSA ease of accessibility; a weighted average of lower than average commuting time to work, mass transit availability, and highway, air, and train accessibility (6) |
| MSA GROWTH | 1990 population of the MSA divided by 1980 population (6) |
| COMMUTE TIME | Time of commute for average person in census block group (5) |
| Sources: (1) Amerestate (1991) housing transaction tape; (2) Ohio Department of Education, Division of Education Management Information Services; (3) *School District Data Book* (MESA Group, 1994), (4) Ohio Environmental Protection Agency Division of Emergency and Remedial Response (1994), (5) U.S. Bureau of the Census (1990), (6) *Places Rated Almanac* (Savageau and Boyer, 1993). All nominal values are deflated by MSA using ACCRA (1991, 1992) data. | |

Table 2
Hedonic Means

| Variable | Akron | Cincinnati | Cleveland | Columbus | Dayton | Toledo |
|---|---|---|---|---|---|---|
| HOUSE PRICE | 10.8 | 11.0 | 10.8 | 10.9 | 10.8 | 10.7 |
| | (0.62) | (0.56) | (0.64) | (0.58) | (0.61) | (0.66) |
| AIR CONDITIONING | 0.19 | 0.41 | 0.14 | 0.41 | 0.36 | 0.25 |
| | (0.25) | (0.35) | (0.23) | (0.37) | (0.32) | (0.31) |
| FIREPLACE | 0.31 | 0.33 | 0.29 | 0.38 | 0.37 | 0.27 |
| | (0.32) | (0.36) | (0.34) | (0.38) | (0.35) | (0.33) |
| OUTBUILDINGS | 0.06 | 0.05 | 0.01 | 0.02 | 0.04 | 0.04 |
| | (0.16) | (0.13) | (0.05) | (0.07) | (0.11) | (0.15) |
| LOT SIZE | 1.21 | 1.10 | 1.00 | 0.86 | 0.97 | 0.87 |
| | (0.97) | (0.80) | (0.93) | (0.59) | (0.57) | (0.68) |
| AGE | 0.50 | 0.53 | 0.55 | 0.44 | 0.47 | 0.51 |
| | (0.20) | (0.25) | (0.24) | (0.25) | (0.23) | (0.26) |
| HOUSE SIZE | 1.36 | 1.44 | 1.43 | 1.43 | 1.39 | 1.36 |
| | (0.33) | (0.39) | (0.38) | (0.40) | (0.41) | (0.43) |
| GARAGE | 0.82 | 0.74 | 0.87 | 0.68 | 0.78 | 0.84 |
| | (0.24) | (0.32) | (0.25) | (0.33) | (0.29) | (0.27) |
