THREE ESSAYS ON REAL ESTATE, ENVIRONMENTAL, AND URBAN ECONOMICS USING THE HEDONIC PRICE MODEL TECHNIQUE

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THREE ESSAYS ON REAL ESTATE, ENVIRONMENTAL, AND URBAN ECONOMICS USING THE HEDONIC PRICE MODEL TECHNIQUE

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THREE ESSAYS ON REAL ESTATE, ENVIRONMENTAL, AND URBAN

ECONOMICS USING THE HEDONIC PRICE MODEL TECHNIQUE

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Andres Jauregui, son of Mario A. Jauregui and Dora M. Danza, was born March 24, 1976, in Salta, Argentina. He graduated from the American Nicaraguan School in Managua, Nicaragua, in 1994. He then attended the International University of the Americas in San Jose, Costa Rica, for five years where he obtained a B.S. in International Economics. In August 2000, he entered Graduate School at Auburn University, Auburn, Alabama. He graduated with a M.Sc. in Economics in August 2004.

DISSERTATION ABSTRACT

THREE ESSAYS ON REAL ESTATE, ENVIRONMENTAL, AND URBAN ECONOMICS USING THE HEDONIC PRICE MODEL TECHNIQUE

Andres Jauregui

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This dissertation is organized into three different topics in the fields of real estate economics, environmental economics, and urban economics, all of them linked by a common econometric technique. The first topic determines the impact of real estate agents on house prices that are located close to an environmental disamenity. The main hypothesis is that real estate agents obtain higher prices than those theoretically expected when the houses are located closer to an environmental disamenity. The analysis takes into consideration the impact of differences in information about the presence of the environmental disamenity between buyers, sellers, and their real estate agent that ultimately have an impact on their bargaining position. The estimated hedonic price model is used to predict house values for transactions done with and without a real estate agent, and calculate their percentage differences at various distance intervals from the landfills.

The second topic concerns the value of open space to residents in agricultural areas. Valuing open space differs from one user to another. Also, open space valuation differs by type of open space. A spatial hedonic price model is formulated to estimate the marginal value of an additional unit of land of different types of open space on residential houses located in urban and suburban areas. The econometric specification corrects for problems arising from spatial correlation and spatial heterogeneity. Further, the price paid for a property is divided into the portion pertaining to the house and the portion pertaining to the land where the house is located. This results in a system of two hedonic equations for housing and land values as a function of their characteristics.

The last topic estimates four demand equations for neighborhood dissimilarities to shed light into the economics of neighborhood residential choice. Theories about the causes of neighborhood segregation, particularly of racial segregation, abound in the urban economics literature, yet they are not consistent about explaining the causal relationships that lead to segregation in the housing market.

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CHAPTER 1: DON'T ASK, DON'T TELL: THE IMPACT OF REAL ESTATE AGENTS ON HOUSE PRICES NEAR ENVIRONMENTAL DISAMENITIES

1.1 Introduction

The impact of environmental disamenities on residential house prices has been broadly examined in the environmental and real estate economics literature. Previous studies have used Rosen's (1974) hedonic price model to demonstrate that potential sources of environmental risks, such as landfills, generate considerable welfare losses from decreased property values (Reichert et al., 1991; Nelson et al., 1992; Hite et al., 2001), yet others have found mixed evidence to suggest such consequences (Anstine, 2003). We extend both the environmental and urban economics literature by examining whether house price impacts of environmental disamenities are affected by the intervention of real estate agents.

The existence of real estate brokerage services is assumed a result of the imperfect flow of information that characterizes transactions in the housing market (Jud, 1983). Real estate agents play an important role in this market by facilitating the matching of potential buyers to sellers. They also have considerable knowledge about the operation of the market and the transfer of properties, providing both buyers and sellers with additional empowerment to bargain over the transaction price of a property (Barlowe, 1986).

In this essay, we consider the impact of information about the presence of a landfill close to a house on buyer, seller and real estate agent' bargaining power, and its subsequent impact on house prices. When homebuyers are informed about the presence of a landfill close to a house, their bargaining power to bid down the house price is potentially increased. On the other hand, a real estate agent, acting as a sellers' agent, has an incentive to avoid providing such information because their commission is based on the selling price.

In this essay, we provide empirical evidence that investigates hypotheses from theoretical studies in the real estate literature. For example, Yavas's (1992) search and bargaining model of the real estate market predicts that in theory, sellers obtain higher prices for their properties when they hire a real estate agent, [1]but the difference between transaction prices with and without an agent is less than the commission fee. Our empirical findings suggest that real estate agents are able to obtain considerable surplus from selling a house when it is located close to an environmental disamenity, but the surplus erodes as distance from the disamenity is increased. We attribute this result to differences in information between buyers, sellers, and real estate agents about the presence of the landfill.

To implement this analysis, our study areas consist of housing transactions made in 1990 around four different landfills in Franklin County, Ohio. The dataset was constructed from auditor's real estate records and augmented with census block group micro data to obtain demographic variables, and with multiple listing service data to

[1] In this paper we assume the real estate agent works only for the seller.

identify Realtor® brokered transactions; variables from maps were also created to account for environmental and neighborhood characteristics. Using this data, we address a second topic of concern in the hedonic literature; that is, we find evidence that studies using the hedonic price technique may underestimate property impacts and implicit prices of characteristics when the data are limited to those obtained from agent mediated transactions alone, such as when using multiple listing service data.

1.2 Literature review

Rosen's (1974) hedonic price model has been extensively used by researchers to examine the impact of a number of factors on house prices. For example, Linneman (1981), Parsons (1986), and Quigley (1984) use this technique to analyze the willingness to pay for housing characteristics, while Hite et al. (2001), Kohlhase (1991), Nelson et al. (1992), and Reichert et al. (1992) study the impact of waste sites on property values. Several studies analyze the importance of information on values of properties that are potentially affected by environmental disamenities. In this vein of research either media coverage or public announcements are used to capture the impact of information about environmental disamenities on property prices. Kohlhase (1991) finds that public releases of information by the Environmental Protection Agency about superfund sites capitalize into lower property values. Kask and Maani (1992) also find that consumer responsiveness to changes in quantity and quality of information can lead to biased hedonic price estimates, while Kiel and McClain (1995) find that property values are inconsistently affected over time by rumors about the construction and operation of an incinerator. In another study, McCluskey and Rausser (2001) find that media coverage increases perceived risk from a hazardous waste site, which in turn, lowers property values.

Anstine (2003) argues that the degree to which polluting activities or other perceived environmental disamenities influence house prices is a function of the information available to homebuyers about the risk associated with their presence. He examines the impact of noticeable and non-visible disamenities on property values. Using information on property values and housing characteristics for 171 houses located in Jonesborough, Tennessee, Anstine finds that the impact of perceivable contaminating activities on house values increases as the distance to the contaminating source is reduced, while the existence of non-perceivable polluting sources are not capitalized in house prices.

This essay is an extension of Hite et al. (2001) using the hedonic price model to quantify the property-value impact of a change in environmental quality near landfills. House prices at various distances from landfills are predicted and it is found that welfare gains measured by property-value increases are positively related to landfill life expectancy. Hite et al. (2001) also account for differences in buyer information about neighborhood characteristics by including a variable that measures the percentage of people that moved to their current location from outside the state or country, under the assumption that local buyers may be better informed about local environmental conditions. They find a positive and significant relationship between house prices and the number of outside movers, implying that outside movers may not be able to bargain down the price of a house because they lack information about local disamenities compared to long-time residents of the area. The results also suggest that if outside movers are more likely to use real estate agents, there may be a discernible interaction between real estate transactions and environmental impacts on house prices.

Hite (1998) uses individual survey data to account for the impact of knowledge about environmental disamenities on property prices. A sample selection model that matches data from a household survey with housing transactions, census data and house characteristics is estimated. Homebuyers are found to be poorly informed about the presence of environmental disamenities, but those who are informed are able to significantly bid down the price. The results are strengthen by the fact that uninformed sellers indirectly benefit from the presence of informed sellers, as they could effectively bring down the average home prices near the disamenity.

McClelland et al. (1990) analyze data from a survey conducted in a Los Angeles, California community located near a landfill site. The study focuses on homeowners' health risk beliefs from being close to the landfill, finding significant differences between homeowners' and expert judgments' perceived risk from being located in an area affected by the presence of a landfill. They estimate the impact of the landfill on property values using the hedonic price technique using a sample of 178 home sales obtained through a real estate information network. Out of sample predictions of community-wide property value losses attributable to health risk beliefs for the 4,100 homes near the site were around $40.2 million or 7.22 percent of the total average market value of the properties before the site stopped accepting new waste shipments, and $19.7 million or 3.54 percent afterwards.

However, none of the previous studies consider the impact that real estate agents could have on house sales near environmental disamenities, nor has this issue been addressed in the urban economics literature. We find considerable literature addressing the impact of real estate agents on the relationships between selling price of a house and the time it takes to sell it, the availability and quality of information on the house, as well as seller heterogeneity (Glower et al., 1998), but no study has determined the impact of real estate agents on hedonic house prices as in the current study.

Yinger (1981) was first to formalize a theoretical model of supply and demand for brokerage services, while Jud (1983) expands the model and provides the first empirical study on the impact of real estate agents on house prices and consumption. He points out that home sellers contract with real estate agents because sellers lack complete information about potential buyers and reservation willingness to pay for the house. Jud finds that real estate agents do not seem to affect house prices, yet they do produce some "form of housing-industry advertising which has an important effect on housing consumption" (page 80). He further suggests that although real estate agents might not be successful in obtaining higher prices for a house, they might persuade buyers to buy bigger and more expensive properties.

Yavas (1992) expands the literature by developing a search and bargaining model of the real estate market. His theoretical results suggest that sellers and buyers' search intensities are reduced when they employ a real estate agent, and that the seller receives a higher price, but the increase in price is smaller than the commission fee. The bargaining powers of the buyer and the seller directly determine the portion of the commission fee covered by the increase in price. Some of these results were tested experimentally in Yavas et al. (2001). They found that agents increase the sale price, but the amount of time to realize an agreement also increases, a result particularly relevant to our study. That is, the proximity of a landfill and the possibility of asymmetric information between the buyer, the seller, and their real estate agent about its presence might result in differences in bargaining power, having an impact on the transaction price of the house when it is closer to the disamenity.

With respect to the impact of type of data in the estimation of hedonic price models, Pollakowski (1995) mentions that "the most complete, albeit possibly the most expensive, source of house price and characteristic data is a combination of two data sources: transaction data and assessment data (page 379)." With this in mind, research papers that estimate hedonic price models using only Multiple Listing Service (MLS) may underestimate the impact of environmental disamenities on property values since the presence of an intermediary in the negotiation period has an impact on house prices. Papers using MLS data include Anglin, Rutherford, and Springer (2003); Harding, Knight, and C. F. Sirmans (2003); Harding, Rosenthal, and Sirmans (2003); and Turnbull and Sirmans (1993).

1.3 The theoretical hedonic framework

Following Rosen (1974), we present the hedonic framework applied to the real estate market. On the demand side, a household purchases a home which is comprised of a bundle of attributes, *Z*, environmental quality, measured by the distance *D* to a landfill, and a numeraire good, *X*, with price equal to one. The household maximizes utility from purchasing the house subject to income *Y*. The utility maximization problem takes the form:

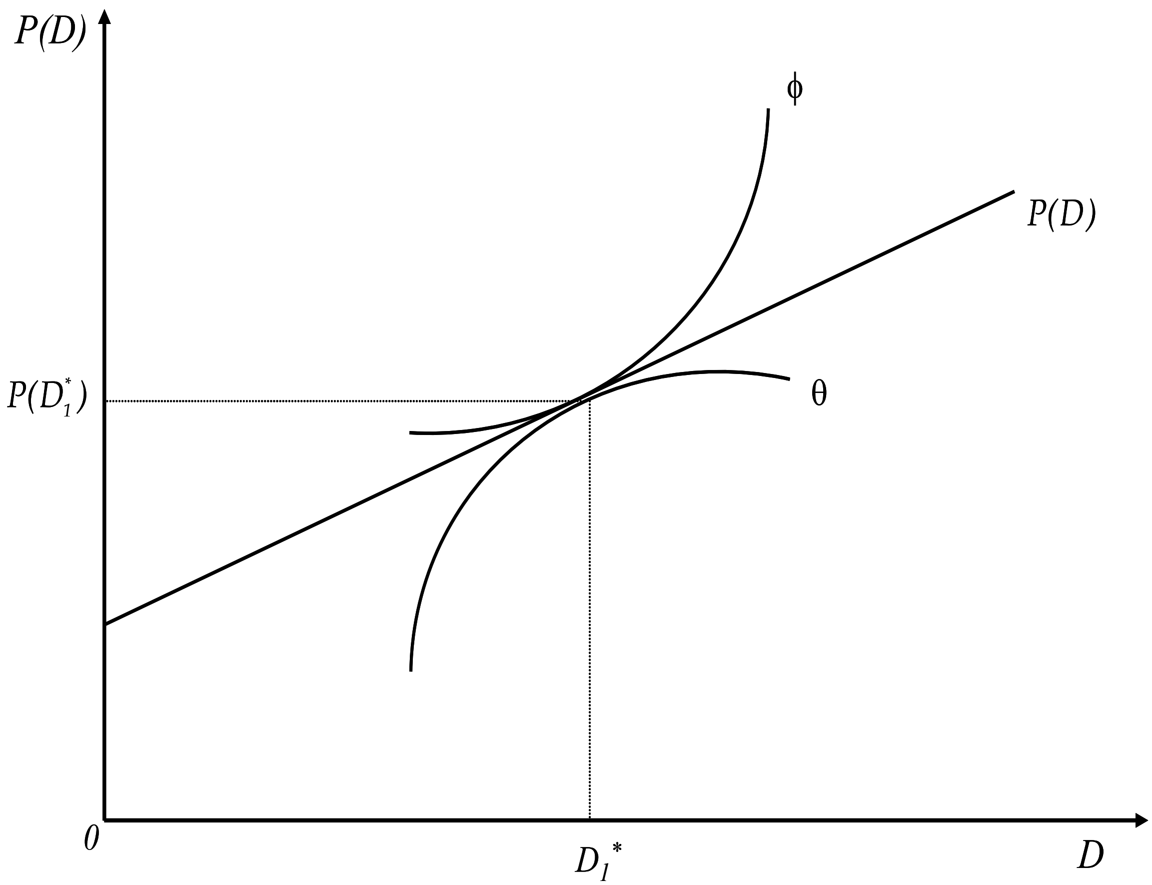
$$Max\, U = u(Z, D, X; \delta, \Theta) \text{ s.t. } Y = P(Z, D) + X \qquad [1]$$

where Z, D, and X are defined as before, δ is a vector of buyer's characteristics, and Θ is the buyer's information on the landfill (whether informed of its presence or not, as well as quality of information).

On the supply side, home sellers maximize profits from sale of the house:

$$Max\ \Pi = P\,(Z, D) - C\,(Z, D, X; \gamma, \Omega) \qquad [2]$$

where all variables are defined as before, C is a cost function which represents the cost of offering a house for sale, γ represents seller's characteristics, and Ω is the seller's information on the landfill (whether informed of its presence or not, as well as quality of information). It is assumed in this case that the house is sold without a real estate agent. From the utility and profit maximization problem, bid and offer functions are derived. In perfectly competitive markets, the hedonic price function $P\,(Z^*, D^*; \delta, \Theta, \gamma, \Omega)$ occurs at the tangency of the bid and offer curves. Each point along the hedonic price function represents an equilibrium price representing the lowest transaction price possible for the house with an optimal set of characteristics paid by buyers, and the highest price possible obtained by sellers. Figure 1.1 presents the basic hedonic price model in perfectly competitive markets. Bid curves (θ) and offer curves (ϕ) are represented as a function of environmental quality, measured by the distance D to the landfill, holding all other characteristics constant. For simplicity of exposition, we assume a hedonic price that is a linear function of distance from the landfill, *ceteris paribus*. The market value of the property at various distances from the landfill is given by the locus of tangencies of the buyers' bid curve (θ), or marginal willingness to pay, and the sellers' offer curve (ϕ), or marginal cost of providing the property's characteristic.



ϕ = offer
θ = bid

Figure 1.1 Expected hedonic price function in competitive markets

When homogenous products are dealt in thick markets, the condition of free entry and exit for many buyers and sellers guarantees that all existing surpluses from transactions made in the market are driven to zero. This situation does not hold in thin markets, such as the real estate market, where products are heterogeneous. Most transactions are highly personal, involving only a few transactions with few buyers and sellers, which most likely will bargain over any existing excess surpluses. Harding, Rosenthal, and Sirmans (2003) suggest that a property is not traded under these conditions, i.e. it is traded in thin markets where bargaining plays an important role in the determination of the characteristic's transaction price (shadow price). When positive excess surplus exists, it is divided into the final buyer and the seller depending on their bargaining power. Figure 1.2 presents the hedonic price function with excess surplus at a distance D_1^* from the landfill, *ceteris paribus*.

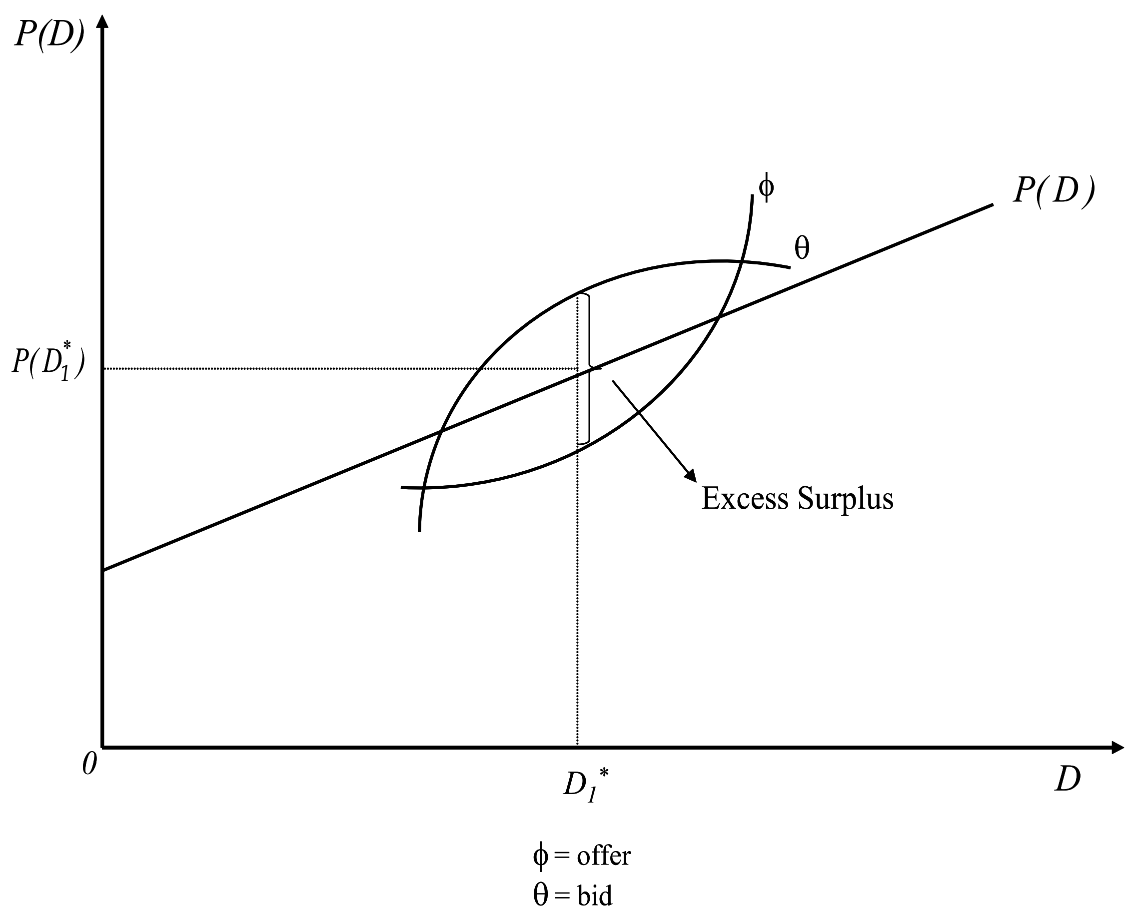


Figure 1.2 Expected hedonic price function with excess surplus without a real estate agent

It is expected that the excess surplus increases with distance from the landfill. Closer to the landfill, sellers are expected to have higher selling costs because of higher advertising and search costs, while bidders are expected to lower their bids for the house, reducing the existing surplus in the market. As in Yavas's (1992) theoretical search and bargaining model of the real estate market we set the ex-post transaction price of a bargaining solution equal to the seller's property valuation plus a portion of the difference between the buyer's property valuation and the seller's property valuation. This result can be used to determine the final transaction price using a hedonic price framework in markets where excess surplus exists.

Assuming all housing characteristics constant except environmental quality, we can assume that the ex-post property price will be:

$$P(D^*)^{NR} = \phi(D^*) + \omega\left[\theta(D^*) - \phi(D^*)\right] \qquad [3]$$

where D^* represents house distance at the utility maximizing level of all house characteristics, ω reflects the portion of surplus between the buyer's bid and the seller's offer that goes to the seller, (1 - ω) is the portion that goes to the buyer, ω E [0,1], and ^{NR} stands for a price obtained without a real estate agent. This price assumes that ω is exogenous and only a function of the seller's and the buyer's bargaining power. The equation states that the final transaction price is equal to the seller's cost of supplying the house at a particular distance from the landfill plus a portion of the difference between what the buyer is willing to pay for the property and the seller's offer. The first derivative of [3] with respect to distance from the landfill is:

$$\frac{\partial P(D^*)^{NR}}{\partial D} = \underset{(-)}{\frac{\partial \phi(D^*)}{\partial D}} + \omega\left[\underset{(+)}{\frac{\partial \theta(D^*)}{\partial D}} - \underset{(-)}{\frac{\partial \phi(D^*)}{\partial D}}\right] \qquad [4]$$

The first partial derivative is expected to be negative since increasing the distance to the landfill results in lower selling costs. The resulting sign of the partial derivatives within the brackets is positive, since it is expected that the surplus increases as we move away from the landfill because of higher bid curves and lower offer curves. The final price is expected to be an increasing function of distance to the landfill.

When a seller uses a real estate agent to sell a house, the seller agrees to pay the broker a commission that is based on the final transaction price. The ex-post price when a real estate agent is used is derived by rewriting Yavas's (1992) model an including distance as an explicit measure of environmental quality. Algebraically we can say that the total net surplus in this case is equal to $\theta(D^*) - \phi(D^*) - cP(D^*)^R$, where c is the commission rate and $P(D^*)^R$ denotes a price when a real estate agent is involved in the transaction. The bargaining solution gives the seller $\omega\left[\theta(D^*) - \phi(D^*) - cP(D^*)^R\right]$ of this surplus. Also, by definition, a transaction price of $P(D^*)^R$ generates a surplus of $P(D^*)^R - \phi(D^*) - cP(D^*)^R$ for the seller. Equating these two surplus equations we obtain:

$$P(D^*)^R = \frac{\phi(D^*) + \omega\left[\theta(D^*) - \phi(D^*)\right]}{1 - c + \omega c} = \frac{P(D^*)^{NR}}{1 - c + \omega c} \qquad [5]$$

This result is consistent with Yavas's (1992) theoretical result, in that real estate agents obtain higher prices for their clients, ceteris paribus, yet the increase in price is less than the commission fee. Figure 1.3 presents the basic hedonic price model for transactions done with and without a real estate agent for properties located at various distances from a landfill, holding all other characteristics constant.

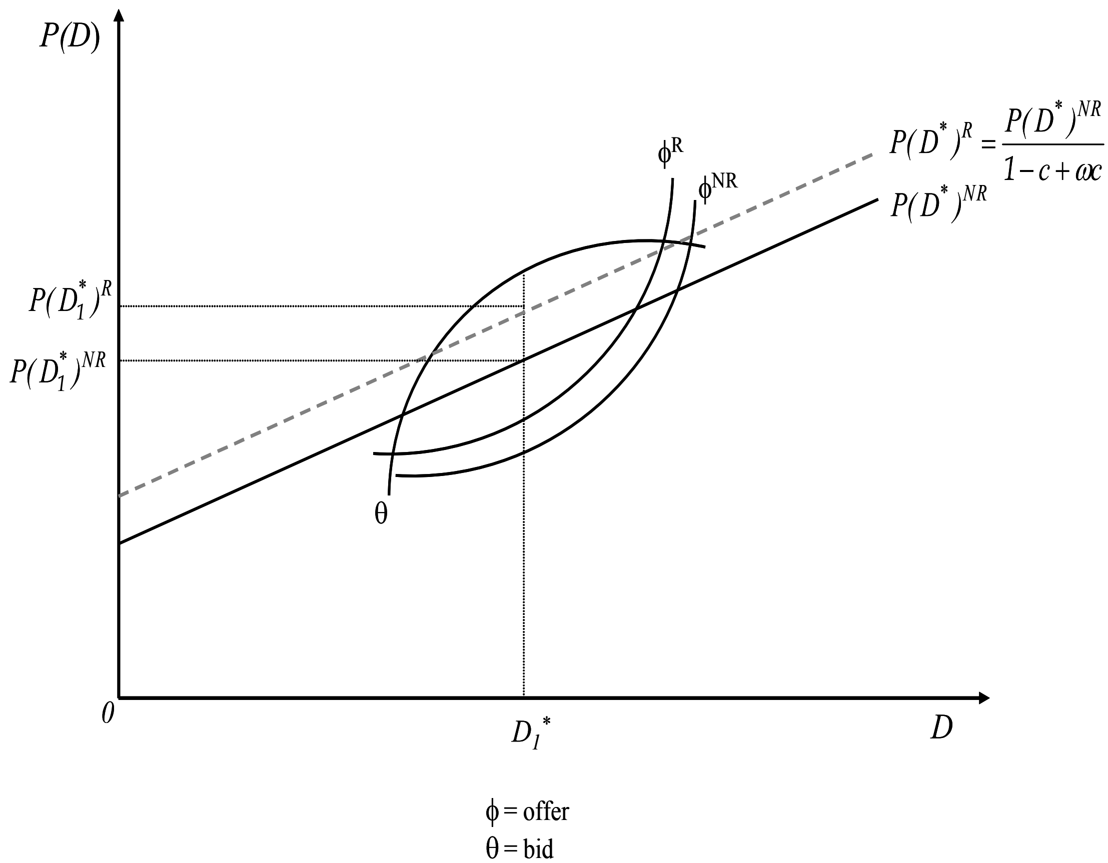


Figure 1.3 Expected hedonic price function with and without a real estate agent

It can be seen that hiring a real estate agent increases the seller's offer function given that the seller needs to pay a fee for the services. This results in a smaller excess surplus and the final transaction price will depend on the size of ω. Formally, we hypothesize that the difference between the price obtained by the real estate agent less the commission rate and the price that the seller could have obtained by selling the house alone may be positive closer to the landfill, but converges towards Yavas's theoretical prediction as we move further from the landfill.

1.4 The hedonic framework with differing information

The previous section provides a theoretical framework for a testable hypothesis on the difference between the price obtained through selling the house alone and the price obtained through selling a house with a real estate agent. This framework, though, assumes that both the buyer's and the seller's set of information on the landfill is constant. In this section we will allow both the buyer and the seller to know or not know about the presence of the landfill. The quality of the information will be held constant, and we will assume that an informed seller who sells the house through a real estate agent provides this information to his or her agent.

For the case of an uninformed buyer meeting an uninformed seller without a real estate agent, the final price is:

$$P(D^*,\Theta_0,\Omega_0)^{NR} = \phi(D^*,\Omega_0) + \omega\left[\theta(D^*,\Theta_0) - \phi(D^*,\Omega_0)\right] = P_{00}^{NR} \qquad [6]$$

where Θ_0 represents an uninformed buyer, Ω_0 represents an uninformed seller, and all other variables are defined as in equation [3].

The case of an informed buyer meeting an informed seller without a real estate agent is:

$$P(D^*,\Theta_1,\Omega_1)^{NR} = \phi(D^*,\Omega_1) + \omega\left[\theta(D^*,\Theta_1) - \phi(D^*,\Omega_1)\right] = P_{11}^{NR} \qquad [7]$$

where Θ_1 represents an uninformed buyer, Ω_1 represents an uninformed seller, and all other variables are defined as in equation [3]. Comparing the two previous cases, it is expected that $P_{00}^{NR} > P_{11}^{NR}$ given that knowledge about the landfill would lower both the seller's offer curve and the buyer's bid curve at any distance from the landfill.

The cases of an uninformed buyer meeting an informed seller or vice versa are interesting to analyze. The final price for an informed seller meeting an uninformed buyer is:

$$P(D^*, \Theta_0, \Omega_1)^{NR} = \phi(D^*, \Omega_1) + \omega\left[\theta(D^*, \Theta_0) - \phi(D^*, \Omega_1)\right] = P_{01}^{NR} \qquad [8]$$

while the final price for an informed buyer meeting an uninformed seller is:

$$P(D^*, \Theta_1, \Omega_0)^{NR} = \phi(D^*, \Omega_0) + \omega\left[\theta(D^*, \Theta_1) - \phi(D^*, \Omega_0)\right] = P_{10}^{NR} \qquad [9]$$

1.5 Data description

The data used in the analysis are based on 2,858 actual transactions on single-family homes and condominiums located near four different landfill areas in Franklin County, Ohio, during 1990. Of the total transactions, 37.47% were done through board-certified real estate agents (Realtors®). This percentage is relatively small, but some transactions may have been actually conducted through non-board agents, and hence are not captured in our data. Two of the landfills were in urban areas and closed (Alum Creek and Obetz), and the other two were in suburban areas and still open (Gahanna and Grove City). Table 1.1 provides information on the characteristics of the four study areas; Figure 1.4 illustrates the geographic areas, while Table 1.2 and Table 1.3 provide variable definitions and some descriptive statistics of transactions made with and without a real estate agent.

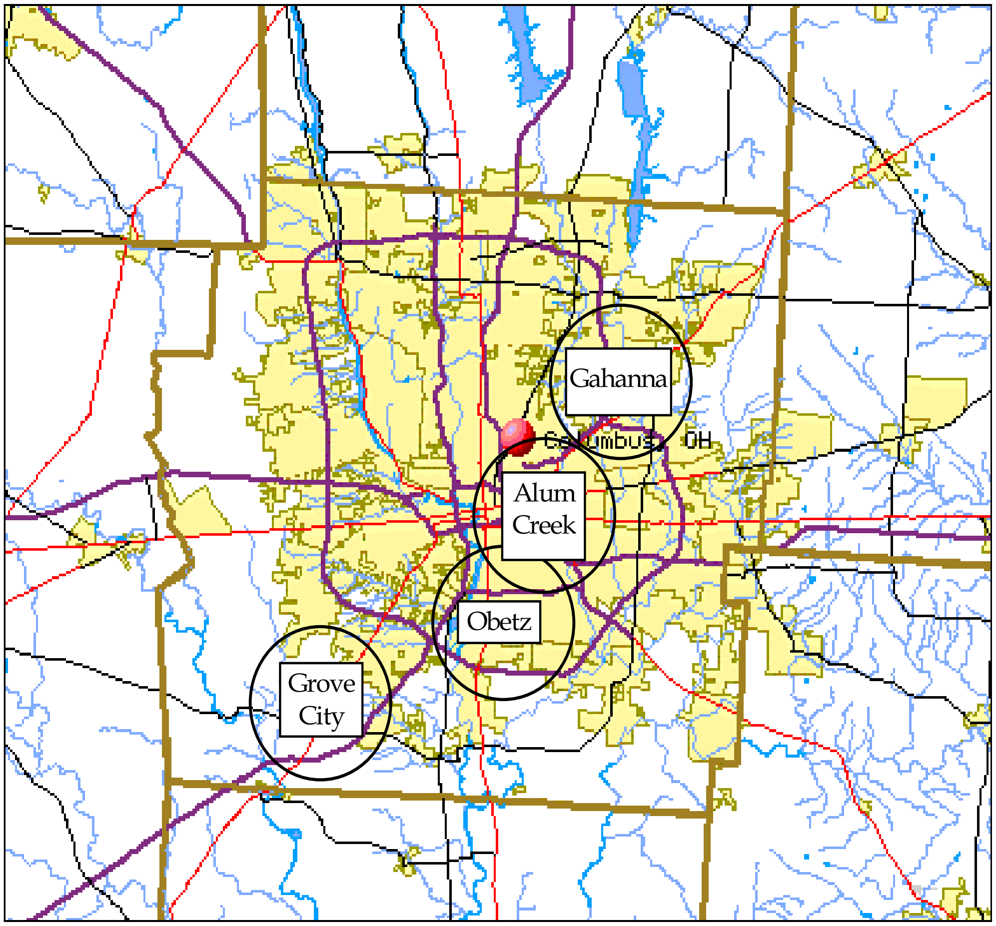
It can be seen that structural characteristics of houses transacted through a real estate agent differ from transactions made without an agent. Real estate agents tend to sell relatively smaller, more expensive, and newer houses, though the average distance to the closest landfill does not differ much between types of transactions. The Gahanna area has the highest average yearly rental equivalent[2] in 1990 with $10,129.22 for transactions made without a real estate agent and $9,331.89 with a real estate agent. The lowest average yearly rental equivalent occurs in Obetz with $4,915.64 for transactions made without a real estate agent and $5,489.12 for transactions made with a real estate agent.

Table 1.1 Characteristics of study area

Study Area	Landfill Type	Life Expectancy	Urban Characteristics
Gahanna	Sanitary	2 Years	Mostly rural
Grove City	Sanitary	20 Years	Mixed rural and suburban
Obetz	Demolition	- 6 Years	Mixed established suburban, established urban
Alum Creek	Demolition	- 11 Years	Mostly suburban

Source: Hite et al. (2001)

[2] Rental equivalents are calculated by using the prevailing mortgage interest rate at the time of sale, times sale price.



Source: Hite et al. (2001)

Figure 1.4 Map of study areas

Table 1.2 Definitions of hedonic regression variables

Variable name	Definition
RENT	Yearly rent equivalent
DISTALC	Distance to Alum Creek landfill
DISTOBZ	Distance to Obetz landfill
DISTGHA	Distance to Gahanna landfill
DISTGRC	Distance to Grove City landfill
DISTCBD	Distance to Central Business District
DISTLF	Distance to closest landfill
CRIMERATE	Crime rate index created from Federal Bureau of Investigation Uniform Crime Statistics. Represent total occurrences of both violent and nonviolent crimes per 1,000 populations
PROXAIRPORT	Dummy variable that takes a value of 1 for transactions falling within a 1.5 miles from the outer perimeter of Port Columbus Airport, 0 otherwise
PROXRR	Dummy variable that takes value of 1 for transactions within 1.5 miles of railroads, 0 otherwise.
SCHOOLINDEX	School competitiveness index constructed from proprietary data obtained from the Ohio State University Admissions Office.
%CBGOUTSTATE	Total percentage of households in a block group that moved to their current location within the five years previous to 1990 from locations outside the state or from outside the country.
SUMMER	Dummy variable with a value of 1 for transactions made in second half of year, 0 otherwise.
REA	Real Estate Agent dummy variable; 1 for transactions made with a real estate agent, 0 otherwise.
NEARFREEWAY	Dummy variable that takes a value of 1 for transactions within 1.5 miles of freeways, 0 otherwise.
FAMILY	Dummy variable that takes a value of 1 for intrafamily transactions, 0 otherwise.

Table 1.1 Definition of hedonic regression variables (continued)

Variable name	Definition
BANK	Dummy variable that takes a value of 1 for transactions in which financial institutions were involved, 0 otherwise.
CORPORATE	Dummy variable that takes a value of 1 for corporate transactions, 0 otherwise.
ESTATE	Dummy variable that takes a value of 1 for transactions purchased from an estate, 0 otherwise.
OUTLIER	Dummy variable that takes a value of 1 for transactions in which prices appeared artificially high or low for a given neighborhood, 0 otherwise.
NEARPARK	Dummy variable that takes a value of 1 for transactions adjacent to parks, 0 otherwise.
COUNTRY	Dummy variable that takes a value of 1 for transactions adjacent to country club, 0 otherwise.
LOTSIZE	Lot size of house, in squared feet.
SQFTSTRUCT	Squared footage of house.
SQFTGARAGE	Squared footage of garage.
NROOMS	Number of rooms in house.
NBEDROOMS	Number of bedrooms in house.
FULLBATH	Number of full bathrooms in house.
HALFBATH	Number of half bathrooms in house.
STRUCTUREAGE	House age.
CENTRALAIR	Dummy variable that takes a value of 1 if the house posses central air conditioning, 0 otherwise.
FIREPLACE	Dummy variable that takes a value of 1 if the house posses a fireplace, 0 otherwise.
BRICK/MASONRY	Dummy variable that takes a value of 1 if the house is made of masonry construction, 0 otherwise.

Table 1.3 Selected descriptive statistics

Variable	Alum Creek		Obetz		Gahanna		Grove City	
	No REA ($N = 890$)	REA ($N = 501$)	No REA ($N = 262$)	REA ($N = 130$)	No REA ($N = 488$)	REA ($N = 342$)	No REA ($N = 147$)	REA ($N = 98$)
RENT	\$6,075	\$7,965	\$4,916	\$5,489	\$10,129	\$9,332	\$7,977	8,785
SQFTSTRUCT	1,419	1,418	1,181	1,170	1,630	1,564	1,412	1,440
SQFTGARAGE	8,635	8,681	9,137	9,056	9,258	9,235	9,404	9,337
STRUCTUREAGE	53.44	46.23	29.10	25.623	22.88	23.45	26.65	24.23
PROXAIRPORT	0.03	0.02	0.38	0.00	0.49	0.39	0.00	0.00
NEARFREEWAY	29.10	23.15	44.27	41.54	13.32	17.54	36.73	19.39
PROXRR	17.98	17.56	44.66	0.40	5.53	1.75	28.57	17.35
%CBGOUTSTATE	3.60	4.34	4.64	4.67	10.43	8.56	41.00	4.66
CRIMERATE	124.27	107.68	72.23	74.36	52.75	53.68	59.14	41.00
SCHOOLINDEX	29.99	38.31	28.34	27.19	66.38	65.77	9.14	59.16
DISTLF	2.13	2.05	1.85	1.85	2.14	2.41	2.62	2.75
DISTCBD	4.76	5.46	8.18	8.06	11.89	12.00	12.22	11.95

Note: REA = Real estate agent

The housing transaction data are merged with a database of housing, neighborhood, transaction types, and environmental characteristics. The housing characteristics come from one year (1990) of county auditor's records and include age of structure, number of rooms, bedrooms, baths, half baths, porches, stories, square footage of structure, garage and lot, and dummy variables for condominiums, central air conditioning, fireplace, and masonry construction. The neighborhood characteristic variables are created from street maps of Franklin County. The variables include dummy variables indicating proximity to the airport and railroads, freeways, parks, country clubs, and continuous variables for crime rate indices and school competitiveness indices. In addition, dummy variables are created for the following transaction types: intra-family transactions, corporate transactions, transactions in which financial institutions are involved, and transactions from an estate. It is thought that inclusion of such variables may help capture unobserved heterogeneity in house quality (Hite, 2005). Further, they are representative market conditions prevailing at the time of the study. The distance of each property to the landfills measures the environmental characteristic.

We also include the total percentage of people moving into the study area from out of state at the census block group level within the five years prior to 1990 to account for differences in buyer information about neighborhood characteristics. Even though this variable is not a direct measure of the different levels of information about the disamenity that may be affecting house prices, it has been found in other studies that persons coming from abroad are less knowledgeable of the real estate market conditions at the time of purchasing a house, and therefore are likely to be uninformed of the presence of a landfill close by. Hite et al. (2001), for example, find a positive and significant price impact for this variable. For more information on the data used, refer to Hite et al. (2001).

1.6 Estimation of the hedonic price function

Various models are estimated to account for the impact of real estate agents on property prices located close to landfills. Significant values of White's test for heteroscedasticity[3] led us to use a heteroscedasticity-consistent covariance matrix estimator. All the following tables present heteroskedasticity-corrected results.

The basic hedonic model is presented in equation [10]. We modify Hite et al.'s (2001) model by including an intercept dummy variable for transactions completed through a real estate agent (REA) plus interactions between the real estate dummy variable and the linear and squared distances of each house to each landfill. The model takes a mixed log-linear specification with the housing characteristics, park proximity, and freeway access segmented over the four study areas, while all other neighborhood characteristics and environmental goods are pooled. We use this specification because Hite et al. (2001) finds it, after a series of combinations of segmentation of neighborhood and environmental variables, to be the best model specification to fit the data (Hite et al., 2001).