| FULL BATHROOMS | 1.23 | 1.33 | 1.19 | 1.28 | 1.30 | 1.16 |
| | (0.31) | (0.39) | (0.31) | (0.36) | (0.38) | (0.29) |
| PART BATHROOMS | 0.28 | 0.23 | 0.30 | 0.31 | 0.23 | 0.30 |
| | (0.31) | (0.28) | (0.34) | (0.34) | (0.27) | (0.36) |
| PORCH | 0.68 | 0.69 | 0.65 | 0.60 | 0.63 | 0.68 |
| | (0.29) | (0.31) | (0.32) | (0.34) | (0.31) | (0.33) |
| PATIO | 0.01 | 0.23 | 0.04 | 0.29 | 0.42 | 0.13 |
| | (0.09) | (0.26) | (0.13) | (0.29) | (0.31) | (0.22) |
| DECK | 0.06 | 0.11 | 0.09 | 0.10 | 0.07 | 0.06 |
| | (0.12) | (0.20) | (0.16) | (0.18) | (0.14) | (0.16) |
| POOL | 0.004 | 0.018 | 0.009 | 0.005 | 0.010 | 0.019 |
| | (0.02) | (0.07) | (0.05) | (0.04) | (0.04) | (0.09) |
| SCHOOL QUALITY | 32.8 | 31.1 | 28.3 | 28.1 | 27.7 | 26.4 |
| | (13.7) | (14.4) | (18.4) | (18.5) | (19.6) | (13.1) |
| %WHITE | 0.82 | 0.82 | 0.73 | 0.79 | 0.78 | 0.84 |
| | (0.30) | (0.29) | (0.36) | (0.29) | (0.34) | (0.25) |
| DISTANCE TO CBD | 5.2 | 9.9 | 11.4 | 5.1 | 5.0 | 5.2 |
| | (4.6) | (5.9) | (8.0) | (4.5) | (4.1) | (3.4) |
| %GRADUATE | 0.10 | 0.08 | 0.09 | 0.09 | 0.07 | 0.06 |
| DEGREE | (0.21) | (0.08) | (0.16) | (0.11) | (0.08) | (0.07) |
| INCOME | 3.33 | 3.83 | 3.63 | 3.68 | 3.48 | 3.64 |
| | (1.91) | (1.98) | (2.14) | (2.05) | (1.65) | (1.73) |
| %POVERTY | 0.14 | 0.12 | 0.13 | 0.14 | 0.14 | 0.13 |
| | (0.15) | (0.13) | (0.14) | (0.16) | (0.15) | (0.13) |
| TAX RATE | 33.9 | 34.8 | 34.5 | 36.3 | 38.5 | 37.5 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (4.5) | (4.4) | (8.6) | (3.7) | (8.2) | (2.8) |
| DISTANCE TO | -0.148 | -0.012 | 0.016 | 0.029 | 0.219 | 0.051 |
| HAZARD | (0.61) | (0.81) | (0.66) | (0.74) | (0.58) | (0.70) |
| GROWTH RATE | 0.014 | 0.030 | 0.031 | 0.030 | 0.010 | -0.019 |
| | (0.08) | (0.07) | (0.07) | (0.09) | (0.04) | (0.05) |
| #Observations | 550 | 911 | 1580 | 875 | 524 | 611 |