[3] Calculated White's test statistic = 2,779.

$$
Rent = exp\left\{\begin{array}{l}
\alpha_{ALC} + \alpha_{OBZ} + \alpha_{GHA} + \alpha_{GRC} \\
+\alpha_5(DISTALC) + \alpha_6(DISTALC)^2 \\
+\alpha_7(DISTOBZ) + \alpha_8(DISTOBZ)^2 \\
+\alpha_9(DISTGHA) + \alpha_{10}(DISTGHA)^2 \\
+\alpha_{11}(DISTGRC) + \alpha_{12}(DISTGRC)^2 \\
+\alpha_{13}\ ln(DISTCBD) + \alpha_{14}(CRIMERATE) + \alpha_{15}(PROXAIRPORT) \\
+\alpha_{16}(PROXRR) + \alpha_{17}(SCHOOLINDEX) \\
+\alpha_{18}(\%CBGOUTSTATE) + \alpha_{19}(SUMMER) \\
+\alpha_{20}(REA) + \alpha_{21}(REA)(DISTALC) + \alpha_{22}(REA)(DISTALC)^2 \\
+\alpha_{23}(REA)(DISTOBZ) + \alpha_{24}(REA)(DISTOBZ)^2 \\
+\alpha_{25}(REA)(DISTGHA) + \alpha_{26}(REA)(DISTGHA)^2 \\
+\alpha_{27}(REA)(DISTGRC) + \alpha_{28}(REA)(DISTGRC)^2 \\
+DV_i\left[\begin{array}{l}
\alpha_{29}(NEARFREEWAY) + \alpha_{30}(FAMILY) + \alpha_{31}(BANK) \\
+\alpha_{32}(CORPORATE) + \alpha_{33}(ESTATE) \\
\alpha_{34}(OUTLIER) + \alpha_{35}(NEARPARK) + \alpha_{36}\ ln(LOTSIZE) \\
+\alpha_{37}\left(\frac{SQFTSTRUCT}{100}\right) + \alpha_{38}\left(\frac{SQFTGARAGE}{100}\right) \\
+\alpha_{39}(NROOMS) + \alpha_{40}(NBEDROOMS) \\
+\alpha_{41}(FULLBATH) + \alpha_{42}(HALFBATH) \\
+\alpha_{43}(STRUCTUREAGE) + \alpha_{44}(CENTRALAIR) \\
+\alpha_{45}(FIREPLACE) + \alpha_{46}(BRICK / MASONRYY)
\end{array}\right]
\end{array}\right\} + \varepsilon \qquad [10]
$$

Conforming to Yavas's theoretical prediction and our main hypothesis, we expect real estate agents to obtain a higher price for sellers at any distance to the landfills, assuming all other housing characteristics are held constant. This impact is captured by a positive real estate agent dummy estimate. Further, with our hypothesis, we expect real estate agents to have an impact on the implicit price of the distance characteristic in the hedonic house price function, *ceteris paribus*. We expect real estate agents to increase the implicit price as we move closer to the landfill. This implies that real estate agents are able to reduce the price impact of proximity to the landfill. We believe that they play an important role in the bargaining process of the transaction, and potentially impact the surplus extracted in the transactions with respect to distance to the landfill, all else held constant.

Table 1.4 presents the estimated basic hedonic price model. In accordance with our expectations, the estimated model coefficient for the real estate agent dummy intercept is significantly positive, while the estimated interaction coefficients with the distance to the landfill are mixed. All the interactions with the linear distances to the four landfills are negative and statistically significant, suggesting that realtors mitigate the extent to which house prices are bid down in the face of a disamenity. On the other hand, realtor interactions with distance squared are positive and significant in Alum Creek and Obetz, negative and significant in Gahanna, and negative and insignificant in Grove City.

Table 1.4 Estimated hedonic price function including real estate agent variable

Common Variables	Parameter Estimate		t-Stat.
α_{ALC}	-0.1389	**	-1.95
α_{OBZ}	1.5753	***	3.69
α_{GHA}	0.0389		0.33
α_{GRC}	2.3139	***	5.00
DISTALC	0.2934	***	6.95
DISTALC ^{2}	0.2820	***	4.09
DISTOBZ	0.1255	***	3.67
DISTOBZ ^{2}	0.4952	***	6.10
DISTGHA	-0.0324	***	-5.06
DISTGHA ^{2}	-0.0161	***	-3.49
DISTGRC	0.0098	**	2.38
DISTGRC ^{2}	-0.0102	**	-1.98
LN(DISTCBD)	-0.4429	***	-3.66
CRIMERATE	-0.0017	**	-2.31
PROXAIRPORT	-0.1572	***	-3.48
PROXRR	-0.0957		-1.59
SCHOOLINDEX	0.0044	***	4.71
%CBGOUTSTATE	1.0427	***	2.85
SUMMER	-0.0077		-0.25
REA	4.8943	***	6.60
REA x DISTALC	-0.1515	***	-3.00
REA x DISTALC ^{2}	0.0295	***	4.50
REA x DISTOBZ	-0.2115	***	-4.64
REA x DISTOBZ ^{2}	0.0146	***	4.51
REA x DISTGHA	-0.1035	**	-2.18
REA x DISTGHA ^{2}	-0.0134	***	-3.13
REA x DISTGRC	-0.2243	***	-2.90
REA x DISTGRC ^{2}	-0.0020		-0.40

Table 1.4 Estimated hedonic price function including real estate agent variable (continued)

Market Segment	Alum Creek		Obetz		Gahanna		Grove City	
Segmented Variables	Parameter Estimate	t-stat	Parameter Estimate	t-stat.	Parameter Estimate	t-stat.	Parameter Estimate	t-stat.
NEARFREEWAY	-0.0841	-1.31	-0.0572	-1.11	0.0483	1.04	0.3096 ***	4.02
FAMILY	-0.6573 ***	-4.73	-0.3542 ***	-3.33	-0.3955 ***	-3.96	-0.7671 ***	-3.76
BANK	-0.1999	-1.60	-0.3272 ***	-4.65	-0.2161 ***	-3.06	-0.2690 ***	-2.54
CORPORATE	-0.1387 **	-2.34	-0.1373 *	-1.73	-0.1607 **	-1.98	0.0146	0.15
ESTATE	0.0172	0.41	-0.0975 *	-1.64	-0.0957 **	-2.07	-0.2406 *	-1.77
OUTLIER	-0.8830 ***	-4.38	-1.6893 **	-2.20	-1.0730 ***	-2.99	-0.3349	-1.19
NEARPARK	0.1182	0.73	0.0370	0.95	-0.0146	-0.16	-0.0571	-0.76
COUNTRY	-	-	-	-	0.1336 *	1.84	-0.3476 ***	-3.47
LN(LOTSIZE)	0.2144 ***	6.51	0.1011 ***	3.24	0.1504 ***	5.42	0.0522	1.41
SQFTSTRUCT	0.0220 ***	4.38	0.0263 ***	2.47	0.0244 ***	3.52	0.0277 ***	4.82
SQFTGARAGE	0.0187 **	2.24	0.0352 ***	5.57	0.0237 **	2.47	0.0530 ***	3.96
NROOMS	-0.0175 *	-1.86	0.0024	0.07	0.0901 **	2.14	0.0562 *	1.88
NBEDROOMS	-0.0244	-0.61	0.0184	0.36	-0.0272	-0.49	-0.0305	-0.73
FULLBATH	0.2090 ***	3.55	0.0714	1.38	0.0246	0.44	0.0695	1.01
HALFBATH	0.0874 **	2.07	-0.0739 *	-1.71	0.1057 **	1.97	-0.0541	-0.75
STRUCTUREAGE	0.0010	0.69	-0.0063 ***	-3.05	0.0012	0.49	-0.0115 ***	-5.45
CENTRALAIR	0.2803 ***	4.28	0.0141	0.48	-0.1549 ***	-2.97	-0.1791 ***	-3.41
FIREPLACE	0.2029 ***	4.40	0.0179	0.33	0.1430 ***	3.62	0.0540	1.03
BRICK/MASONRY	0.0538	1.31	0.0580	1.15	-0.0235	-0.57	0.0213	0.39
N: 2,858								
Adjusted R^2: 0.8225								

1.7 Assessing endogeneity and sample selection bias

Two major concerns are addressed in this section: first, the possibility that the real estate variable is endogenously determined, and second, that sellers near landfills purposely engage with real estate agents in hopes of improving their bargaining power with respect to potential buyers, resulting in selection bias. Endogeneity in this case would occur if hiring a real estate agent is correlated with unobservable characteristics that affect the yearly rent equivalent relegated to the error term. For example, the market's thickness has an impact on both the number of transactions conducted by a real estate agent as well as the final transaction price of the property. We tested for endogeneity of the real estate agent variable by modeling the probability of hiring a real estate agent as a function of the percentage of people in the Census Block Group (CBG) with college degree, the CBG average income, and the distance of each house to the closest landfill. We also included the housing turn over rate (TRNOVER) as an explanatory variable to capture some unobservable characteristics of the local housing market. A calculated Likelihood Ratio test statistic of 0.00 for the restricted rent equation without the predicted probability of hiring a realtor versus the unrestricted rent equation indicates that the real estate variable can be treated as exogenous.

Two possible sources of selection bias are considered in this essay. First, it is possible that house sellers located close to the landfills might be choosing to sell their properties through a real estate agent given knowledge about the properties' proximity to the landfill. In other words, proximity to the landfills might increase the use of real estate agent services. This could result from house sellers' beliefs that a real estate agent's expertise in the real estate market might result in a better chance of obtaining a higher than expected price for their properties. Second, selection bias could occur from real estate agents' steering outside movers to properties located close to landfills because of the informational disadvantage they have about local market conditions.[4] We use a two-step sample-selection bias procedure (Greene, 2000; Maddala, 1983) in order to correct for the possible bias of real estate agents being hired by sellers closer to the landfill to affect the price of a property. The first step of the procedure is a logistic maximum likelihood estimate from which the inverse Mill's ratio (λ) is obtained. This ratio is then included in the hedonic price model to correct for sample selection bias. Table 1.5 presents this model. The inverse Mill's ratio (λ) was estimated using the estimates of the linear predictor from the model specification in Table 1.6. We are primarily interested in how the estimated parameters of the real estate agent variable and the interactions with the distances to the landfills changes when correcting for any possible selection bias in hiring a real estate agent. The change in the estimated coefficient is small and the new estimates are lower. It should be mentioned that lambda resulted statistically significant, suggesting selection bias exists in the data. Table 1.5 presents results for the realtor probit selection model.

[4] We calculated the correlation coefficient between the percentage of outside movers in the Census Block Group and the average yearly rental equivalent for the whole sample and the average yearly rental equivalent from houses sold by real estate agents in the four study areas. We found that most areas exhibit a relatively high negative correlation closer to the landfill, which decreases as we move further away.

Table 1.5 First-step sample selection model: Estimated equation for real estate agent selection

Probit Maximum Likelihood Estimates Dependent variable = Real estate agent (0, 1) Number of observations: 2,858		
Variable	Parameter Estimate	Standard Error
INTERCEPT	-1.9849***	0.38
COLLDEG	0.6511***	0.21
AVGWORK	0.0010***	0.00
TRNOVER	-2.5028*	1.39
LNDISTLF	0.1740***	0.06
Association of predicted probabilities		
Percent Concordant: 57.2		
Somers' D: 0.156		
Percent Discordant: 41.6		
Gamma: 0.158		
Percent Tied: 1.2		
Tau-a: 0.073		
Pairs: 1913877		
C: 0.578		

Table 1.6 Estimated hedonic price function including real estate agent variable and lambda

Common Variables	Parameter Estimate	t-Stat.
α_{ALC}	-0.1309**	-1.93
α_{OBZ}	1.6205*	3.05
α_{GHA}	0.0360	0.38
α_{GRC}	2.2932***	5.25
DISTALC	0.2989***	10.21
$DISTALC^2$	0.2950***	6.83
DISTOBZ	0.1325***	6.01
$DISTOBZ^2$	0.4926***	11.85
DISTGHA	-0.0323***	-8.78
$DISTGHA^2$	-0.0167***	-5.64
DISTGRC	0.0092***	4.22
$DISTGRC^2$	-0.0103***	-4.56
LNDISTCBD	-0.4426***	-8.20
CRIMERATE	-0.0017***	-3.35
PROXAIRPORT	-0.1605***	-5.20
PROXRR	-0.0949***	-2.60
SCHOOLINDEX	0.0045***	8.07
%CBGOUTSTATE	1.0116***	5.13
SUMMER	-0.0084	-0.64
REA	4.8982***	11.64
REA x DISTALC	-0.1550***	-5.08
REA x $DISTALC^2$	0.0290***	6.06
REA x DISTOBZ	-0.2109***	-6.66
REA x $DISTOBZ^2$	0.0145***	5.27
REA x DISTGHA	-0.1049***	-3.34
REA x $DISTGHA^2$	-0.0129***	-4.72
REA x DISTGRC	-0.2311***	-5.08
REA x $DISTGRC^2$	-0.0014	-0.53
LAMBDA	-0.1173**	-2.17

Table 1.6 Estimated hedonic price function including real estate agent variable and lambda (continued)

Market Segment	Alum Creek		Obetz		Gahanna		Grove City	
Segmented Variables	Estimate	t-Stat.	Estimate	t-Stat.	Estimate	t-Stat.	Estimate	t-Stat.
NEARFREEWAY	-0.0862***	-2.50	-0.0586	-0.76	0.0389	1.06	0.3210***	5.05
FAMILY	-0.6552***	-4.72	-0.3608	-0.97	-0.3970***	-2.75	-0.7665***	-2.80
BANK	-0.2040**	-2.02	-0.3240	-1.34	-0.2249**	-2.42	-0.2828	-0.81
CORPORATE	-0.1400***	-2.70	-0.1380	-0.83	-0.1385**	-2.68	0.0090	0.04
ESTATE	0.0131	0.39	-0.1001	-0.51	-0.0928	-0.96	-0.2366	-1.52
OUTLIER	-0.8898***	-3.51	-1.6910	-0.88	-1.0506***	-3.28	-0.3260	-0.88
NEARPARK	0.1188***	3.48	0.0398	0.39	-0.0188	-0.44	-0.0599	-0.41
COUNTRY	-	-	-	-	0.1284***	3.87	-0.3650***	-4.27
LOTSIZE	0.2189***	16.88	0.0993*	1.87	0.1518***	11.85	0.0544	1.41
SQFTSTRUCT	0.0220***	23.45	0.0264	1.38	0.0266***	6.88	0.0273***	4.42
SQFTGARAGE	0.0173***	5.31	0.0349**	2.30	0.0241***	3.13	0.0525***	3.37
NROOMS	-0.0184***	-3.30	0.0002	0.00	0.0854***	3.92	0.0534	1.58
NBEDROOMS	-0.0240*	-1.90	0.0224	0.21	-0.0259	-0.89	-0.0267	-0.50
FULLBATH	0.2092***	11.81	0.0735	0.70	0.0417	1.18	0.0729	1.08
HALFBATH	0.0819***	4.88	-0.0672	-0.77	0.0988***	3.46	-0.0499	-0.73
STRUCTUREAGE	0.0007	1.32	-0.0064**	-2.18	0.0013	1.26	-0.0118***	-5.20
CENTRALAIR	0.2829***	13.45	0.0146	0.21	-0.1594***	-6.31	-0.1731***	-2.78
FIREPLACE	0.2052***	7.87	0.0181	0.17	0.1403***	3.79	0.0562	0.81
BRICK/MASONRY	0.0546**	2.23	0.0581	0.62	-0.0223	-0.77	0.0207	0.34

N: 2,858

Adjusted R^2: 0.8228

1.8 Discussion

Figure 1.5 presents the case when a real estate agent obtains excess surplus from selling a house located close to a landfill; Yavas's (1992) theoretical result is observed only after distance D^* from the landfill. The line P^R denotes the price function that a real estate agent obtains. The line $P^R(1\text{-}c\text{+}\omega c)$ denotes the price line that the seller obtains after paying for the real estate agent's commission. Before D_1^*, the difference between what the seller actually obtains from selling the house through a real estate agent less her commission is greater than what the seller would have obtained had she sold the house alone. This difference represents a surplus for the seller.

A simple test can be designed to verify our hypothesis that real estate agents obtain higher than expected prices for a property closer to a landfill. Using the results from the sample-selection corrected hedonic model, we present in Table 1.7 through Table 1.10 the predicted rent values at various distance intervals (holding all other characteristics constant at their means) from a landfill in the four study areas. We calculate predicted rent values for transactions made with and without a real estate agent, then predict as if all transactions are made through a real estate agent, and as if all transaction are made without a real estate agent. The percentage difference between these two last predicted rent values, calculated as $\frac{(\hat{P}^R - \hat{P}^{NR})}{\hat{P}^{NR}}$, represents the mean percentage gain from selling the house through a real estate agent. Table 1.7 through Table 1.10 also report the *t*-statistics based on paired differences to examine if the differences are significant. It can be seen that the mean percentage difference between the rent value for all transactions made through a real estate agent and the rent value for all transactions made without a real estate agent in three out of the four study areas is higher closer to the landfill, but decreases as we move away from it.

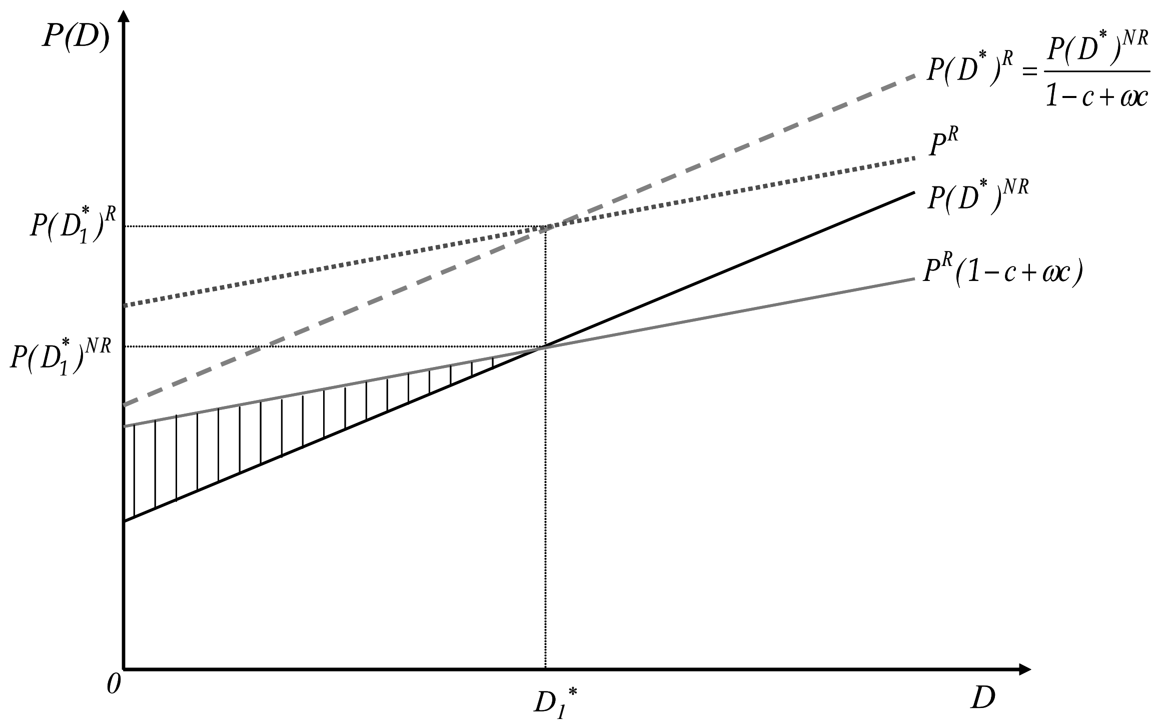


Figure 1.5 Hedonic price function with a real estate agent

Table 1.7 Predicted rent with and without a real estate agent in Alum Creek, in dollars ($)

Distance	N	Predicted rent all REA (a)		Predicted rent no REA (b)		% (a) - (b)		
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	t
d ≤ 0.75	70	5,673.42	3,815.81	4,224.08	2,926.85	36.47	5.50	55.53
0.75< d ≤ 1.50	529	6,144.42	4,438.52	5,277.79	3,878.41	17.00	8.02	48.77
1.50 < d ≤ 2.25	341	7,793.15	9,609.75	7,190.4	9,250.79	14.38	51.60	5.14
2.25 < d ≤ 3.00	372	7,596.39	11,836.77	7,420.79	11,741.02	6.98	43.89	3.07
d ≥ 3.00	56	6,623.75	2,901.74	6,607.85	2,974.8	0.70	5.84	0.89

Table 1.8 Predicted rent with and without a real estate agent in Obetz, in dollars ($)

Distance	N	Predicted rent all REA (a)		Predicted rent no REA (b)		% (a) - (b)		
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	t
d ≤ 0.75	56	4,814.28	1,168.85	3,928.35	1,020.93	24.65	16.31	11.31
0.75< d ≤ 1.50	182	5,320.79	1,368.19	4,337.33	1,462.94	27.63	21.23	17.56
1.50 < d ≤ 2.25	110	6,340.83	1,759.39	5,738.22	2,096.72	15.66	16.38	10.03
2.25 < d ≤ 3.00	44	5,661.91	1,882.23	5,102.04	3,040.49	19.53	16.23	7.98
d ≥ 3.00	-	-	-	-	-	-	-	-

Table 1.9 Predicted rent with and without a real estate agent in Gahanna, in dollars ($)

Distance	N	Predicted rent all REA (a)		Predicted rent no REA (b)		% (a) - (b)		
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	t
d ≤ 0.75	55	12,174.49	2,632.55	10,954.24	2524.66	11.3	3.09	27.13
0.75< d ≤ 1.50	211	9,106.00	4,562.72	9,514.64	4,377.44	-4.81	10.39	-6.73
1.50 < d ≤ 2.25	180	8,511.56	4,457.93	9,242.88	4,675.72	-7.01	10.70	-8.79
2.25 < d ≤ 3.00	296	10,579.87	7,199.43	11,181.62	7,271.13	-6.29	10.27	-10.53
d ≥ 3.00	111	6,536.11	2,507.19	7,196.7	2,865.42	-7.94	9.89	-8.46

Table 1.10 Predicted rent with and without a real estate agent in Grove City, in dollars ($)