Means shown with standard deviation in parentheses below.

Table 3
Hedonic Results

| Variable | Akron | Cincinnati | Cleveland | Columbus | Dayton | Toledo |
|---|---|---|---|---|---|---|
| AIR CONDITIONING | 0.006 | 0.088** | 0.016 | 0.065** | 0.052 | 0.032 |
| | {0.023} | {0.094} | {0.001} | {0.000} | {-0.006} | {0.026} |
| | (0.2) | (18.0) | (0.2) | (6.4) | (4.0) | (1.6) |
| FIREPLACE | 0.047** | 0.119** | 0.029 | 0.128** | 0.079** | -0.015** |
| | {0.119} | {0.035} | {0.019} | {-0.018} | {-0.060} | {-0.065} |
| | (8.0) | (20.6) | (3.8) | (25.6) | (8.2) | (1.4) |
| OUTBUILDINGS | 0.104** | 0.011 | 0.138 | -0.004 | 0.130 | 0.109 |
| | {0.341} | {0.168} | {0.077} | {-0.227} | {-0.138} | {-0.106} |
| | (6.8) | (1.0) | (2.4) | (2.2) | (2.0) | (3.8) |
| LOT SIZE | 0.039** | 0.128** | 0.107** | 0.136** | 0.114** | 0.176** |
| | {-0.115} | {-0.139} | {-0.074} | {0.136} | {0.066} | {-0.149} |
| | (6.6) | (8.2) | (7.0) | (14.0) | (4.0) | (14.8) |
| LOT SIZE SQUARED | -0.003 | -0.012 | -0.009* | -0.012** | -0.014 | -0.016* |
| | {0.007} | {0.014} | {0.006} | {-0.025} | {-0.034} | {0.013} |
| | (0.6) | (2.8) | (5.4) | (9.4) | (2.6) | (5.8) |
| AGE | -1.03** | -0.100 | -1.18** | -1.01** | -0.569* | -0.770** |
| | {0.529} | {0.699} | {0.771} | {-0.012} | {0.859} | {1.825} |
| | (16.4) | (2.6) | (50.6) | (22.8) | (5.0) | (25.6) |
| AGE SQUARED | 0.144 | -0.302* | 0.330** | 0.697** | 0.001 | -0.002** |
| | {-0.314} | {-0.448} | {-0.592} | {0.027} | {-0.723} | {-1.271} |
| | (1.0) | (5.4) | (23.0) | (16.4) | (4.4) | (13.8) |
| HOUSE SIZE | 0.730** | 0.285* | 0.523** | 0.336** | 0.651** | 0.591** |
| | {-0.072} | {0.050} | {-0.106} | {-0.410} | {0.455} | {-0.081} |
| | (17.4) | (5.2) | (23.6) | (9.0) | (23.6) | (23.8) |
| HOUSE SIZE SQUARED | -0.078 | 0.026 | -0.065* | 0.007** | -0.073 | -0.055 |
| | {-0.076} | {-0.035} | {0.039} | {0.134} | {-0.162} | {0.015} |
| | (3.0) | (2.2) | (4.8) | (8.4) | (4.4) | (2.6) |
| GARAGE | 0.176** | 0.148** | 0.124** | 0.069** | 0.167** | 0.235** |
| | {-0.112} | {-0.038} | {-0.042} | {0.000} | {0.071} | {-0.148} |
| | (30.3) | (26.4) | (25.0) | (9.0) | (28.0) | (49.0) |
| FULL BATHROOMS | 0.033 | 0.032 | 0.021** | 0.011** | -0.010 | 0.020 |
| | {-0.070} | {-0.067} | {-0.056} | {-0.133} | {-0.025} | {-0.094} |
| | (2.2) | (2.6) | (6.0) | (13.2) | (0.4) | (1.6) |
| PART BATHROOMS | 0.026 | -0.013 | -0.013 | -0.046 | 0.046 | 0.039 |
| | {0.019} | {-0.002} | {-0.011} | {0.001} | {0.060} | {0.049} |
| | (1.0) | (0.4) | (0.8) | (3.0) | (3.4) | (2.8) |
| PORCH | 0.000 | -0.008 | 0.031* | 0.050* | -0.002 | -0.025** |
| | {-0.053} | {-0.048} | {-0.003} | {-0.015} | {0.035} | {-0.100} |
| | (1.0) | (0.8) | (5.4) | (5.8) | (0.6) | (6.0) |
| PATIO | 0.265* | -0.023 | -0.029 | 0.058** | -0.010 | -0.002 |
| | {0.206} | {-0.036} | {0.000} | {0.019} | {-0.102} | {0.096} |
| | (5.8) | (1.0) | (0.4) | (7.6) | (3.8) | (1.6) |