Distance	N	Predicted rent all REA (a)		Predicted rent no REA (b)		% (a) - (b)		
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	t
d ≤ 0.75	-	-	-	-	-	-	-	-
0.75< d ≤ 1.50	6	2,214.6	7,916.01	2,315.14	7,099.59	12.25	10.28	4.77
1.50 < d ≤ 2.25	55	3,232.19	8,232.65	2,863.73	8057.23	3.92	9.66	3.17
2.25 < d ≤ 3.00	109	3,978.7	8574.99	4006.71	8,808.62	-0.84	12.60	-0.64
d ≥ 3.00	75	3,685.03	8179.41	4,037.03	7,670.73	4.85	12.07	3.48

Assuming that a real estate agent obtains about a 7 percent commission on the final transaction price, hiring a real estate agent to sell a house closer to a landfill results in sellers obtaining a percent increase in the price greater than the commission rate. The percentage increase is highest in the Alum Creek and Obetz study areas, where a real estate agent obtains an additional surplus up to 3 miles away from the landfill. After 3 miles, the percentage gain drops to less than 7 percent, but still remains positive. Impacts in the other two areas are dissimilar: in Gahanna, the percentage gain is only greater than 7 percent for transactions made less than 0.75 miles away from the landfill, after which the gain becomes negative, while in Grove City, real estate agents obtain higher prices, but the increase in price is less than the assumed commission rate at every distance interval. It should be noted that the greatest percentage gain is obtained in urbanized areas with closed landfills.[5]

There are several potential explanations why real estate agents are able to get higher than expected prices closer to the landfills. We argue that when sellers use agents, differences in information (whether informed or not informed about the landfill presence) between buyers and sellers, perceptions of the landfill's potential hazardous impact, the distribution of informed sellers, buyers, and real estate agents, and each party's changing bargaining power are determinants of the final transaction price, particularly in closer proximity to the landfill. For informed sellers who hire real estate agents, the marginal cost of selling their houses increases as they move closer to the landfill. The real estate

[5] In this paper we do not address the fact that landfills emit odors that may be perceived by both sellers and buyers. Closed landfills most likely do not have this effect, which reduces the chances of potential buyers noticing the landfill.

agent may experience higher advertising costs, increased time showing the house to potential buyers, as well as an expected increase in the bargaining period. Previous researchers find that the degree of atypicality increases the time it takes to sell a house; we can therefore think of proximity to a landfill as an atypical characteristic that real estate agents need to consider when offering a house for sale. Haurin (1988) finds that houses with a great amount of atypical features have greater expected duration of marketing time, and a higher expected difference between the list price and the selling price. Though real estate agents are experts at promoting houses for sale, they could experience increased time spent searching for information about the landfill's potential impact. The time spent in these activities increases the agent's opportunity cost. To compensate for higher costs, a higher price would most likely be asked closer to the landfill. The real estate agent recommends a price for the house based on the price of houses with similar characteristics in the neighborhood, but most likely disregards the impact of proximity to the landfill. With higher asking prices, the possibility of obtaining a higher than expected final price increases closer to the landfill. Real estate agents are not obliged to disclose information about the landfill unless they are asked to,[6] so finding potential uninformed buyers might strengthen their bargaining positions. Real estate agents can steer uninformed potential buyers to properties that are affected by the

[6] The State of Ohio stipulates in their "Agency Disclosure Statement" form that in a seller's agency, the agent is required to disclose to the seller all material information obtained from the buyer or from any other source. Nothing is mentioned about disclosing information to the buyer. In a dual agency, where the agent represents both the seller and the buyer, the agent may not disclose any confidential information that would place one party at an advantage over the other party.

presence of an environmental disamenity.[7] As previously mentioned, outside movers, though already more likely to hire a real estate agent because of lack of information on the local environment, might be guided by real estate agents to buying a house that matches their housing characteristic requirements, the *visible* characteristics, but those house may be potentially affected by *non-visible* ones. Also first-time movers, though they might already be familiar with the local environment, are likely less experienced about how the real estate market[8] functions and may end up paying higher house prices because of relatively weak bargaining power.

When a real estate agent is employed to sell a house, her impact on the final transaction price is influenced by her own persuasive capabilities. Most theoretical and empirical work in the real estate literature assumes that buyers' and sellers' relative bargaining power is unaffected by the presence of a real estate agent. This is certainly a valid assumption, yet a seller might not only hire an agent to match them with potential buyers, but also to strengthen their bargaining position. A weak seller, for example, might consider that hiring a real estate agent to sell a house that is located close to a landfill would result in a greater probability of obtaining a higher price than if she were to do it alone.[9]

[7] The impact of real estate agents in *steering* minorities to different geographic areas than whites has been a long time concern in the real estate literature. To our knowledge, no formal study has been concerned with the issue of real estate agents *steering* home buyers, of any racial background, to houses located close to environmental disamenities.
[8] Harding, Rosenthal, and Sirmans (2003) find that first-time buyers are weak bargainers relative to experienced repeat buyers.
[9] For example, it has been found in several studies (Ayres and Siegelman, 1995; Harding et al., 2003) that single women have less bargaining power than men. No references were found to support the idea that hiring a real estate agent would increase bargaining power to the buyer or seller.

Another important determinant of the final transaction price is the difference between the seller's and the buyer's perceived risk from being close to the landfill and the real estate agent's impact on modifying these perceptions. Additional information about the landfill's potential hazardous impact affects the seller's and the buyer's valuation of the property (through their risk valuations). Obtaining additional information increases their opportunity cost, but it might provide them with sufficient experience to modify their risk perceptions from being close to the landfill. Also, the impact of additional information depends on how close the property is to the landfill. The closer it is, the more valuable will be additional information, yet its cost also increases. The rule would be to search for additional information up to the point where marginal benefits equal marginal costs. Hiring a real estate agent might also affect the seller's perceived risk from being close to the landfill. It has been argued that experts' risk judgments associated with environmental disamenities is inconsistent with homeowners' perceived risks (McClelland, 1990). The role of the real estate agent, once informed about the landfill, is to try to bring the seller's and the buyer's risk perceptions into line with the experts', and mitigate the impact on property value. This will have an impact on buyers' and sellers' relative bargaining power.

1.9 Conclusion

We have demonstrated that real estate agents have a considerable impact on the final transaction price of houses located close to an environmental disamenity. We find empirical evidence that supports theoretical predictions that real estate agents obtain higher prices for their clients. In particular, we find that the increase in price is highest closer to the landfill, most likely due to differences in information regarding the presence of the landfill and its impact on perceived risk between the players involved in the bargaining process. It is also found that the excess surplus is related to the time the landfill has been closed or remains open at the time of the sale. Real estate agents may play an important role in minimizing the perceived risk associated from being close to the landfill, therefore increasing the chance of obtaining higher than expected prices.

Future research should address the impact of locational factors on house prices. It is argued in the spatial econometrics literature that spatial dependence and unobserved spatial heterogeneity (Brasington and Hite, 2005; LeSage, 1999) might affect the data and therefore not accounting for these factors may lead to misleading results. The use of spatial hedonic models could improve the estimated impact of landfills on property prices, as well as of real estate agents in the bargaining process. Received knowledge suggests that real estate agents most likely consider the price of neighboring houses when recommending an (optimal) asking price. By using spatial models we can control for this effect and extract the 'pure' impact of real estate agents on property prices.

CHAPTER 2: THE VALUE OF OPEN SPACE IN RURAL AND SUBURBAN AREAS: A SPATIAL HEDONIC APPROACH

2.1 Introduction

The importance of preserving open space lands has been of major concern in recent years. Governments, economists, environmentalists, and many others have long recognized the social value of open space lands. They not only provide scenery aesthetics, but are potential sources of food, fiber, and recreation, among others (Fausold and Lilieholm, 1996). The preservation of open space land, though, is in conflict with growing urbanization; urban growth has occurred at the expense of open space. Several policy issues have arisen because of conflicting interests in the use of land, particularly open space land.

Land valuation is a function of a potential user's interests, as different users value land differently. An urban developer, for example, values land for its urbanization potential, while an environmentalist might value the land for its aesthetic and habitat value, and knowing that it will be there in the future. Not only does valuation of open space differ by he benefits it brings potential users, but it is also affected by its relative scarcity compared to other land uses.

This essay attempts to estimate the value of open space land to property owners in agricultural areas. Land in agricultural areas has many uses: cropping, grazing, forestry, recreation, among others. The concept of open space has an entirely different meaning for a homeowner who is not involved in agricultural production, but who lives in an agricultural area. Homeowners' perceptions of the value of open space lands may be consistently in conflict with farmers'. For example, the view of a field of corn is different from the view of a forest. Creating economic measures of these values is most commonly achieved by estimating a traditional hedonic price model (HPM). In the HPM, house prices are regressed on various house and neighborhood characteristic variables, as well as environmental and land use variables. Results from these models can be used to calculate relative values of different environmental quality and land use characteristics. These results will be useful for policy makers in developing strategies for protecting environmental resources and developing land use plans. The estimated models can be used to simulate price differences for properties that are affected by possible competing land use policies. For example, house and land prices can be predicted assuming that area dedicated to a specific land use, i.e. agricultural land, is converted into a recreational area versus converted into a residential area.

2.2 Problem statement

This essay addresses several issues related to the impact of different land uses on property prices. First, it addresses an issue that the urban economics and land economics literature has consistently disregarded, which is failing to account for the link between land only transactions and house transaction from the land's fixity and continuity. Two separate approaches have been used in the literature to measure the impact of different land uses on property values. One vein of literature concentrates on measuring the impact of proximity to open space lands, such as proximity or visibility of forests and parks, on transacted properties that include a house and its characteristics. Similar studies estimate the scenic value of open space lands. In this literature, the house is the object of study while physical attributes, such as the parcel where the house is located and all its characteristics, are considered to contribute to its value. Another area of the literature concerns the impact of surrounding land uses on land-only transactions. This literature considers the price of land to be the main object of study and regards any physical characteristics within the parcel as land characteristics. These two approaches have never been combined. The literature considers these two markets as independent of each other, when in reality both markets are linked by the fixity and continuity of land. In this essay we address this problem by explicitly recognizing that transactions involving land only are influenced by transactions involving a house (and land) and vice versa. For example, the prices of undeveloped parcels located within a residential area are affected by the prices and characteristics of neighboring properties.

Second, we account for spatial effects in the estimated hedonic price models. Most of the hedonic literature fails to account for the spatial nature of the housing and land markets. The spatial econometrics literature suggests that using ordinary least squares (OLS) in the presence of spatial effects may lead to biased, inefficient and inconsistent hedonic parameter estimates (Anselin, 1988; LeSage, 1999, Brasington and Hite, 2005). Therefore, estimating a *spatial hedonic price model* would provide less biased estimates about the different valuations of environmental amenities to residents of agricultural areas.

The third issue addressed in this essay, and the main motivation for our empirical examination, is to compare land use impacts on land and house prices in different time periods. As the area dedicated to open space land is converted into residential land in predominantly suburban areas, the impact of the remaining open space lands on property prices changes with time. At a given point in time, the area that has the highest development potential will be quickly converted into residential use, leaving less valued land undeveloped. In comparing house and land prices in two time periods, for example, it is expected that the marginal impact of surrounding land uses on house and land prices will change. The primary purpose of this essay is thus to determine how increases in land dedicated to residential uses affect property prices over time.

2.3 Open space and the housing market

The hedonic price model has been used extensively in the urban and regional economics literature to determine the impact of different types of open space lands on house prices (Irwin, 2002). Results have been mixed due to the different kinds of open space considered, specification of the open space variables, and differences across study regions (Ready and Abdalla, 2003). Most studies estimate the impact of changes in area dedicated to forests, parks, lakes, golf courses, and other open space amenities on house prices. Garrod and Willis (1992) estimate the impact of various attributes of forest amenities on house prices in Great Britain; they find that changes in the relative proportions of different categories of trees have varying effects on house prices. In a similar study in Finland, Tyrväinen and Miettinen (2000) find that increasing the distance to the nearest forested area decreases the house's market price, while houses with a view of forests are more expensive than houses with otherwise similar characteristics.

Espey and Owusu-Edusei (2001) estimate the effect of proximity to small and medium size parks with various degrees of attractiveness on house prices. Their dataset comes from single family homes in Greenville, South Carolina, sold between 1990 and 1999. They find that the value of park proximity varies with respect to park size and amenities. The presence of small basic neighborhood parks located within 300 feet of the house reduces property values by about fourteen percent, but this effect becomes positive as distance away from the neighborhood park is increased. Homes located within 600 feet of small attractive parks have property values as much as eleven percent higher than other homes. For attractive medium size parks, results showed statistically significant impacts on houses located within 200 and 1,500 feet, raising values by about 6 percent, while unattractive medium size parks were estimated to have a significant negative impact on house values located within 600 feet of the park, reducing housing values by about fifty percent.

Sohngen et al. (2000) estimate the relationship between house prices and house and environmental characteristics in Delaware County, Ohio. They estimate a linear hedonic model using various measures of distances to amenities and other structural characteristics. Their findings are summarized into four results: first, the marginal value of an extra acre of land for development is $22,150 per acre near the central city, but declines by $1,554 per acre for each mile further away. Second, homeowners near a city do not value proximity to agriculture, but value other open space amenities like golf courses. Third, homeowners prefer to live close to agriculture rather than in subdivisions as one moves further away from the central city. Fourth, homeowners prefer lower quality agricultural sites for houses.

The previous studies do not explicitly model the structure of spatial dependence in the data. We find papers that address spatial dependence by explicitly accounting spatial dependence in the model estimation; others use an instrumental variable approach to account for the endogeneity of land use data and the possibility of omitted variables correlated with the error term. In the last few years spatial models in hedonic housing studies have been increasingly used due to better understanding of spatial models, improvements in the field of Geographic Information Systems (GIS) data collection and processing, as well as improved, highly efficient and accurate computer software.

Geoghegan, Wainger, and Bockstael (1997) develop a spatial hedonic model to explain how the value of a parcel in residential land use is affected by the pattern of surrounding land uses. They first estimate a traditional double-log hedonic model with the inclusion of two spatial variables that capture the pattern of landscape surrounding the parcel. These variables are diversity, which measures the extent to which landscape is dominated by a few or many land uses, and fragmentation, which measures the potential loss of function of land use due to decreased size or loss of diversity[10]. None of these variables individually result in statistically significant estimates, although they are jointly significant. In a second model, they estimate a spatial expansion model where the parameters vary linearly and quadratically with distance to the central business district. Their results suggest that increases in diversity and/or fragmentation in the immediate neighborhood of a house are undesirable features.

[10] See Table 1 of Geoghegan, Wainger, and Bockstael (1997).

Paterson and Boyle (2002) use GIS data to develop variables representing the physical extent and visibility of surrounding agricultural land, development land, forests and surface water in a hedonic model of residential area of the Farmington River Valley of Connecticut. They develop two types of variables: first, a variable measuring the percentage of land area occupied by residential and commercial development, agriculture, forest, and surface water within a one-kilometer radius around each property; and second, the percentage of land area visible overall within one kilometer and the percentage of land visible in each land use/cover in the same radius. They estimate a first-order spatial autoregressive model to account for spatial autocorrelation. Their estimates indicate that visibility is an important environmental variable and conclude that its omission can lead to incorrect deductions regarding the significance and signs of other environmental variables.

Irwin and Bockstael (2001) address two estimation problems when estimating land use spillovers. First, they address the problem of endogeneity that arises when testing whether the residential value of a parcel is affected by whether a neighboring parcel is developed. Second, they address the problem of omitted variables that may be correlated with the error term. In the presence of these effects, estimated coefficients on open space are biased. To correct for these problems, they attempt to obtain consistent parameter estimates using instrumental variables. They find that the estimated coefficients on open space are higher with instrumental variable estimation. In a similar paper, Irwin (2002) addresses the same problems using instrumental variables estimation with a randomly drawn subset of data that omits nearest neighbors. Her results show a premium associated with permanently preserved open space relative to developable agricultural and forested lands, supporting the hypothesis that open space is most valued for providing absence of development, rather than for providing a particular bundle of open space amenities.

2.4 The value of agricultural land

A similar line of literature is related to our study. Previous studies are primarily concerned with the impact of housing characteristics, i.e. environmental amenities, on house prices. Other studies in the urban economics literature ask the same question, but are concerned with the value of land, and in particular, agricultural land. These studies also use the hedonic price model to estimate the marginal contribution of various land characteristics, such as slope, soil quality, land productivity, and improvements, among others, on the price of agricultural land. The use of GIS data and productivity measures has been an important development in this area of research. However, no previous study has jointly estimated the impact of house characteristics and land characteristics on the price of a property as is done in this essay. This area is potentially interesting to explore; estimating a joint hedonic housing price equation and a hedonic land price equation as function of their characteristics would provide relevant and accurate information regarding marginal value changes associated with a property's characteristics and the characteristics of surrounding properties.

Various papers have determined the impact of productivity on land prices. Results show that land productivity has a significantly positive impact on land prices. Boisvert, Schmit, and Regmi (1997) use field-level data to determine the impact of land productivity, location, and the land's potential for environmental contamination on farmland value in the Lower Susquehanna River Basin. Their results suggest that land productivity and spatial orientation are the most important variables explaining the value of agricultural land.

Roka and Palmquist (1997) use data from the June Agricultural Survey (JAS) to estimate hedonic models of farmland values in Illinois, Indiana, Iowa, Missouri, and Ohio. Their findings suggest the primary influences on land values are presence of cropland, presence of prime farmland, acreage, average yields, and population density. The impact of various site land characteristics has also been studied. Xu, Mitelhammer, and Barkley (1993) estimate a hedonic land price model to determine the impact of different combinations and qualities of site characteristics on the value of agricultural land in six sub-state regions in Washington State. They find that site characteristics, especially, permanent improvements such as the presence of a house and its size, the existence of irrigation systems, barns, and machinery, among others, are significant factors in determining land values. They also find that land markets in Washington State are highly regional.

Kennedy, et al. (1997) follow a two stage hedonic price technique to estimate the effects of rural real estate characteristics on the value of rural land in Louisiana. The first stage concentrates on physical and locational characteristics of a tract of land, while the second stage investigates the effects of socio-economic variables on the marginal implicit prices of land characteristics. The results suggest that land value is heavily influenced by the income-producing potential of the land, but this influence declines with decreasing land quality and specialization. The use of GIS data is argued to significantly improve the analysis, but the study does not include variables reflecting environmental amenity values.

Some previous studies are concerned with the impact of environmental amenities on land prices. Bastian et al. (2002) estimate a hedonic land price model using GIS data to determine the impact of recreational and scenic amenities associated with rural land in Wyoming. Statistically significant amenity variables include scenic view, elk habitat, sport fishery productivity and distance to town. Pearson, Tisdell, and Lisle (2002) estimate the impact of proximity and view of a headland section of Noosa National Park on surrounding land values in an urban area. The study found that a glimpse of the park generates an increase of seven percent in land value of affected properties, while being in close walking distance to the park has little impact upon the value of land unless it can be viewed. In another paper, Boisvert, Schmit, and Regmi (1997) find that environmental vulnerability of land has a minor statistically significant impact on land values, except in cases where the vulnerability is large and persistent from year to year.

This essay expands the literature by estimating the impact of different land uses on land and house transactions, but also accounting for the spatial nature of the data. We explicitly account for the presence of spatial dependence in the estimation of the impact of different land uses on land and house prices, and further account for the connectivity between the land and the house markets.

2.5 The theoretical hedonic framework

Rosen's (1974) hedonic framework applied to the land and housing markets is as follows. On the demand side, a consumer purchases a property comprised of a bundle of housing attributes, Z, land attributes, L, and a numeraire good, X, with price equal to one. The consumer maximizes utility from purchasing a property subject to income Y. The utility maximization problem takes the form:

$$Max\,U = u(L, Z, X) \quad \text{s.t. } Y = P(L) + P(Z) + X \qquad [1]$$

where *L*, *Z*, and X are defined as before.

On the supply side, property sellers maximize profits from sale of the property:

$$Max\,\Pi = [P(L) + P(Z)] - C(L, Z, X) \qquad [2]$$

where all variables are defined as before, and C is a cost function which represents the cost of offering a property for sale.

From the utility and profit maximization problem, bid and offer functions are derived. In perfectly competitive markets, the hedonic price function $P(Z^*, L^*)$ occurs at the tangency of the bid and offer curves. Each point along the hedonic price function represents an equilibrium price representing the lowest transaction price possible for the property with an optimal set of characteristics paid by buyers, and the highest price possible obtained by sellers.

2.6 Empirical models

Traditional hedonic land and house price models

The traditional hedonic land price model is specified as:

$$V = L\alpha_1 + O\alpha_2 + N\alpha_3 + S\alpha_4 + \varepsilon \qquad [3]$$

where V is a vector of land prices, L is a matrix of land characteristics, O is a matrix of neighboring land use variables, N is a matrix of neighborhood characteristics, and S is a vector of structural and other environmental variables.

The traditional hedonic house price model is specified as:

$$P = L\beta_1 + H\beta_2 + O\beta_2 + N\beta_3 + S\beta_4 + \varepsilon \qquad [4]$$

where P is a vector of house prices, L is a matrix of land characteristics, H is a matrix of house characteristics, O is a matrix of neighboring land use variables, N is a matrix of neighborhood characteristics, and S is a matrix of structural and other environmental variables. Both the traditional hedonic land and house price models are generally estimated by Ordinary Least Squares (OLS), corrected for heteroskedasticity.

In this essay, we specify the traditional hedonic land and house price equations with the natural log of the price of land and the natural log of the price of house as the dependent variables.

Spatial hedonic models

Most previous house and land studies that use the hedonic price model do not take into consideration the possible spatial nature of housing and land data. The literature on spatial econometrics focuses on two types of spatial effects that can arise when sample data has a locational component: (1) spatial dependence and (2) unobserved spatial heterogeneity (LeSage, 1999). Spatial dependence refers to the fact that one observation associated with a location depends on other observations in adjacent locations. For example, the price of a house in a particular location depends on the prices and characteristics of neighboring houses. Unobserved spatial heterogeneity refers to variation in relationships over space. Anselin (1988) suggests that spatial effects lack uniformity, that is, the impact of spatial characteristics on the spatial units vary from one region to another. For example, the impact of house characteristics on house prices located close to a forest is different from the impact of housing characteristics on house prices located close to a lake. Traditional hedonic price models that use Ordinary Least Squares fail to account for these effects which in turn may result in biased, inefficient and inconsistent parameter estimates (Anselin, 1998; LeSage, 2001, Brasington and Hite, 2004). In order to incorporate spatial effects into a regression model we consider two model specifications that have been commonly used in the urban economics literature: the spatial error model and the spatial-lag model.

Spatial error hedonic price model

The spatial error model is used when the spatial dependence is present in the error term (Kim et al., 2003). The spatial error hedonic land price model takes the form:

$$\begin{aligned} V &= L\alpha_1 + O\alpha_2 + N\alpha_3 + S\alpha_4 + \varepsilon \\ \varepsilon &= \lambda W\varepsilon + \mu \end{aligned} \qquad [5]$$

where λ is a parameter on the spatially correlated errors, W is a standardized spatial weight matrix, μ is assumed to be a vector of i.i.d. errors, and all other variables are defined as before. In this case the price at any location is a function of the local characteristics and of omitted variables at neighboring locations that follow a spatial pattern (Kim et al., 2003).

Spatial-lag hedonic price model

The spatial-lag model is an appropriate tool when capturing neighborhood spillover effects. The spatial-lag hedonic land price model takes the form:

$$V = \rho WV + L\alpha_1 + O\alpha_2 + N\alpha_3 + S\alpha_4 + \varepsilon \qquad [6]$$

where ρ is a coefficient spatial autocorrelation parameter and all other variables are defined as before. This specification assumes that the spatially weighted sum of neighboring land prices enters as an explanatory variable in the specification of land price formation (Kim et al., 2003). The spatial-lag hedonic house price model takes a similar form with house prices instead of land prices plus the addition of a house characteristics vector in the right-hand side of the equation.

Spatial weight matrices

To capture spatial dependence in the house and land hedonic models, spatial weight matrices must be constructed. Each transaction in the 1988 and 1998 datasets were geo-referenced. These coordinates can then be used to find the nearest neighbors to each property and construct spatial weight matrices. The matrices are then normalized to have row-sums of unity. Following Kim et al. (2003), we experimented with a series of different weights and report results from the best fitting models.

Seemingly Unrelated Regression (SUR) models

Previous empirical studies have assumed that the impact of transactions in the land market is independent of transactions occurring in the house market and vice versa. It was argued earlier in this essay that the literature fails to account for the link between these two markets. The main argument for assuming linkage of the two markets comes from the fact that land is continuous. For example, the price of land-only transactions may be affected by the price of house transactions if they share common boundaries. Therefore the impact of different land uses on house prices is not independent of the impact of land uses on land prices. Though the impact of land use variables is accounted for individually in both single equations, it is reasonable to believe contemporaneous correlations exist between the two markets through the unexplained portions of the equations. Given that both the land price equation and the house price equation share similar characteristics that affect one another, as well as possible existence of common omitted factors that are not accounted for in each equation, we can argue that the errors between the two equations may be contemporaneously correlated. A model of this structure calls for a seemingly unrelated regression estimation (SURE) approach.

Neighborhood land characteristic variables

It is necessary to address the construction of the neighborhood land use variables. Properties are surrounded by other properties, some of which may be residential properties, parks, bodies of water, and golf courses, among others. Various approaches can be used to account for the various land uses surrounding a property. The first approach is based on the concept of contiguity. Figure 2.1 shows that the parcel where house H1 is located is contiguous to two types of land uses: agriculture (A1 and A2) and forest (F1 and F2). One way of accounting for the impact of different land uses is to specify fixed effects for each of the different land uses that are contiguous to the property. In our example, H1 would have a 1 for agricultural land and forest land, and zeros for all other land types. When estimating the hedonic function, these fixed effects would capture changes in the estimated intercept.

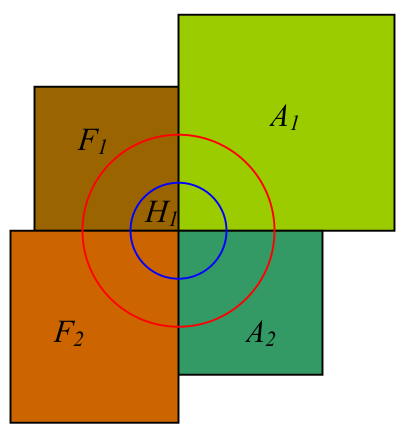


Figure 2.1 Buffers and land uses

Another approach would be to calculate the percentage of different land uses of parcels that are immediately contiguous (or higher order contiguities) to the house.

Estimated coefficients on these variables would measure the impact of marginal changes in percentages of land use types surrounding a house on its price.

It is also common in the literature to specify buffers of different radii around each house and calculate the percentage area of each land use within the buffers. This procedure provides a better way to capture the impact of spatial heterogeneity on house prices. Several buffers sizes can be specified to better capture the impact of proximity on house prices. The circles in Figure 2.1 demonstrate the way buffers around H1 would be measured; the areas of different land uses within each buffer would then be calculated as a percentage of the area of the buffer. It is expected that the relative impact of different land uses diminishes as the size of the buffer increases. In this essay we follow the buffer approach in order to be consistent with previous urban and land economics literature.

2.7 Data description

The dataset used in this essay consists of land and house transactions that took place in two time periods in Delaware County, Ohio: first, a total of 582 land transactions and 1,718 house transactions from July 1987 to June 1988, and second, a total of 1,268 land transactions and 1,881 house transactions from July 1997 to June 1998. Delaware County is located north of the city of Columbus, and is a fast-growing part of Ohio. It contains not only high quality agricultural land, but also high value land for development (Sohngen et al., 2000). Table 2.1 presents variables definitions and sources, while Table 2.2 presents summary statistics by time period and type of transaction on structural housing characteristics, parcel characteristics, and neighborhood characteristics used in the hedonic regressions.

Table 2.1 Definitions and sources of hedonic regression variables

Variable name	Definition (source)
PLANDA	Price of land per acre transacted in 1988 and 1998[1], deflated by the average quarterly Ohio Housing Price Index2 (I Qtr 1988=100), in dollars
PHOUSEA	Price of house per acre transacted in 1988 and 1998[1], deflated by the average quarterly Ohio Housing Price Index[2] (I Qtr 1988=100), in dollars
NOTINACITY	1 for properties not in a city, 0 otherwise
FLOODZONE	1 for properties in flood zone areas, 0 otherwise
CORNYIELD	Yield of corn on land (bushels per acre)
SLOPE	Percentage slope of property[1]
AGE	Age of the house in years, up to the year transacted (1988 or 1998) [1]
STORYHGT	Number of stories in house[1]
BASEMENT	Size of basement coverage[1]
ROOMS_TOT	Total number of rooms in house[1]
BATHS_TOT	Total number of bathrooms in house (half bath = 0.5) [1]
GARAGE_CAP	Cars fitting in garage[1]
ATTIC	1 for houses with an attic, 0 otherwise[1]
POP_DENS	Population density in census block[3]
INCPRCAP	Income per capita in block, in dollars[3]
LNSOUTHBND	Log of the distance to the southern boundary in miles[4]
PCTAGB1	Percentage of agricultural land in 0.25 miles radii buffer, in 1988 and 1998[4]
PCTGOLFB1	Percentage of golf course land in 0.25 miles radii buffer, in 1988 and 1998[4]
PCTPARKB1	Percentage of park land in 0.25 miles radii buffer, in 1988 and 1998[4]
PCTRESB1	Percentage of residential land in 0.25 miles radii buffer, in 1988 and 1998[4]
PCTOTHERSB1	Percentage of other land uses in 0.25 miles radii buffer, in 1988 and 1998[4]
PCTAGB2	Percentage of agricultural land in 0.50 miles radii buffer, in 1988 and 1998[4]
PCTGOLFB2	Percentage of golf course land in 0.50 miles radii buffer, in 1988 and 1998[4]
PCTPARKB2	Percentage of park land in 0.50 miles radii buffer, in 1988 and 1998[4]
PCTRESB2	Percentage of residential land in 0.50 miles radii buffer, in 1988 and 1998[4]
PCTOTHERSB2	Percentage of other land uses in 0.50 miles radii buffer, in 1988 and 19984

Sources:[1] Delaware County Auditor;[2] Federal Housing Enterprise Oversight;[3] Census data; [4] Calculated using ArcView

Table 2.2 Hedonic variable means

Year	1988				1998			
	Land (N=582)		House (N=1,718)		Land (N=1,268)		House (N=1,881)	
Variable name	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
PLANDA	$75,764	$202,885	-	-	$250,690	$1,301,482	-	-
PHOUSEA	-	-	$253,561	$244,603	-	-	$334,270	$226,104
NOTINACITY	0.37	0.48	0.14	0.35	0.75	0.43	0.61	0.49
FLOODZONE	0.03	0.18	0.01	0.09	0.02	0.15	0.03	0.16
CORNYIELD	94.04	11.96	92.58	6.72	94.48	16.91	93.46	17.47
SLOPE	3.53	1.80	3.91	1.59	3.41	4.18	3.80	4.21
AGE	-	-	15.43	28.60	-	-	14.18	26.47
STORYHGT	-	-	1.52	0.60	-	-	1.75	0.41
BASEMENT	-	-	0.80	0.40	-	-	0.91	0.29
ROOMS_TOT	-	-	6.81	2.52	-	-	7.33	1.48
BATHS_TOT	-	-	2.34	1.15	-	-	2.65	0.83
GARAGE_CAP	-	-	1.65	1.06	-	-	1.94	0.87
ATTIC	-	-	0.09	0.29	-	-	0.06	0.25
POP_DENS	962	702	1,295	491	405	1,091	828	1,701
INCPRCAP	$14,470	$3,897	$13,818	$1,836	$20,058	$8,820	$20,236	$9,155
SOUTHBND	5.30	4.78	4.56	4.31	4.83	4.53	4.54	4.08
PCTAGB1	43.16	34.83	27.23	28.75	23.86	25.99	18.92	21.69
PCTGOLFB1	1.40	6.57	1.88	6.78	1.56	7.57	1.75	7.15
PCTPARKB1	3.19	8.23	3.97	10.45	2.51	6.98	2.78	7.00
PCTRESB1	33.41	24.84	42.96	23.06	51.31	23.08	55.18	19.56
PCTOTHERSB1	12.13	15.04	12.55	10.27	18.73	20.09	19.51	15.12
PCTAGB2	41.02	29.85	42.27	29.22	30.72	25.43	27.19	22.01
PCTGOLFB2	1.36	4.00	1.79	4.90	1.72	6.46	1.82	6.30
PCTPARKB2	5.25	8.34	4.99	8.35	3.57	7.63	4.52	8.38
PCTRESB2	37.06	21.97	36.60	20.97	41.72	18.43	43.22	16.61
PCTOTHERSB2	12.88	11.65	11.97	10.75	18.69	17.75	19.59	14.37

The average real land price in dollars/acre[11] for the 1988 period and the 1998 period is $75,764.33 and $250,689.68 respectively, while real house prices in dollars/acre in the same period is $253,561.40 and $334,270.26 respectively.

Several sources comprise the dataset. All house and land information comes from the Delaware County Auditor[12]. Housing characteristics include the total number of rooms in a house, the total number of bathrooms (the sum of full baths and half baths), the total garage capacity, and the age of a house in years, as well as dummy variables for the presence of an attic, basement, and central air conditioning.

The land characteristics include parcel area in acres and the percentage slope (measured by rise/run) and soil type of the parcel. Also included are dummy variables for whether the parcel is located in a flood zone and/or in a city area. Further, since most land price studies are concerned with the impact of land characteristics, such as productivity, on land prices, we include the potential average corn yield of the transacted parcel. Neighborhood demographic characteristics include income per capita and population density collected at the census block group level. These variables come from the U.S. Census Bureau database. Following the urban economics literature, a set of distance measures is included to capture proximity to urbanized areas. These variables, calculated using ArcGIS®, are the distances in miles from each transacted house and parcel to the city of Columbus and the city of Delaware.

[11] House and land prices are deflated by the quarterly housing price index at the time of sale (1988 = base year) obtained from the Federal Housing Enterprise Oversight.
[12] The Delaware County Office operates a project named *Delaware Appraisal Land Information System* (DALIS) whose mission is to collect GIS data in Delaware County, OH. Special thanks go to Shoreh Elhami, GIS Director of DALIS Project, for her assistance with the data.

The land uses layers included in the hedonic regressions are also obtained from Auditor's records. They include eight categories: agricultural parcels, residential parcels, governmental parcels, golf course parcels, industrial parcels, commercial parcels, parks, and bodies of water. Since this essay is primarily concerned with the impact of residential, agricultural and open space lands on property values, we have grouped governmental, industrial, and commercial land and bodies of water into one category.

The primary variables of interest in this study are percentages of land use types in buffers around a property. A review of the literature does not suggest a specific number or size of buffers to be included in hedonic regressions. Irwin (2002) suggests that a visual inspection of the land use distribution could be a first indicator to determine the specification of the neighborhood extent; she uses a 0.25-mile radius buffer (400-meters); Patterson and Boyle (2002) use a 0.62-mile radius buffers (1-kilometer); Espey and Owusu-Eudsei (2001) use various buffer sizes for different park types. To avoid collinearity problems, the hedonic regressions in this essay do not include all of the land uses calculated within the buffers. Since it is of interest to determine the impact of open space lands and residential land on land and house prices, the regressions only include the percentage of agricultural land, residential land, parks, and golf courses within a buffer of 0.25 miles radii. A second buffer of 0.5 miles radii is also created. The percentages of land uses in the buffers are calculated using ArcGIS®.

2.8 Expected results

The coefficients of main interest in this essay are of the different land use variables (Table 2.3). It is expected that marginal increases in the percentage of agricultural land surrounding a property might negatively impact land and house prices, whereas an increase in the area dedicated to residential land is expected to positively impact land and house price. Further, marginal changes in the area dedicated to parks and golf course are expected to increase land and house prices.

Table 2.3 Expected signs

	Expected sign	
Variable name	Price of land	Price of house
NOTINACITY		-
LNCORNYIELD	+	
LNSLOPE	-	+
STORYHGT		+
ROOMS_TOT		+
BATHS_TOT		+
GARAGE_CAP		+
LNAGE		-
BASEMENT		+
LNPOP_DENS	+	
LNINCPRCAP	+	+
LNSOUTHBND	-	-
PCTAGB1	-	-
PCTGOLFB1	+	+
PCTPARKB1	+	+
PCTRESB1	+	+
PCTAGB2	-	-
PCTGOLFB2	+	+
PCTPARKB2	+	+
PCTRESB2	+	+

2.9 Model specification

In this section we address several specification issues: first, we determine a list of potential explanatory variables for each equation based on theory and what has been used in previous hedonic studies. Second, we perform collinearity diagnostic tests on these variables based on the Belsley, Kuh, Welsch variance-decomposition diagnostic for detecting colinearity among variables in an explanatory matrix. This procedure is capable of determining the number of near linear dependencies in a given matrix of explanatory variables, and the diagnostic identifies which variables are involved in each linear dependency (page 83; Anselin, 1999). Third, we perform tests for the best model specification (traditional ordinary least squares versus spatial-lag versus spatial error). Last, we test for the presence of contemporaneous correlation in the land and house price equation in a given year. The starting model specifications are the traditional hedonic land price and house price models.

List of explanatory variables

A review of the literature suggests that the price of land might be a function of whether the land is located in a city or not, the natural logarithm of the average slope of the parcel, the natural logarithm of the expected corn yield, the natural logarithm of the income per capita at the census block group level, the natural logarithm of the distance to the southern boundary (Franklin County border line), and the land use variables.

For the house equations, we expect the price of a house to be a function of whether the house is located in a city or not, the expected corn yield and the slope of the parcel where the house is located, the number of rooms, bathrooms, the garage capacity, the age of the house, income per capita at the census block group level, the natural logarithm of the distance to the southern boundary, and the land use variables. Table 2.3 presents the expected signs for all the included variables.

Collinearity diagnostic test

Empirical tests performed by Belsley, Kuh, and Welsch (1980) determined that variance-decomposition proportions in excess of 0.5 indicate that the covariates involve specific linear dependencies. The joint condition of magnitudes for *K(x)* greater than 30 and values of the variance decomposition proportions greater than 0.5 indicate the presence of strong collinear relations. The collinearity diagnostic tables present only the cases that meet these conditions.

Model specification tests

A series of model specification tests are performed in order to determine the most appropriate model specification for the land price and house price equations in 1988 and 1998. The first test (Test 1) is a Lagrange Multiplier test of the traditional hedonic land and house price models against the spatial error alternative. The test statistic follows an asymptotic χ^2 distribution with 1degree of freedom. Failing to accept the null hypothesis of no spatial correlation in the residuals favors specifying the models as a spatial error process.

The second test (Test 2) is a Lagrange Multiplier test of the traditional hedonic land and house price models against the spatial-lag alternative. The test statistic also follows an asymptotic χ^2 distribution with 1degree of freedom. Rejecting the null hypothesis of no spatial correlation in the residuals favors specifying the models as a spatial error process.

Next, robust forms (Test 3 and Test 4) of the previous tests, that is, a Lagrange Multiplier test for spatial error model robust to spatial lag, and a Lagrange Multiplier test for the spatial lag model robust to the spatial error model, are performed. For details on the construction of each test statistic refer to Anselin (1988).

Test for the presence of contemporaneous correlation

Once the land and house price models in each year have been specified, we further test for contemporaneous correlation in the errors across equations. This test determines whether the land price and house price equations in the same year need to be estimated as a seemingly unrelated regression model. The test suggested by Griffiths et al. (page 561; 1992) takes the following form:

H_0: the contemporaneous covariances σ_{ij} are zero, for $i \neq j$.

H_1: at least one covariance is nonzero

The test statistic under the normal linear model is given by:

$$\lambda = T\sum_{1=2}^{M}\sum_{j=1}^{i-1} r_{ij}^2 \qquad [11]$$

where r_{ij}^2 is the squared correlation $r_{ij}^2 = \hat{\sigma}_{ij}^2 \Big/ \hat{\sigma}_{ii}^2 \hat{\sigma}_{jj}^2$ and

$\hat{\sigma}_{ij}^2 = (y_i - X_i b_i)'(y_i - X_i b_j)/T$. Under H_0, λ has an asymptotic χ^2 distribution with M(M-1) degrees of freedom, where M is the number of equations and the estimated error correlations are used in the computation of λ.

The previous test statistic requires the estimation of the correlation between errors in different equations. This is easily attainable when the number of observations in each equation is the same, yet it is more complicated when the equations have unequal number of observations. The approach taken here for estimating a set of land price and house price equations in 1988 and 1998 with unequal number of observations follows Judge et al. (page 480, 1980). Judge et al. state that the consequences of this type of structure are that the generalized least square estimator of the coefficients from all the equations is not the same as when the number of observations is equal, and further, estimating the disturbances covariance matrix is problematic.

Next we describe the procedure used to estimate the SUR equations in each year. First, run separate regressions for the land and house price models in each year using the appropriate specification; the first equation has N_1 number of observations and K_1 explanatory variables. The second equation has $N_1 + N_2$ observations and K_2 explanatory variables. The full system has $(2N_1 + N_2)$ number of observations and $(K_1 + K_2)$ explanatory variables. Obtain the vector of errors from each equation. Let $\hat{e}_1$ and $\hat{e}_2$ be the least squares residuals from the first and second equations, respectively. Further let $\hat{e}_2' = (\hat{e}_{2N_1}', \hat{e}_{2N_1}')$ be partitioned conformably with the number of observations in the second equation. The estimated variance-covariance matrix of disturbances is then defined as:

$$\hat{\Sigma} = \begin{bmatrix} S_{11} - (N_2/(N_1 + N_2))(S_{12}/S_{22N_1})^2(S_{22N_1} - S_{22N_2}) & S_{12}(S_{22}/S_{22N_1})^{1/2} \\ S_{12}(S_{22}/S_{22N_1})^{1/2} & S_{22} \end{bmatrix}$$

where $S_{11} = \hat{e}_1' \hat{e}_1/N_1$, $S_{12} = \hat{e}_1' \hat{e}_2/ N_1$, $S_{22}\ N_1 = \hat{e}_{1T}' \hat{e}_{2\ N_1}/ N_1$, $S_{22N_2} = \hat{e}_{2N_2}' \hat{e}_{2N_2}/N_2$, and $S_{22} = \hat{e}_2' \hat{e}_2/ N_1$. This variance-covariance matrix can be used to test for the presence of contemporaneous correlations, and then used to transform the dependent and independent variables in each model to estimate the new set of coefficients in each equation. For details on the procedure refer to Judge et al. (1980).