| | | | | | | |
|---|---|---|---|---|---|---|
| DECK | 0.033 | 0.072 | 0.048 | 0.012 | -0.104* | 0.058 |
| | {-0.305} | {0.117} | {0.039} | {-0.026} | {-0.028} | {0.156} |
| | (1.8) | (4.2) | (3.4) | (0.2) | (4.8) | (2.2) |
| POOL | 0.000 | 0.218 | 0.063 | -0.085 | 0.106 | 0.066 |
| | {0.000} | {-0.481} | {-0.055} | {0.000} | {0.621} | {-0.303} |
| | (0.0) | (3.6) | (0.2) | (0.2) | (2.4) | (1.4) |
| SCHOOL QUALITY | 0.002** | 0.002* | 0.008** | 0.009* | 0.001* | 0.004 |
| | {0.004} | {-0.004} | {-0.001} | {-0.007} | {0.001} | {0.001} |
| | (20.2) | (5.6) | (88.4) | (5.2) | (5.8) | (2.2) |
| %WHITE | 0.457** | 0.384** | 0.238** | 0.080** | 0.018** | 0.256** |
| | {0.053} | {-0.259} | {-0.086} | {0.179} | {0.322} | {0.023} |
| | (81.4) | (36.8) | (44.8) | (33.4) | (37.8) | (28.4) |
| DISTANCE TO CBD | -0.005 | 0.003 | -0.010** | -0.030** | 0.014 | 0.023 |
| | {-0.003} | {-0.006} | {0.006} | {0.022} | {-0.019} | {-0.010} |
| | (1.8) | (2.2) | (8.2) | (6.0) | (2.6) | (4.2) |
| %GRADUATE DEGREE | 0.741** | 0.695** | 0.387** | 0.491** | 0.354* | 0.794** |
| | {0.131} | {0.662} | {-0.060} | {0.766} | {0.269} | {0.647} |
| | (69.8) | (33.2) | (45.2) | (70.6) | (5.8) | (15.2) |
| INCOME | 0.027** | 0.015 | 0.026** | 0.002 | 0.009* | 0.010* |
| | {0.017} | {-0.004} | {-0.007} | {-0.015} | {0.011} | {-0.005} |
| | (12.4) | (3.4) | (22.0) | (2.8) | (5.6) | (4.8) |
| %POVERTY | -0.064** | -0.145** | -0.569** | -0.399** | -0.693** | -0.266* |
| | {-0.255} | {-0.518} | {-0.468} | {-0.379} | {0.047} | {-0.083} |
| | (6.4) | (9.6) | (117.8) | (47.0) | (41.2) | (5.8) |
| TAX RATE | 0.000 | 0.003 | 0.003 | -0.001 | -0.004 | 0.008 |
| | {0.008} | {0.000} | {-0.002} | {0.005} | {-0.011} | {-0.016} |
| | (4.2) | (1.8) | (2.8) | (0.6) | (4.4) | (1.8) |
| DISTANCE TO HAZARD | 0.063* | 0.053** | 0.011** | 0.034** | 0.004 | 0.010** |
| | {0.084} | {-0.014} | {-0.017} | {-0.045} | {-0.004} | {-0.005} |
| | (5.4) | (9.8) | (6.4) | (15.4) | (4.0) | (6.2) |
| GROWTH RATE | -0.122 | 0.096 | -0.771** | -0.047 | 0.072 | 1.58 |
| | {-0.154} | {0.078} | {0.490} | {0.121} | {0.215} | {-1.349} |
| | (2.2) | (0.6) | (10.0) | (1.0) | (0.6) | (1.2) |
| CONSTANT | 0.678** | 0.798** | 0.918** | 0.883** | 0.841** | 0.626** |
| | (108.2) | (168.0) | (1146.2) | (438.8) | (139.0) | (84.0) |
| Unrestricted log likelihood | -838.0 | -1906.8 | -3576.2 | -1740.8 | -780.6 | -1013.2 |
| Optimal spatial lag | 0.32 | 0.27 | 0.18 | 0.24 | 0.18 | 0.42 |
| coefficient, ρ | (26.8) | (28.6) | (86.4) | (57.4) | (8.0) | (57.4) |
| Sum of squared errors | 6.6 | 15.7 | 94.1 | 37.6 | 5.8 | 9.4 |
| Total sum of squares | 208.6 | 286.1 | 645.8 | 294.3 | 195.1 | 266.9 |
| Adjusted R-square | 0.97 | 0.95 | 0.85 | 0.87 | 0.97 | 0.96 |
| #Observations | 550 | 911 | 1580 | 875 | 524 | 611 |

Parameter estimates shown, with spatial lag estimates $\alpha$ in brackets below, and likelihood ratio (LR) statistic in parentheses below that. **=statistically significant at 0.05, *=statistically significant at 0.10. Dependent variable is HOUSE PRICE, which is logged. LR = -2(optimal unrestricted log likelihood – optimal restricted log likelihood), which is asymptotically distributed as chi-square with degrees of freedom equal to the number of restrictions (two in this case: the variable and its spatial lag are set equal to zero). To avoid decimal problems in Spacestatpack, the constant term is set equal to 9. The null hypothesis of no significant spatial effects is rejected at the 0.01 level for all hedonics.