2.10 Results

Collinearity diagnostic test results

Table 2.4 presents the variance-decomposition proportions for the potential explanatory variables included in the land and house price equations in 1988 and 1998 respectively. Results indicate a strong collinearity between the intercepts and the natural log of the per capita income in all four equations. In order to overcome this problem, we replace LNINCPRCAP with INCPRCAP. Further tests suggest this variable eliminates collinearity problems with the intercept term. Second, NOTINACITY and LNSLOPE are nearly collinear in the Model 2 land equation in 1988, yet we believe this should not pose any estimation problems.

Table 2.5 and Table 2.6 present the estimated coefficients and corresponding t-statistics for the traditional hedonic land price and house price models. The significance levels of resulting *t*-statistics are given at the 10 (*), 5 (**), and 1 (***) percent levels. Model 1 includes only the land use variables measured within the 0.25 miles radii buffer from each transacted property, whereas Model 2 includes only the land use variables measured within the 0.50 miles radii buffer.Model specification test results

Table 2.4 Belsley, Kuh, Welsch variance-decomposition of explanatory variables

	1988					1998			
	Land			House		Land		House	
	Model 1	Model 2		Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
K(x)	3431	169	3359	6252	6726	1993	1901	2009	1902
INTL88	1.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
NOTINACITY	0.07	0.87	0.06	-	-	0.00	0.00	0.01	
LNCORNYLD	0.00	0.01	0.00	-	-	0.00	0.00	0.00	
LNSLOPE	0.00	0.51	0.00	0.00	0.00	0.00	0.00	0.01	0.01
STORYHGT	-	-	-	0.00	0.00	-	-	0.01	0.01
ROOMS_TOT	-	-	-	0.01	0.01	-	-	0.00	0.00
BATHS	-	-	-	0.02	0.02	-	-	0.00	0.01
GARAGE_CAP	-	-	-	0.00	0.00	-	-	0.00	0.00
LNAGE	-	-	-	0.01	0.01	-	-	0.01	0.00
BASEMENT	-	-	-	0.00	0.00	-	-	0.92	0.00
LNPOP_DENS	-	-	-	0.08	0.09	-	-	0.15	0.02
LNINCPRCAP	0.99	0.00	0.98	0.99	0.99	0.98	0.98	0.00	0.93
LNSOUTHBND	0.03	0.06	0.05	0.01	0.00	0.28	0.25	0.02	0.14
PCTAGB1	0.00	-	-	0.00	-	0.01	-	0.01	-
PCTRESB1	0.01	-	-	0.00	-	0.03	-	0.02	-
PCTPARKB1	0.00	-	-	0.00	-	0.02	-	-	-
PCTGOLFB1	0.00	-	-	0.00	-	0.01	-	-	-
PCTAGB2	-	0.01	0.03	-	0.00	-	0.02	-	0.00
PCTRESB2	-	0.02	0.02	-	0.00	-	0.10	-	0.11
PCTPARKB2	-	0.00	0.01	-	0.00	-	0.01	-	0.01
PCTGOLFB2	-	0.00	0.00	-	0.00	-	0.03	-	0.06

Table 2.5 Results for the traditional hedonic land price and house price models, in 1988

	1988							
	Land				House			
	Model 1		Model 2		Model 1		Model 2	
Variable	Estimate	t-Stat	Estimate	t-Stat	Estimate	t-Stat	Estimate	t-Stat
INTERCEPT	10.4225***	3.44	11.4861***	3.56	16.9562***	6.00	15.0346***	4.91
NOTINACITY	-1.4112***	-8.35	-1.9783***	-12.95	-	-	-	-
LNCORNYIELD	0.0998***	3.11	0.0839***	2.50	-	-	-	-
LNSLOPE	-0.0533	-0.53	-0.0394	-0.37	0.2940***	5.80	0.3321***	6.03
STORYHGT	-	-	-	-	0.4353***	7.34	0.4967***	7.73
ROOMS_TOT	-	-	-	-	-0.0485***	-2.32	-0.0127	-0.57
BATHS_TOT	-	-	-	-	0.0786*	1.63	0.0246	0.47
GARAGE_CAP	-	-	-	-	0.1163***	3.35	0.0322	0.86
LNAGE	-	-	-	-	0.0314***	8.36	0.0240***	6.09
BASEMENT	-	-	-	-	-0.0979	-1.18	0.0200	0.22
LNPOP_DENS	-	-	-	-	0.4861***	14.51	0.7256***	23.44
LNINCPRCAP	0.1699	0.53	0.0473	0.14	-0.8412***	-2.90	-0.9500***	-3.02
LNSOUTHBND	-0.3004***	-5.35	-0.4489***	-8.60	-0.1262***	-4.35	-0.2213***	-8.35
PCTAGB1	-0.0257***	-9.02	-	-	-0.0249***	-17.47	-	-
PCTRESB1	-0.0183***	-5.54	-	-	-0.0125***	-8.74	-	-
PCTPARKB1	-0.0166***	-2.33	-	-	-0.0071***	-2.54	-	-
PCTGOLFB1	-0.0073	-0.87	-	-	-0.0055	-1.32	-	-
PCTAGB2	-	-	-0.0126***	-2.88	-	-	-0.0027	-1.19
PCTRESB2	-	-	-0.0161***	-2.87	-	-	0.0003	0.11
PCTPARKB2	-		-0.0204***	-2.42	-	-	-0.0045	-1.04
PCTGOLFB2	-	-	-0.0213	-1.40	-	-	0.0027	0.41
N	582		582		1,718		1,718	
Adjusted R^2	0.5208		0.4603		0.5333		0.4490	

Table 2.6 Results for the traditional hedonic land price and house price models, in 1998

	1998							
	Land				House			
	Model 1		Model 2		Model 1		Model 2	
Variable	Estimate	t-Stat	Estimate	t-Stat	Estimate	t-Stat	Estimate	t-Stat
INTERCEPT	7.4486^{***}	5.22	9.2490^{***}	6.29	10.8682^{***}	15.52	11.2639^{***}	14.92
NOTINACITY	$-.6022^{***}$	-4.98	$-.6171^{***}$	-5.13	-	-	-	-
LNCORNYIELD	0.0544^{***}	3.20	0.0516^{***}	3.09	-	-	-	-
LNSLOPE	0.1751^{***}	3.07	0.1372^{**}	2.43	-0.0084	-0.32	-0.0127	-0.49
STORYHGT	-	-	-	-	0.2606^{***}	3.88	0.2895^{***}	4.31
ROOMS_TOT	-	-	-	-	0.0191	0.92	-0.0052	-0.25
BATHS_TOT	-	-	-	-	0.1986^{***}	4.53	0.2022^{***}	4.60
GARAGE_CAP	-	-	-	-	-0.0100	-0.30	-0.0163	-0.50
LNAGE	-	-	-	-	-0.0271^{***}	-8.65	-0.0296^{***}	-9.49
BASEMENT	-	-	-	-	0.0703	0.85	0.0578	0.69
LNPOP_DENS	-	-	-	-	0.0716^{***}	4.81	0.0755^{***}	5.07
LNINCPRCAP	0.4813^{***}	3.28	0.2768^{*}	1.80	0.0936	1.27	0.0352	0.44
LNSOUTHBND	$-.2075^{***}$	-4.49	$-.1473^{***}$	-2.97	-0.1092^{***}	-5.00	-0.0936^{***}	-4.02
PCTAGB1	$-.0278^{***}$	-10.02	-	-	-0.0245^{***}	-15.19	-	-
PCTRESB1	-0.0049^{*}	-1.73	-	-	-0.0102^{***}	-5.88	-	-
PCTPARKB1	-0.0111^{*}	-1.64	-		-0.0072^{**}	-2.03	-	
PCTGOLFB1	0.0104^{*}	1.69	-	-	0.0006	0.17	-	-
PCTAGB2	-	-	$-.0275^{***}$	-9.21	-	-	-0.0213^{***}	-13.16
PCTRESB2	-	-	0.0022	0.63	-	-	-0.0048	-2.28
PCTPARKB2	-		-0.0104^{*}	-1.64	-		0.0010	0.32
PCTGOLFB2	-	-	0.0404^{***}	5.62	-	-	0.0091^{***}	2.31
N		1,268		1,268		1,881		1,881
Adjusted R^2		0.2872		0.3088		0.3674		0.3659

Table 2.7 Spatial tests

	1988				1998			
	Land		House		Land		House	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Test 1	46.25	78.20	198.12	314.18	436.26	370.95	464.50	442.43
Test 2	10.33	27.73	2.02	11.56	31.44	26.61	72.80	63.84
Test 3	24.56	35.34	178.68	266.68	296.37	254.40	322.58	309.98
Test 4	0.17	2.64	3.63	1.18	7.64	5.91	3.70	2.21

Table 2.7 presents test results for the presence of spatial correlation in the residuals of the Ordinary Least Squares regressions presented in Table 2.5 and Table 2.6. The critical value for these tests is 6.63. Any calculated value greater than the critical value rejects the null hypotheses of no spatial correlation in the residuals. The spatial econometrics literature specifies that when both the spatial error test (Test 1) and the spatial-lag test (Test 2) fail to reject the null hypothesis, it is necessary to calculate robust forms of these tests that are exclusive of one another (Test 3 and Test 4). Results presented in Table 2.7 indicate that the best spatial process for both the land and house price equations in 1988 and 1998 is the spatial error model.

Contemporaneous correlation test results

Test statistics of λ_{1988}=50.24 and λ_{1998}=141.12 for the 1988 and 1998 equations respectively fail to reject the null hypothesis of the cross land and house price equation error covariances equal to zero ($\chi^2_{(1,\ 0.05)}$ =3.84). The land and house markets are thus found to be contemporaneously correlated. Estimating these equations as seemingly unrelated regression estimations would provide consistent estimates of the impact of various land uses on land and house prices.

2.11 Regression results

Spatial error regression results

Table 2.8 and Table 2.9 present estimates for the 1988 and 1998 spatial error land price and house price models. For the land equations in 1988, Model 1 has a higher adjusted goodness of fit. Both models present the same coefficient signs and the magnitudes of the coefficients do not differ considerably. Parcels located outside of the city limits sell at lower prices than those located within the city limits. The coefficient for the natural log of corn yield is positive and statistically significant, meaning that higher expected corn yield translates into higher land prices. Parcels that are better suited for agricultural production sell at higher prices, reflecting the land's productivity potential and likely retarding its conversion into residential land. At the same time, the parcel's slope negatively affects its price, but this impact is not statistically significant. Though a parcel's slope most likely affects agricultural production, its impact does not translate into lower land prices. Also, parcels located further away from the southern boundary sell at lower prices. This is expected: the southern part of Delaware County is located close to urbanized areas and to major employment centers along the northern part of the city of Columbus, in Franklin County (Sohngen et al, 2000). With respect to the land use variables in Model 1, increases in the percentage of agricultural land or residential land relative to other land uses, *ceteris paribus,* have a statistically significant negative impact on land prices. Results for Model 2 are similar, though the magnitudes of impact are smaller. The coefficient for percentage of parks surrounding each transacted land is also significant in Model 2.

Goodness of fit-statistics suggest the house equations in 1988 are better explained by the explanatory variables than are the land equations. All variable coefficients in Model 1 are statistically significant, with the exception of the presence of a basement. The parcel's slope has a positive effect on house prices. Most of the housing characteristics follow their expected signs. Results for Model 2 differ in the number of variables that are statistically significant. Slope is still positive and significant, but with the exception of STORYHGT and LNAGE, the housing characteristics are not statistically significant. Again, both model estimates suggest that houses located further away from the southern boundary sell at lower prices as predicted by urban theory. With respect to the land use variables, results are statistically significant in Model 1. None of the coefficients for these variables are statistically significant in Model 2.

Table 2.9 presents results for 1998; these are similar to 1988, though coefficient sizes are smaller. A considerable difference exists with respect to the LNSLOPE variable. Results in 1998 are opposite to 1988: slope has a positive and significant impact on land prices, and a negative and insignificant impact on house prices. In the land equation in Model 1, only the percentage of agricultural land coefficient is statistically significant. In Model 2, the agricultural land, residential and golf courses coefficients are statistically significant. In this case, the percentages of residential land and golf course have a positive impact on land prices relative to other land uses.

The Model 1 house equation in 1998 performs relatively better than Model 2. With the exception of PCTGOLFB1, all other land use variables are statistically significant. This suggests that with increased residential development, surrounding land uses take on more importance.

Table 2.8 Results for the spatial error hedonic land price and house price models, in 1988

	1988							
	Land				House			
	Model 1		Model 2		Model 1		Model 2	
Variable	Estimate	t-Stat	Estimate	t-Stat	Estimate	t-Stat	Estimate	t-Stat
INTERCEPT	11.8027***	36.19	11.4084***	25.28	14.7516***	64.77	11.3074***	40.50
NOTINACITY	-1.3471***	-8.51	-1.7060***	-11.52	-	-	-	-
LNCORNYIELD	0.1013***	3.38	0.0850***	2.82	-	-	-	-
LNSLOPE	-0.0710	-0.72	-0.0587	-0.58	0.2784***	5.92	0.2852***	5.93
STORYHGT	-	-	-	-	0.3190***	5.73	0.3300***	5.79
ROOMS_TOT	-	-	-	-	-0.0412**	-2.08	-0.0268	-1.33
BATHS_TOT	-	-	-	-	0.0890**	2.02	0.0665	1.48
GARAGE_CAP	-	-	-	-	0.0760**	2.27	0.0351	1.02
LNAGE	-	-	-	-	0.0349***	8.61	0.0326***	7.62
BASEMENT	-	-	-	-	-0.0742	-0.94	-0.0222	-0.28
LNPOP_DENS	-	-	-	-	0.4070***	12.65	0.5322***	17.39
INCPRCAP	0.00001***	8.33	0.000003***	2.35	-0.5288***	-17.46	-0.3778***	-6.90
LNSOUTHBND	-0.3229***	-4.91	-0.4847***	-7.43	-0.2058***	-5.28	-0.3200***	-8.17
PCTAGB1	-0.0245***	-7.42	-	-	-0.0237***	-12.78	-	-
PCTRESB1	-0.0161***	-4.21	-	-	-0.0112***	-5.76	-	-
PCTPARKB1	-0.0119	-1.55	-	-	-0.0065*	-1.86	-	-
PCTGOLFB1	-0.0127	-1.37	-	-	-0.0171***	-3.06	-	-
PCTAGB2	-	-	-0.0093**	-2.29	-	-	-0.0004	-0.22
PCTRESB2	-	-	-0.0096*	-1.90	-	-	0.0015	0.61
PCTPARKB2	-	-	-0.0150**	-1.93	-	-	-0.0018	-0.49
PCTGOLFB2	-	-	-0.0170	-1.24	-	-	0.0016	0.29
Lambda	0.2780***	11.44	0.3560***	15.61	0.4190***	40.11	0.5230***	38.78
N	582		582		1,718		1,718	
Adjusted R^2	0.5611		0.5344		0.5996		0.5766	

Table 2.9 Results for the spatial error hedonic land price and house price models, in 1998

	1998							
	Land				House			
	Model 1		Model 2		Model 1		Model 2	
Variable	Estimate	t-Stat	Estimate	t-Stat	Estimate	t-Stat	Estimate	t-Stat
INTERCEPT	12.0378***	45.37	11.8675***	43.59	9.7831***	43.20	10.2003***	49.34
NOTINACITY	-0.9151***	-5.98	-0.9868***	-6.43	-	-	-	-
LNCORNYIELD	0.0334**	2.27	0.1146**	2.06	-	-	-	-
LNSLOPE	0.1299**	2.35	0.0308**	2.07	-0.0050	-0.20	-0.0137	-0.54
STORYHGT	-	-	-	-	0.0654	1.15	0.0708	1.25
ROOMS_TOT	-	-	-	-	0.0472***	2.49	0.0407	2.14
BATHS_TOT	-	-	-	-	0.1118***	2.93	0.1150***	3.01
GARAGE_CAP	-	-	-	-	0.0247	0.85	0.0190	0.65
LNAGE	-	-	-	-	-.0086***	-2.45	-0.0090***	-2.55
BASEMENT	-	-	-	-	-0.0040	-0.05	-0.0236	-0.32
LNPOP_DENS	-	-	-	-	0.0333**	1.95	0.0356**	2.06
INCPRCAP	0.00001***	14.07	0.00001***	2.68	0.2500***	12.39	0.1752***	9.22
LNSOUTHBND	-0.2999***	-5.56	-0.2883***	-4.89	-.1072***	-3.41	-0.0946***	-2.77
PCTAGB1	-0.0216***	-6.31	-	-	-.0208***	-9.96	-	-
PCTRESB1	-0.0007	-0.21	-	-	-.0085***	-3.85	-	-
PCTPARKB1	-0.0072	-0.92	-	-	-0.0095**	-2.19	-	-
PCTGOLFB1	0.0058	0.76	-	-	-0.0007	-0.14	-	-
PCTAGB2	-	-	-0.0168***	-4.61	-	-	-0.0174***	-7.60
PCTRESB2	-	-	0.0069*	1.77	-	-	-0.0019	-0.69
PCTPARKB2	-	-	-0.0005	-0.06	-	-	0.0017	0.38
PCTGOLFB2	-	-	0.0378***	3.97	-	-	0.0092	1.53
Lambda	0.4509***	34.29	0.4310***	18.03	0.5380***	65.82	0.5460***	65.48
N		1,268		1,268		1,881		1,881
Adjusted R^2		0.5023		0.4960		0.5352		0.5322

Seemingly Unrelated Spatial error regression results

Table 2.10 and Table 2.11 present results for the 1988 and 1998 land price and house price equations treated as seemingly unrelated regressions. In order to estimate these coefficients, we follow the following procedure. First, we obtain the vector of disturbances from a first stage spatial error regression with land and house transaction pooled for a given year. Second, we estimate the variance-covariance matrix of disturbances using Judge et al.'s (page 482, 1980) procedure when each equation has different number of observations. This variance-covariance matrix of disturbances is used to re-estimate the seemingly unrelated model (without spatial effects).
All seemingly unrelated regression results perform considerably better in terms of adjusted R^2 than the traditional hedonic models and the spatial error models, though individual variable performance is similar. In comparing the land use variables across models in the same year, we find that coefficient magnitudes do not differ, though accounting for cross-correlation in the disturbances across equations improves the statistical performance of the land use variables. In 1988, it is consistently found that changes in the percentages of agricultural, residential, golf courses, and parks have a negative effect on land and house prices. In 1998, results are mixed; the coefficient for the percentage of agricultural land is negative in the land equation in both Model 1 and Model 2, but coefficients for the other land use variables are positive. With the exception of the percentage of golf course land in Model 2, all other land use variables are statistically insignificant in the house equations.

Table 2.10 Results for the SUR spatial error hedonic land price and house price models, in 1988

	1988							
	Land				House			
	Model 1		Model 2		Model 1		Model 2	
Variable	Estimate	t-Stat	Estimate	t-Stat	Estimate	t-Stat	Estimate	t-Stat
INTERCEPT	0.0011***	2.85	0.0012***	2.81	0.0038***	3.33	0.0034***	3.01
NOTINACITY	-1.5694***	-10.05	-2.110***	-13.08	-	-	-	-
LNCORNYIELD	0.0973***	4.62	0.0803***	4.20	-	-	-	-
LNSLOPE	-0.0327	-0.31	-0.0184	-0.17	0.2914***	6.02	0.3281***	6.48
STORYHGT	-	-	-	-	0.4471***	7.85	0.5045***	8.01
ROOMS_TOT	-	-	-	-	-0.0365*	-1.64	-0.0047	-0.20
BATHS_TOT	-	-	-	-	0.0224	0.36	-0.0175	-0.28
GARAGE_CAP	-	-	-	-	0.1368***	3.07	0.0539	1.19
LNAGE	-	-	-	-	0.1100***	4.33	0.0916***	3.49
BASEMENT	-	-	-	-	-0.0803	-1.03	0.0290	0.34
LNPOP_DENS	-	-	-	-	0.8544***	27.70	0.5606***	16.73
INCPRCAP	1.2630***	49.42	1.2229***	24.01	0.5362***	14.29	0.7643***	22.91
LNSOUTHBND	-0.2696***	-4.46	-.4081***	-7.26	-0.0998***	-2.87	-0.2103***	-6.16
PCTAGB1	-0.0254***	-9.90	-	-	-.0239***	-16.58	-	-
PCTRESB1	-0.0194***	-6.44	-	-	-0.0116***	-8.68	-	-
PCTPARKB1	-0.0166**	-2.26	-	-	-0.0080***	-2.99	-	-
PCTGOLFB1	-0.0065	-0.88	-	-	-0.0014	-0.18	-	-
PCTAGB2	-	-	-0.0099**	-2.08	-	-	-0.0020	-0.88
PCTRESB2	-	-	-0.0131**	-2.06	-	-	0.0014	0.50
PCTPARKB2	-	-	-0.0170**	-2.02	-	-	-0.0029	-0.74
PCTGOLFB2	-	-	-0.0187	-1.10	-	-	0.0040	0.66
N	582		582		1,718		1,718	
Adjusted R^2	0.9781		0.9753		0.9695		0.9646	

Table 2.11 Results for the SUR spatial error hedonic land price and house price models, in 1998

	1998							
	Land				House			
	Model 1		Model 2		Model 1		Model 2	
Variable	Estimate	t-Stat	Estimate	t-Stat	Estimate	t-Stat	Estimate	t-Stat
INTERCEPT	0.0378***	1.26	0.0388	1.31	0.0536*	1.73	0.0528*	1.66
NOTINACITY	-0.5541***	-4.52	-0.5939***	-4.70	-	-	-	-
LNCORNYIELD	0.1037**	2.35	0.1012**	2.33	-	-	-	-
LNSLOPE	0.3035**	2.23	0.2625***	2.00	-0.0347	-1.14	-0.0392	-1.33
STORYHGT	-	-	-	-	0.5022***	3.89	0.5055***	3.81
ROOMS_TOT	-	-	-	-	0.0800	1.46	0.0675	1.19
BATHS_TOT	-	-	-	-	0.1427**	2.42	0.1551***	2.61
GARAGE_CAP	-	-	-	-	-0.0265	-0.68	-0.0241	-0.60
LNAGE	-	-	-	-	-0.0326***	-7.84	-0.0347***	-8.79
BASEMENT	-	-	-	-	0.3575	1.54	0.3657	1.51
LNPOP_DENS	-	-	-	-	0.9260***	4.79	0.9306***	4.85
INCPRCAP	1.1304***	11.33	1.1080***	9.66	0.2239***	2.72	0.2310***	2.85
LNSOUTHBND	-0.1494**	-1.93	-0.0915	-0.92	0.0274	1.10	0.0240	0.90
PCTAGB1	-0.0211***	-2.78	-	-	-0.0119	-1.36	-	-
PCTRESB1	0.0027	0.29	-	-	-0.0028	-0.35	-	-
PCTPARKB1	0.0028	0.26	-	-	0.0102	1.21	-	-
PCTGOLFB1	0.0136*	1.88	-	-	0.0058	0.63	-	-
PCTAGB2	-	-	-0.0193**	-1.97	-	-	-0.0103	-1.20
PCTRESB2	-	-	0.0096	0.73	-	-	-0.0042	-0.51
PCTPARKB2	-	-	0.0056	0.46	-	-	0.0149**	2.11
PCTGOLFB2	-	-	0.0411***	4.14	-	-	0.0056	0.71
N		1,268		1,268		1,881		1,881
Adjusted R^2		0.9606		0.9612		0.9795		0.9796

Table 2.12 Average marginal implicit prices for changes in the percentage land uses, in real dollars ($)

	Land 88		House 88		Land 98		House 98	
	Buffer 1	Buffer 2	Buffer 1	Buffer 2	Buffer 1	Buffer 2	Buffer 1	Buffer 2
Agricultural land	-929.22	-64.52	-4,389.36	-335.90	-1,834.06	-894.68	-3,314.70	-2,814.08
Residential land	-708.20	46.29	-2,135.26	240.99	235.19	-429.33	-888.37	-1,350.40
Golf courses	-606.88	-93.80	-1,474.64	-488.31	239.77	1,339.13	2,984.38	4,212.04
Parks land	-238.45	129.56	-248.75	674.47	1,177.48	355.52	1,145.88	1,118.22

2.12 Discussion

Results from the seemingly unrelated regressions are used to compare marginal impacts from land use changes on land and house prices over time where land changes are measured as percentage changes in land uses in buffers around each property. Table 2.12 presents marginal values for the four categories of land uses. The impact of changes in the percentage of agricultural land is consistently negative in both years on land and house values. In 1988, a 1% increase in agricultural land in a parcels' buffer decreases its land value by $929.22 and its house value by $4,389.36. This effect abruptly decreases when considering a larger buffer size surrounding the property. In 1998, the same effect occurs, yet the impact from the bigger buffer is greater in magnitude. These results may indicate that property values for homeowners in agricultural areas are depressed. The land use classification, though, only captures whether the surrounding land is categorized as agricultural land or not; it does not capture whether the land is actually being used for agricultural production. This effect may be causing greater negative impacts in 1998, considering that the percentage of agricultural land dropped considerably over the ten years in study. Further, the percentage of residential land has a negative impact on house prices in 1998 in both buffers, but the magnitude of impact compared to the percentage of agricultural land is considerably smaller. This effect is reverted of 1988.

Both land and house prices are negatively affected by residential land within the smaller buffer, yet increases in the percentage of residential land in the larger buffer have a positive effect on land and house values. This reflects the potential development of land; also, people moving from urban areas to suburban areas expect further development of these residential areas and most likely want to enjoy both the fact that they are in areas of low development but they also do not want to be completely isolated. As time passes, though, this effect is reversed. Results in 1998 indicate that residential land in close proximity to a property positively affects land values but negatively affects house values. Residential expansion has occurred at the expense of conversion of the highest potential development land, leaving out less suitable land. Homeowners in 1998 do not value more residential land because residential expansion over the years has increased residential density, that is, residential congestion has increased and what was once part rural, part residential now is mostly residential. Further, the preferences of the growing residential population are manifested in a higher valuation of golf courses and parks.

In 1988, golf courses had a negative impact on land and house values. As residential expansion occurred over the years, the preferences of the new residents favored recreational areas, particularly golf course. It is expected that people coming from urban areas into expanding suburban areas enjoy natural habitats not only for aesthetic enjoyment, but as part of other activities that are complement to the scenery. Golf courses are a typical example: they are privately owned, they are permanently taken care of, and they provide a recreational activity for people that are most likely working in urban areas but live in suburban areas.

Simulations

The empirical land and house price models estimated in this essay can be used to predict the impact of land use changes on house and land prices as development progresses over time. Concerns over the impact of increased urban and suburban growth on agricultural areas and open space lands have led many cities and counties in the United States to pass laws to protect farmland and the environment discouraging the expansion of suburban areas. It is arguable that these policies have unpredictable effects on land and house prices. One way to asses this impact is to simulate price changes in the hedonic price models imposing certain conditions on the land use variables. Table 2.13 presents results for price simulations on land and house prices in 1998. We predict land and house prices assuming that the average percentage area of the different land uses in 1998 approximates the averages in 1988.

Table 2.13 Actual predicted prices in 1998 versus predicted prices in 1998 assuming 1988 land use averages remain constant

	Land		House	
	Buffer 1	Buffer 2	Buffer 1	Buffer 2
Actual price prediction	$86,845.53	$92,621.07	$292,799.74	$290,461.41
Simulated price prediction	$69,910.89	$77,301.65	$291,061.39	$272,816.63
% change	-26.82	-19.49	-4.12	-10.54

The results for the land price simulations in 1998 indicate that actual predicted land prices in 1998 are considerably higher than the simulated prices (all prices are deflated prices). This indicates that land use changes in the ten year period between 1988 and 1998 had a positive price impact on land prices. Results for the house price simulations in 1998 are similar, yet the percentage increase is considerably smaller than the percentage change in land prices. The results suggest there are other forces causing price increases beyond inflation and surrounding land use percentages.

2.13 Conclusion

This essay addresses concerns over the impact of urban and suburban expansion into predominantly agricultural areas. We estimate land and house prices in two different time periods as a function of land and house characteristics as well as of the percentages of different land uses surrounding each property. The estimated models are relevant policy making tools that allow us to predict how land use changes affect the value of land and house price transactions.

This essay represents a contribution to the literature because it estimates households' valuations of different types of land uses on land and house transactions considering the fact that both markets are linked by the continuity and fixity of land. Empirical results determine that households' valuation of open space lands differ between land transactions and housing transactions. Further, we can predict changing preferences over time: residential movers in 1988 have different preferences compared to those in 1998.

The following concerns need to be addressed in future research. First, the land uses in this essay do not provide information about whether the parcels are developable or idle. It was mentioned earlier that this might generate endogeneity problems of neighboring parcels' land uses. Further, it was not possible to determine whether the parcels classified as agricultural land were actually being used for agricultural production. The marginal impact of additional agricultural land most likely differs by types of agricultural operations. It has been found in the literature that certain agricultural activities have a negative impact on property values, such as swine production farms, whereas others might have positive impacts. The last concern relates to the impact of congestion externalities on property values. Most conversion of agricultural land into residential land accompanies fragmentation of large plots into smaller plots. The increase in housing congestion as measured by density of built structures per unit of land, for example, is not captured within the percentage of residential land surrounding a property. Over time the percentage increases, but at the same time the number of houses built on the parcels also increases. It is possible that the impact of residential land use on property values may differ by the capital intensity surrounding the property, an effect which is outside the scope of this study.

CHAPTER 3: ESTIMATING THE DEMAND FOR RACIAL, INCOME, EDUCATION, AND AGE NEIGHBORHOOD SEGREGATION

3.1 Introduction

Social scientists, including economists and sociologists, recognize that inhabitants of metropolitan areas in the United States are sorted into homogenous neighborhoods consisting of individuals of similar socioeconomic characteristics. Several theories and hypotheses have been formulated and empirically tested to explain the possible causes and consequences of residential segregation, primarily segregation of African-Americans (Cutler, Glaeser and Vigdor, 2002; Massey and Denton, 1993, Cutler et al., 1999). The mechanism under which sorting into neighborhoods takes place is still not well understood. Most of the literature focuses on relating neighborhood segregation to factors such as income distribution, poverty, education, capital formation, and transportation costs and commuting time to work, as well as to preference for racial homogeneity, government spending, and religion (Kain, 1968; Schelling, 1971; Galster, 1992; Vandell, 1995; Cutler and Glaeser, 1997; Ihlanfeldt and Scafidi, 2002). This issue has long been an important subject in the economic and social policy arena because of the impact of segregation on human capital formation as well as on public housing policy and local government finances (Vandell, 1995; Borjas, 1995).

In this essay we depart from traditional racial segregation studies, and consider occurrence of neighborhood segregation by multiple criteria. That is, we hypothesize neighborhood clustering occurs by age, education level, income level, as well as by race. The Tiebout hypothesis (1956) states that, provided a level of governmental amenities in a particular neighborhood, household consumers will sort by moving into neighborhoods with the combination of amenities that maximize utility. It has been argued that income differences between whites and blacks, for example, result in blacks being clustered in neighborhoods that are separated from main jobs centers, from the influence of positive role models, and access to high quality local public goods (Cutler and Glaeser, 1997). Our essay broadens the literature by investigating whether households may sort or self-segregate along dimensions other than race. For example, differences in amenity preferences between retired persons and families with children might result in neighborhoods that consist predominantly of a particular age group. In addition, most of the existing literature measures sorting at the Metropolitan Statistical Area (MSA) or census tract level. This essay examines the issue of segregation at a much finer scale based on census block group geography.

This essay lays out an empirical model based on Rosen's (1974) hedonic framework to estimate implicit prices and empirical demand functions for racial, income, education, and age neighborhood segregation. We use the demand estimates to calculate price elasticities and consumer surplus variation that occur as a result of changes in the percentage of people that need to move from a geographical area to make it evenly distributed by age, race, education attainment, and income. Further, the structure of the model allows us to examine the way different types of segregation may instigate or compound effects of one another.

3.2 Theories on segregation

A primary concern of social scientists has been the impact of racial segregation on the performance of the segregated group, as well as in finding the reasons why such a phenomenon occurs. The literature on the relationship between personal preferences and residential outcomes for racial and ethnic groups in metropolitan areas is split into three groups. A number of scholars hypothesize that it is the preferences of whites and blacks that keep metropolitan areas racially segregated. This group contends that blacks and whites self-segregate into neighborhoods because they prefer living with people of their own race. It has been argued, though, that empirical studies provide only indirect evidence of the validity of the self-segregation hypothesis (Ihlanfeldt and Scafidi, 2002). For example, King and Mieszkowski (1973) found that blacks in New Haven, Connecticut, are willing to pay more for housing in the ghetto than in racially mixed areas, while whites are willing to pay less for housing in racially mixed areas than in white areas. In another paper, Galster (1982) finds evidence of black aversion to living in predominantly black neighborhoods in St. Louis, Ohio, in 1967, as well as white aversion to living in neighborhoods with blacks in St. Louis in 1967 and Wooster, Ohio, in 1975. More recently, Ihlanfeldt and Scafidi (2002) argue that their results provide the first direct empirical test of the black self-segregation hypothesis; their results suggest that blacks' preferences in Atlanta, Detroit, and Los Angeles to live with their own peers has a minor effect on the racial composition of predominantly African-American neighborhoods.

A second group contends that, combined with household preferences, complex market forces result in neighborhoods that predominate in one particular race. Both demand shifters in the housing market such as income differences between whites and blacks, job locations, and information, as well as supply factors such as differences in housing costs, have an impact on the racial composition of neighborhoods in metropolitan areas. Also, a growing literature is concerned with the positive and negative effects of spatial separation of racial and ethnic groups on their economic performance. Cutler and Glaeser (1997), for example, find strong evidence that African-American outcomes in schooling, employment and single parenthood are far worse in racially segregated cities than they are in more integrated cities.

A third vein of literature suggests that non-market forces play a deterministic role in the racial composition of neighborhoods. Such non-market forces include discrimination in the lending and real estate markets (Massey and Denton, 1993; Galster, 1988; Schill and Wachter, 1995; Galster and Godfrey, 2005), as well as public housing policies such as local government regulations and federal regulation of subsidized housing programs (Schill and Wachter, 1995). For a recent review of the literature on residential segregation, refer to Adelman (2005).

3.3 Household sorting and the Tiebout model

The Tiebout model has been extensively studied and referenced since its publication in 1956. It has become the basis for economists' deliberation over how households sort themselves into communities in a metropolitan area (Wassmer, 2002). The basic premise of the model is that independent local governments can provide public amenities through a price mechanism, thus avoiding the free-rider problem typical of public goods. Households are assumed to be drawn to communities that provide their desired level of housing, community, and local public services that best maximize their utility (Margulis, 2001). Accordingly, peoples' abilities to acquire units of the public good determine the composition of the neighborhood. In other words, differences in income lead to differences in neighborhood composition. Race has been linked to income in many ways. Empirically, whites have higher average incomes than blacks or other minorities. As a result, whites will be able to afford to live in neighborhoods that provide certain levels of public amenities. This suggests an important research question that we aim to address: if there are no income differences between whites and blacks or other minorities, would there still be neighborhood segregation? Previous research (Galster, 1982; Kain, 1985; Clark, 1991) finds evidence that whites self-segregate into predominantly white neighborhoods and bid higher for properties located in white neighborhoods.

Much of the debate over segregation has concentrated on the causes and consequences of racial segregation. Not much attention has been given to other possible types of neighborhoods segregation. For example, segregation by age groups is also possible. People of advanced age most likely prefer to settle into areas that offer certain amenities that are not necessarily of interest to young families with children. Education is another example. Skilled or educated people most likely identify more strongly with people of similar educational background. Age, education, and income segregation could actually be a part of the unsolved problem of racial segregation.

In this essay we argue that neighborhood segregation occurs in many dimensions. It is an empirical question whether neighborhood racial, income, age, and education segregation are found to occur jointly with one another. Racial segregation has been linked to income differences between whites and blacks, yet no effort has been made to link segregation to other characteristics, or to examine sorting interactions over different characteristics.

3.4 Analytical framework

The purpose of this research is to estimate a system of demand equations for neighborhood segregation using Rosen's (1974) two stage hedonic framework. This framework has been regularly used to estimate demand equations for markets that do not have an observable price. In this essay we use Rosen's framework to develop a system of demand equations for racial, income, age, and education neighborhood segregation as a function of their instrumented implicit prices and other important shift variables.

The hedonic model

Rosen's (1974) hedonic price model has been extensively used by researchers to examine the impact of a number of factors on house prices. For example, Linneman (1981), Parsons (1986), and Quigley (1984) use the technique to analyze willingness to pay for housing characteristics, while Hite et al. (2001), Kohlhase (1991), Nelson et al. (1992), and Reichert et al. (1992) study the impact of waste sites on property values. We also find several studies that address the role of information on property values affected by environmental disamenities. Examples include Kohlhase (1991), Kask and Maani (1992), Kiel and McClain (1995), and McCluskey and Rausser (2001), and Hite (1998). In a recent paper, Brasington and Hite (2005) use Rosen's hedonic framework to estimate a demand curve for environmental quality, incorporating the effect of spatial dependence of property values and characteristics. Other studies that estimate demand curves for housing characteristics include Cheshire and Sheppard (1998), Chattopadhyay (1999), and Brasington (2000 and 2002).

The hedonic price function

Rosen's (1974) hedonic framework applied to the real estate market is as follows. On the demand side, a household purchases a home which is comprised of a bundle of attributes, *Z*, and a numeraire good, *X*, with price equal to one. Included in *Z* are structural characteristics such as the number of rooms and the age of the house, as well as expenditures on neighborhood characteristics, such as local public goods. The household maximizes utility by purchasing a house with a given set of characteristics subject to income *Y*. The utility maximization problem takes the form:

$$Max\, U = u(Z; X, \delta) \text{ s. t. } Y = P(Z) + X \qquad [1]$$

where Z are housing characteristics, δ is a vector of buyer's characteristics, and X is a numeraire good, and P(Z) represents the price of housing services for a house with characteristics vector Z.

On the supply side, home sellers maximize profits from sale of the house:

$$Max\ \Pi = P(Z) - C(Z, X; \gamma) \qquad [2]$$

where all variables are defined as before, C is a cost function which represents the cost of offering a house for sale, and γ represents seller's characteristics[13].

From the utility and profit maximization problem, bid and offer functions are derived. In perfectly competitive markets, the hedonic price function $P\,(Z^*;\, \delta,\, \gamma)$ occurs

[13] In empirical application of HPM, supply is assumed fixed in the short-run, justifying use only of demand curve.

at the tangency of the bid curve and offer curve. Each point along the hedonic price function represents an equilibrium point representing the lowest transaction price possible for the house with an optimal set of characteristics paid by buyers, and the highest price possible obtained by sellers.

Deriving demand curves

Rosen (1974) was the first to recognize that marginal implicit prices from a first stage hedonic could be used to estimate a demand function in a second stage of analysis. To implement the method, however, it is necessary to instrument these prices, and exogenous shift variables are included to estimate the demand for racial, income, education, and age neighborhood segregation.

A characteristic's demand curve is derived from the indirect utility function obtained from substituting *Y-P(Z)* into equation [1]:

$$V = U(Z, Y - P(Z)); \delta) \qquad [3]$$

Maximizing V with respect to characteristic z_i and X yields:

$$V_x = U_x(Z, Y - P(Z)); \delta) = 0 \qquad [3.1]$$

$$V_{z_i} = U(Z, Y - P(Z)); \delta) - U_x \frac{\partial p}{\partial z_i} = 0 \qquad [3.2]$$

Rearranging the previous conditions results in inverse demand curves or Marginal Willingness to Pay (MWTP) curves:

$$\frac{\partial p}{\partial z_i} = \frac{U_{z_i}(Z, Y - P(Z); \delta)}{U_x(Z, Y - P(Z); \delta)} = h_i(Z, Y - P(Z); \delta) \qquad [4]$$

The previous condition says that, in equilibrium, an individual's utility is maximized at the point where marginal willingness to pay for an additional unit of a characteristic is equal to the marginal implicit price (Hite, 1995).

Empirical models

In this essay, we employ a two-stage hedonic for four dissimilarity indices, which represent measures of segregation. From the first stage hedonic estimations, we derive marginal implicit prices for racial, income, education, and age neighborhood segregation. These prices are then used to estimate the following empirical demand curve:

$$DI_i = \alpha_{i1} + \alpha_{ik} P_{ik} + \alpha_{im} S_i + \delta_i \quad [5]$$

where DI_i is the dissimilarity index value (i=1, 2, 3, 4), P_{ik} is a vector of implicit prices, S is a vector of demand shifters, α_i's are parameters to be estimated, and δ_i is a vector of normally distributed errors.

Functional form, segmentation and identification

Rosen's (1974) paper provides a theoretical framework for estimating implicit prices for housing characteristics, as well as individual demand curves, yet specific econometric issues pertaining to hedonic models must be addressed in order to have consistent results (Kim et al., 2003). In this section we consider two of these issues: 1) functional form and 2) identification. The first issue, functional form, has been extensively reviewed in the literature. The hedonic price function represents the locus equilibrium of all individual buyers and sellers in the real estate market, and as such, economic theory suggests no a priori assumptions in the form that it takes. There is a common assumption that house price are log-normally distributed. In this essay, we use the semilog-linear functional form for the first stage hedonics after testing for goodness of fit.