Table 4
Demand for Environmental Quality Results

| | 2SLS | LIML | Fixed Effect | ***Spatial*** | Means (Std Errors) |
|---|---|---|---|---|---|
| CONSTANT | 2.88**<br>(5.8) | 0.976**<br>(4.6) | -7.108**<br>(37.1) | ***0.091*****<br>***(25.6)*** | —<br>— |
| LOG PRICE OF ENV QUALITY | 0.057<br>(1.4) | -0.308**<br>(37.6) | -0.811**<br>(167.3) | ***-0.123*****<br>***{0.140}***<br>***(6.8)*** | 0.943<br>(0.583) |
| PRICE OF SCHOOL QUALITY | -0.0001<br>(1.3) | 0.85x$10^{-4}$**<br>(3.0) | 0.00038**<br>(18.9) | ***-0.178****<br>***{0.175}***<br>***(4.8)*** | 4.470<br>(2.345) |
| PRICE OF HOUSE SIZE | -0.3x$10^{-4}$**<br>(4.8) | 0.11x$10^{-4}$**<br>(13.9) | 0.22x$10^{-4}$**<br>(55.9) | ***0.284*****<br>***{-0.373}***<br>***(16.6)*** | 3.202<br>(0.375) |
| PRICE OF LOT SIZE | 0.1x$10^{-4}$*<br>(1.7) | -0.14x$10^{-7}$<br>(0.5) | -0.25x$10^{-7}$<br>(1.6) | ***0.002***<br>***{0.000}***<br>***(0.6)*** | 7.844<br>(1.966) |
| INCOME | 0.066**<br>(6.6) | 0.055**<br>(8.8) | 0.022**<br>(6.6) | ***0.015*****<br>***{0.005}***<br>***(46.6)*** | 2.9251<br>(1.3656) |
| CLIMATE | -0.445**<br>(6.2) | 0.100**<br>(2.6) | 2.23**<br>(59.9) | ***-0.113***<br>***{0.000}***<br>***(2.2)*** | 5.648<br>(0.2142) |
| %GRADUATE DEGREE | 0.284**<br>(2.8) | 0.180**<br>(3.1) | 0.085**<br>(3.1) | ***0.180*****<br>***{-0.115}***<br>***(15.2)*** | 0.081<br>(0.133) |
| %WITH CHILDREN | 0.313**<br>(2.7) | 0.359**<br>(5.6) | -0.044<br>(1.5) | ***0.035****<br>***{0.055}***<br>***(5.4)*** | 0.333<br>(0.114) |
| Optimal spatial lag coefficient, ρ | - | - | - | ***0.77***<br>***(6976.4)*** | - |
| Adjusted R-square | 0.03 | 0.25 | 0.86 | ***0.90*** | - |

Parameter estimates shown with T-ratio in parentheses below for non-spatial model. For the spatial model, spatial lag estimate α is shown in brackets below, and likelihood ratio (LR) statistic is shown in parentheses. Dependent variable is DISTANCE TO HAZARD, which is logged. **=statistically significant at 0.05, *=statistically significant at 0.10. To avoid decimal problems in Spacestatpack, the constant term is set equal to 9. The null hypothesis of no significant spatial effects is rejected at the 0.01 level for the spatial model. Number of observations is 5051.

[1] Beron, et al. (2001) use segmentation by year instead of by housing market.

[2] Our use of a maximum likelihood technique in the empirical section also may help with identification (Epple, 1987).

[3] This is the form the Chow tests take. First it is desirable to test whether all six metropolitan areas can be pooled or not. With a critical F value of 1.96, the Chow test F value of 164.4 suggests that there is sufficient variation in the housing markets to make it improper to run a single pooled regression containing all six MSAs. Next six additional Chow tests are run. Each tests whether the MSA in question is significantly different from the remaining five. With a critical F value of 1.96, the following F values are obtained: Akron, 54.0; Cincinnati, 60.7; Cleveland, 24.7; Columbus, 28.0; Dayton, 3.9; Toledo, 28.0. Thus each MSA is significantly different from the remaining five.

[4] One reason a simple spatial autoregressive model is not estimated is that SAS could not handle the large data set. SpaceStatPack statistical software has been designed by Kelley Pace (2000) to specifically handle large data sets, and it uses the spatial Durbin model. Thanks to Kelley Pace for providing SpaceStatPack free of charge at http://finance.lsu.edu/re/kelleyresume.html and www.spatial-statistics.com.

[5] In this paper we have the advantage of using census block group data rather than census tract data. For example, in the CBGs used in our dataset, there is an average of 10.27 transactions per CBG, whereas census tracts average 36.94 transactions each. Furthermore, the geographic extent of CBGs is just 2.5 $KM^2$, where it is over 7 $KM^2$ for census tracts.

[6] In addition, our use of spatial statistics helps control for the presence of the second- and third-nearest hazards.

[7] See Brasington (1999b) for a classification of the central city and suburban school districts in the six largest metropolitan areas in Ohio used in the current study. Also, the 2,004 rural census block groups have twice the proportion of agricultural workers and almost half the population density of the 5,051 urban census block groups.

[8] Haurin and Hendershott (1991) were the first to suggest that sample selection bias might be an issue in house price regressions, and Jud and Seaks (1994) were the first to correct for it. With a 4.6 critical value at the 0.10 level, our calculated LR statistics for our inverse Mills ratios are 2.6 (Akron), 2.0 (Cincinnati), 1.2 (Cleveland), 0.8 (Columbus), 1.2 (Dayton), and 1.0 (Toledo). Full probit and hedonic results available upon request.

[9] The Nelson and Startz (1990) critical value is 2. The calculated Nelson and Startz statistics are 2115 for environmental quality; 21,809 for school quality; 2717 for house size and 2390 for lot size.

[10] It should be noted that the variables used to instrument the implicit prices are aggregated at differing levels. We believe that this further reduces correlations between the instrumented variables much in the same way as in ranking or grouping methods (Bowden and Turkington, p 59, 1984).

[11] Because our estimated demand curves are representative of a census block group, and not an individual, there is some concern that shifters like income and education may not be entirely exogenous shifters. Experimentation with the models suggests that these variables are valid shifters in that, when omitted, the effects on the estimated own price parameters are large. In addition, part of the argument for using spatial statistics is that it helps to eliminate bias from endogeneity. We are grateful to a referee who pointed out this potential problem to us.

[12] With a critical LR statistic of 44.3 at the 0.01 level of significance, the calculated LR statistics are the following: Akron, 121.8; Cincinnati, 112.0; Cleveland, 179.0; Columbus, 171.0; Dayton, 77.8; Toledo, 157.2.

[13] Thanks to a referee for making this interesting observation.

[14] Table 2 fixed period effects model.

[15] While the 2SLS, LIML, and Fixed Effects regressions are corrected for generated regressor bias, the Spatial results are not. The statistical package we use for the spatial model, Spacestatpack, is not able to save residuals or predicted values. We are not overly concerned because the generated regressor correction did not change the t-ratios much for the three non-spatial models. We are indebted to a referee for pointing out the generated regressor problem. This appears to be only the second two-stage hedonic demand study to correct for generated regressor bias (Brasington, 2002).

[16] Akron is the reference MSA in this model.

[17] The calculated LR statistic is 6987.8; the critical value at 0.01 is 20.1.

[18] Recall that the variables are averages over census block groups. Therefore the general wording "lot size…unrelated to environmental quality" is correct, for example, but the meaning more specifically reflects the relationship between average lot size in a census block group and the average level of environmental quality in a census block group. Thanks to a referee for pointing this out.

[19] Although the 2SLS model has an even less elastic demand, we do not consider it for comparison given the insignificance and contrary sign of the coefficient.

[20] Of course, since the area in a concentric circle around a hazard would shrink significantly between 1.037 and 0.537 miles, the calculated surplus change would have to be adjusted to estimate changes in aggregate welfare.

[21] See footnote 18.

[22] The per household consumer surplus gain for a move from 1 to 1.5 miles is estimated to be $4,464.