The second issue pertains to the second-stage hedonics. It is argued in the literature that the main shortcoming of Rosen's second-stage demand estimation is that the estimated implicit prices may not contain any information beyond what the first stage hedonic provides. Aside from the problem of identifying the proper functional form for the demand equations, this is the only new information placed on the demand equation. Without any additional information, the demand for any housing characteristic cannot be identified from the hedonics.

A number of empirical practitioners in hedonic the literature have relied on using segmented markets to overcome this problem (Brown and Rosen, 1982; Palmquist, 1984; Brasington, 2000, 2003; Zabel and Kiel, 2000; Brasington and Hite, 2005). A separate hedonic house price function is estimated for each market segment. In this essay, market segments consist of the seven major metropolitan statistical areas (MSA) in Ohio: Akron, Cincinnati, Cleveland, Columbus, Dayton, Toledo, and Youngstown.

Estimating hedonic functions for the seven MSAs separately generates seven different parameter estimates for the relationship between racial, income, age, and education neighborhood segregation and house price, from which the implicit prices are calculated. The implicit prices are then instrumented and pooled to estimate the demand equations. Justification for this solution comes from the fact that market segmentation arises between MSAs but not within a metro area because of different construction costs and job availability (Brasington and Hite, 2005).

First stage hedonic analysis: Incorporating spatial effects

In this essay we consider another issue that has been recently addressed in the hedonics literature. It has been argued, primarily in the urban and real estate economics literature, that using ordinary least squares in models with spatially correlated data may result in inconsistent, biased and inefficient estimates (Anselin, 1988; Pace et al., 1998, LeSage, 2001; Kim et al., 2003; Brasington and Hite, 2005). We address this problem by estimating a general spatial model (GSM). This model includes a spatial lag of the dependent variable and a spatial lag in the error term. First, we introduce the traditional hedonic price model, which takes the form:

$$P = X\beta + u, u \sim N(0, \sigma^2 I_n) \qquad [3]$$

where P represents a vector of housing transaction prices, X is a matrix of explanatory variables, and u is the traditional error term.

We thus use Anselin's (1988) GSM applied to housing market data in order to incorporate the effects of spatial dependence of housing data into the estimation of relevant coefficients. The GSM takes the following form:

$$\begin{aligned} P &= \rho WP + X\beta + \varepsilon \\ \varepsilon &= \lambda W\varepsilon + \mu, \mu \sim N(0, \Omega) \end{aligned} \qquad [4]$$

where P is the price of a house, ρ is a spatial lag coefficient, W is an n x n spatial weight matrix, X is an n x k matrix of explanatory variables, β is a k x 1 vector of parameters, λ is spatial error coefficient, and μ is normally distributed with a general diagonal covariance matrix Ω. Anselin (1988) shows that using maximum likelihood approach to estimate ρ, β, and λ will yield consistent estimates.

Equation (4) requires interpretation of the spatial components in the model. The parameter ρ is a measure of spatial dependence or correlation in the data. In this case, it measures the average influence of neighboring house prices on the price of a house. W is a spatial weight matrix constructed to reflect proximity of the closest neighbors to each house. The matrix has zero values along the main diagonal, and non-zero entries for houses that are located in close proximity to a house. Overall, ρWP measures the total variation in P across the spatial sample that is explained by each house's dependence on its neighbors (LeSage, 1999). Next, λ measures the degree to which housing values depend on omitted variables at neighboring locations that follow a spatial pattern. For estimation and computational details on the *general spatial model*, refer to Anselin (1988) and LeSage (1999).

3.5 Data description

The data set used in the analyses consists of 85,255 house transactions located in 6,032 census block groups (CBG) in seven large Metropolitan Statistical Areas (MSA) in Ohio, which took place during 2000. The MSAs included are Akron, Cincinnati, Cleveland, Columbus, Dayton, Toledo and Youngstown. The basic individual housing characteristics data come from the First American Real Estate Solutions, and each transaction is geocoded and matched to census demographic data, school quality data, and environmental data. The census data come from the GeoLytics Census CD 2000 Long Form (Release 2.0). The school quality variables come from the Ohio Department of Education, while the environmental variables come from the National Emission Trends (NET) database (October, 2001) of the United States Environmental Protection Agency (EPA). This is a comprehensive collection of accurate data on point and non-source toxic releases (carbon monoxide, nitrogen oxides, particulate matter, sulfur dioxide, volatile organic compounds, and ammonia) into the air and water by type of facility. The environmental variables are aggregated at the census block group level and matched to each transacted house.

Choice of hedonic variables

The hedonic variables included in the first stage model are classified into structural house characteristics and neighborhood characteristics. Within the neighborhood characteristics we find variables capturing quality of education, income level, environmental quality, and neighborhood composition in the following four dimensions: race, income, education, and age segregation as measured by dissimilarity indices. The next section addresses the construction of each of dissimilarity index as well as the data used.

The following continuous structural house characteristics are included in the first stage hedonic model: the parcel size in square feet, the house size in square feet, the number of rooms in the house, the number of full and partial bathrooms, as well as the age of the house. Also included are dummy variables for houses with central air, fireplace, porch, garage, patio, and pool. Though it is common to include the squares of lot size, house size, and age of the house because these variables may influence a house's value in a non-linear fashion, we did not include them in this stage because they created problems with collinearity.

In order to conform to local public economic theory, urban economic theory, and the amenity literature, we include various neighborhood characteristics in the first stage hedonics: the percentage of the population in the CBG that is black, the median income of households in the CBG, the percent of households in the CBG living below the poverty threshold, school district average proficiency test scores, schools district property tax rate, as well as number of offenses per thousands of persons in a given police jurisdiction. All else constant, it is expected that higher income levels and improved school quality will have a positive impact on house values. People with high incomes can afford to demand better houses and better schools. Increased tax rates, higher crime rates, and increased poverty should lower house prices. An increase in the percentage of blacks in the CBG has a decreasing effect on property values. Also, according to standard urban theory, we include the average commute time for a person at the CBG level in order to capture the opportunity cost of time traveling to work.

Two measures of environmental quality are included in the first stage hedonics. First we have data from Ohio's seven MSAs on the precise location of point-specific pollution sites where there is supporting evidence of contamination of air, water and soil. A variable measuring the distance in miles of each property to the nearest environmental hazard thus represents environmental quality. Proximity to a hazard should be associated with depressed house prices. We also include the square of the distance to each hazard because it is expected that the effects of a local hazard on property prices may decay in a non-linear way. The mean distance to the nearest hazard for houses in the seven MSAs is 1.13 miles. The minimum is 0.002 miles, and the maximum is 8.78 miles, with 0.89 miles as the median. The second environmental variable captures the level of air pollution emitted by facilities for all industries in Ohio, aggregated at the CBG level. These emissions include the sum of fugitive air emissions and point source air emissions. The mean CBG air emission level for houses in the seven MSAs is 4,644.49 pounds.

Measuring segregation: The dissimilarity indices

Many measures of segregation have been developed since Duncan and Duncan's (1955) seminal paper on segregation indices. Massey and Denton (1988) provide an extensive analysis of various segregation indices, and classify them into five key dimensions: evenness, exposure, concentration, centralization, and clustering. In this essay we use one of the most widely popular measures of evenness, the dissimilarity index. This measure can be interpreted as the "the proportion of minority members that would have to change their area of residence to achieve an even distribution, with the number of minority members moving being expressed as the proportion of the number that would have to move under conditions of maximum segregation" (Massey and Denton, 1988). In other words, it measures the degree of relative separation between two groups across geographical areas. Cutler, Glaeser, and Vigdor (1999), and Cutler and Glaeser (1997 and 2002) use this index in their empirical analyses of the socioeconomic impact of racial segregation. Now, the calculation of these indices in this essay differs from previous studies in that we consider the Census Block Group to be the lowest level of data aggregation, and calculate the indices at the Census Tract level. Previous studies use the Census tract as the lowest and the city or MSA as the highest level of aggregation. Thus, in effect, the measure here should be interpreted as the degree of neighborhood segregation as opposed to the degree of MSA segregation as in the previous literature.

Definition of the dissimilarity indices

The focus of this essay is not only to measure racial segregation, but also measure other dimensions of neighborhood segregation or sorting.

The Racial Dissimilarity Index most commonly used in the racial segregation literature is calculated as:

$$Racial\ Dissimilarity\ Index = \frac{1}{2}\sum_{i=1}^{N}\left|\frac{Black_i}{Black_j} - \frac{NonBlack_i}{NonBlack_j}\right| \qquad [5]$$

where $Black_j$ and $Nonblack_j$ are, respectively, the number of blacks and non-blacks in census tract j, while $Black_i$ and $Nonblack_i$ are the number of blacks and non-blacks in census block group i (a subdivision of census tract j). Following Cutler and Glaeser (1997), the interpretation of this index is as follows: it measures the proportion of blacks that would have to move across CBGs in order to have an even distribution with respect to non-blacks within each CBG in a census tract. A value of zero indicates an even racial distribution throughout the area of aggregation, whereas a value of one indicates that blacks and non-blacks never reside in the same census block. For example, from Table 3.2 the average racial dissimilarity index across census tracts in Akron is 0.46[14]. This implies that 46% of the black population in the census block group would have to move to another census block group to make blacks and non-blacks evenly distributed across the census tract in which the block group is located. Youngstown has the highest average racial dissimilarity index with 0.51, while all other MSAs have an average racial dissimilarity index between 0.35 and 0.45.

The other indices are calculated in a similar fashion. These include the Age Dissimilarity Index*,* defined as:

$$\text{Age Dissimilarity Index } = \frac{1}{2}\sum_{i=1}^{N}\left|\frac{AgeBelow_i}{AgeBelow_j} - \frac{AgeAbove_i}{AgeAbove_j}\right| \quad [6]$$

where $AgeBelow_j$ denotes the number of persons in census block group i that have an age less than the median age of census tract j, while $AgeAbove_j$ denotes the number of people in census block group i that have an age greater than the median age in census tract j. $AgeBelow_j$ and $AgeAbove_j$ are, respectively, the total number of persons in census tract j that have an age less and greater than the median age in the tract. This index measures the proportion of people below the median age at the census tract level that would have to move across census block groups in order to have an even distribution with respect to the proportion of people above the median. For example, from Table 3.2 the average age dissimilarity index in Cincinnati is 0.09. This implies that 9% of the population in the census block group that is less than the median age of the census tract would have to move to another census block group in order to make the age distribution across all neighborhoods even.

The Income Dissimilarity Index is defined as:

$$\text{Income Dissimilarity Index } = \frac{1}{2}\sum_{i=1}^{N}\left|\frac{IncBelow_i}{IncBelow_j} - \frac{IncAbove_i}{IncAbove_j}\right| \quad [7]$$

where $IncBelow_j$ denotes the number of persons in census block group i that have income less than the median income of census tract j (a subdivision of census tract j), while $IncAbove_j$ denotes the number of people in census block group i that have income greater than the median income of census tract j. $IncBelow_j$ and $IncAbove_j$ are, respectively, the total number of persons in census tract j that have income less and greater than the median income. The income dissimilarity index measures the proportion of people below the median income at the census tract level that would have to move across census block groups in order to have an even distribution with respect to the proportion of people above the median income. For example, from Table 3.2 the average income dissimilarity index in Youngstown is 0.14. This implies that 14% of the population in the census block group whose income is less than the median income of the census tract would have to move to another census block group in order to make the income distribution across all neighborhoods even.

Similarly, the *Education Dissimilarity Index* is calculated as:

$$\text{Education Dissimilarity Index} = \frac{1}{2}\sum_{i=1}^{N}\left|\frac{EducBelow_i}{EducBelow_j} - \frac{EducAbove_i}{EducAbove_j}\right| \qquad [8]$$

where $EducBelow_j$ denotes the number of persons in census block group i that have an education attainment less than the weighted number of years of education attained in census tract j (a subdivision of census tract j), while $EducAbove_j$ denotes the number of people in census block group i that have an education attainment greater than the weighted number of years of education attained in census tract j. $EducBelow_j$ and $EducAbove_j$ are, respectively, the total number of persons in census tract j that have an education attainment less than and greater than the weighted number of years of education attained. The education dissimilarity index measures the proportion of people below the weighted average number of years of education at the census tract level that would have to move across census block groups in order to have an even distribution with respect to the proportion of people above the weighted average number of years of education. For example, from Table 3.2 the average education dissimilarity index in Columbus is 0.13. This implies that 13% of the population in the census block group whose education attainment is less than the average attainment of the census tract would have to move to another census block group in order to have an equally distribution of people's education attainment level.

Table 3.1 presents variable definitions and sources; Table 3.2 presents descriptive statistics for the characteristics by MSA. One striking observation from Table 3.2 is that, while levels of segregation by age, income, and education are fairly low, averaging indices between 0.10 and 0.16, racial segregation levels are high.

Choice of demand variables

Each of the demand equations for age, income, education, and race segregation require a set of implicit prices: the price of race segregation, the price of income segregation, the price of education segregation, and the price of age segregation. Following Brasington (2000), the demand equations also include the implicit price of school district tax rates. Each of the implicit prices are calculated for each property in the seven MSAs from the general spatial hedonic model specification and pooled together in conformity with the traditional two-stage hedonic demand literature. Also, given that they are endogenous, the implicit prices need to be instrumented from variables that are uncorrelated with the segregation indices.[15] Definitions and sources for these variables are found in Table 3.1.

[15] The instruments chosen for all dissimilarity indices are PCTURBAN_CBG, PCTMAR_CBG, TCHPAY_SD, PTRATIO_SD, ATTRATE_SD, DROPRTE_SD, PCTHS_CBG, PCTBA_CBG, UNEMP_CBG, and HU100_CBG. All instruments pass the Nelson and Starz test for irrelevant instruments.

Table 3.1 Definitions and sources of first-stage hedonics variables

Variable name	Definition (source)
RENT	House sale transaction amount (1) multiplied by the interest rate (2) prevailing at the time of the sale divided by 100, in log
AGEDI	Age Dissimilarity Index - Demographic measure of evenness with which people younger and older than the median age in a census tract (CT) are distributed across census block groups (CBG)
INCDI	Income Dissimilarity Index - Demographic measure of the evenness with which people with income less and greater than the median income in a census tract (CT) are distributed across census block groups (CBG)
EDUCDI	Education Dissimilarity Index - Demographic measure of the evenness with which people with an education level less or greater than the weighted average number of years of education in a census tract (CT) are distributed across census block groups (CBG)
RACEDI	Racial Dissimilarity Index - Demographic measure of the evenness with which blacks and whites are distributed across census block groups (CBG) within a census tract (CT)
ROOMS	Number of rooms in house (1)
AGE	Age of house, where 2000 is the base year (1)
LOT SIZE	Size of lot where the house is located, in square feet (1)
HOUSE SIZE	Size of house, in square feet (1)
FULLBATH	Number of full bathrooms in the house (1)
HALFBATH	Number of full half bathrooms in the house (1)
PORCH	Number of porches in the house (1)
FIREPLACE	Number of fireplaces in the house (1)
AIR	1 for houses with air conditioning, 0 otherwise (1)
GARAGE	1 for houses with garage, 0 otherwise (1)
PATIO	1 for houses with patio, 0 otherwise (1)
POOL	1 for houses with pool, 0 otherwise (1)
INCOME	Median income of households in CBG in dollars (2)
BLACK	Percentage of population in CBG that is black, non-Hispanic (2)
POVERTY	Percentage of persons in the CBG living in a family whose total family income is below the poverty threshold appropriate for that family (2)

Table 3.1 Definitions and sources of first-stage hedonics variables

Variable name	Definition (source)
COMMUTE	Average commute time in minutes for persons 16 years and over not working at home in CBG (2)
SCHOOLQL	Percentage of 9th grade students in school district who passed all five sections (citizenship, reading, writing, math, science) of Ohio proficiency test in 2000-01 school year (3)
TAX RATE	Taxes received from all real properties multiplied by 1,000 divided by total real property valuation (2)
OFFENSES	Grand total of actual offenses in police district per thousands of persons (4)
HAZARD	Distance from each house to nearest environmental hazard, in miles (5)
$HAZARD^2$	Distance squared from each house to nearest environmental hazard, in miles
AIREMISN	Fugitive air releases (emissions not released through a confined air stream) plus point source air emissions (from confined air streams) in pounds (5)
ATTRATE_SD	Average daily attendance divided by average daily membership for students, by school district, for 1998 (3)
DROPRTE_SD	Number of dropouts divided by Grade 7-12 enrollment(JVS included) By school district, for 1998 (3)
HU100_CBG	Number of housing units in the census block group in hundreds of units (2)
PCTBA_CBG	Percentage of persons 25 years or older in census block group whose highest educational attainment a Bachelor's degree (2)
PCTHS_CBG	Percentage of persons 25 years or older in census block group whose highest educational attainment is a high school diploma, including equivalency (2)
PCTMAR_CBG	Percentage of persons married with spouse present in census block group (2)
PCTURBAN_CBG	Percentage of population in census block group living in urbanized area or urban cluster (2)
PTRATIO_SD	Pupil/teacher ratio (3)
TCHPAY_SD	Average teacher salary in school district in dollars
UNEMP_CBG	Percentage of labor force in census block that is unemployed (2)

Sources: (1) First American Real Estate Solutions; (2) GeoLytics CensusCD 2000 Long Form Release 2.0; (3) Ohio Department of Education, Division of Information Management Services (1995); (4) 2000 GeoLytics CrimeReportsCD 1.0; (5) Ohio Environmental Protection Agency Division of Emergency and Remedial Response (1994); All nominal values are deflated by MSA using ACCRA (1991, 1992) data.

Table 3.2 Hedonic means and standard deviations

Variable Name	Akron		Cincinatti		Cleveland		Columbus		Dayton		Toledo		Youngstown	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
RENT	10,040	5,749	10,811	5,509	10,689	5,277	10,942	5,587	8,832	4,540	9,033	4,890	7,276	4,021
AGEDI	0.10	0.05	0.09	0.06	0.08	0.06	0.09	0.06	0.10	0.07	0.09	0.05	0.11	0.06
INCDI	0.15	0.09	0.16	0.09	0.12	0.09	0.16	0.10	0.14	0.09	0.16	0.09	0.14	0.08
EDUCDI	0.15	0.08	0.13	0.08	0.11	0.08	0.13	0.08	0.13	0.09	0.15	0.08	0.12	0.07
RACEDI	0.46	0.36	0.41	0.31	0.40	0.30	0.35	0.26	0.45	0.52	0.45	0.26	0.51	0.45
ROOMS	6.40	1.50	6.29	1.48	6.28	1.53	6.26	1.41	6.05	1.33	6.16	1.39	5.99	1.64
AGE	46.37	28.20	41.90	29.25	49.76	28.25	37.03	31.30	45.93	28.18	51.99	30.06	48.69	23.94
LOT SIZE	19.57	41.25	20.66	57.63	19.04	43.23	19.90	53.97	18.97	48.36	16.29	45.19	24.12	47.01
HOUSESIZE	1.51	0.62	1.63	0.63	1.56	0.64	1.61	0.59	1.54	0.63	1.51	0.58	1.45	0.60
FULLBATH	1.36	0.54	1.48	0.58	1.28	0.53	1.50	0.56	1.45	0.57	1.28	0.51	1.23	0.47
HALF BATH	0.44	0.54	0.43	0.52	0.41	0.53	0.50	0.52	0.34	0.51	0.37	0.52	0.37	0.52
PORCH	0.02	0.16	0.57	0.71	0.06	0.30	0.15	0.48	0.13	0.41	0.89	0.84	0.81	0.79
FIREPLACE	0.48	0.61	0.52	0.55	0.44	0.57	0.52	0.57	0.46	0.55	0.34	0.52	0.46	0.57
AIR	0.04	0.19	0.11	0.31	0.21	0.40	0.55	0.50	0.54	0.50	0.08	0.26	0.10	0.30
GARAGE	0.11	0.32	0.60	0.49	0.76	0.42	0.63	0.48	0.79	0.40	0.83	0.37	0.31	0.46
PATIO	0.00	0.02	0.17	0.38	0.01	0.07	0.03	0.16	0.09	0.28	0.19	0.39	0.00	0.05
POOL	0.02	0.13	0.02	0.15	0.01	0.09	0.01	0.10	0.02	0.14	0.01	0.11	0.05	0.23
INCOME	49.85	20.97	54.05	21.00	50.86	19.07	54.56	22.49	48.08	17.30	47.80	17.93	41.35	12.71
BLACK	0.10	0.20	0.10	0.20	0.12	0.25	0.11	0.20	0.10	0.21	0.07	0.16	0.05	0.12
POVERTY	0.08	0.09	0.07	0.08	0.07	0.09	0.07	0.08	0.08	0.08	0.08	0.09	0.08	0.08

Table 3.2 Hedonic means and standard deviations (continued)

	Akron		Cincinatti		Cleveland		Columbus		Dayton		Toledo		Youngstown	
Variable Name	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
COMMUTE	24.42	3.45	25.41	3.96	25.55	3.69	24.88	3.95	22.56	3.49	21.66	3.27	22.02	3.61
SCHOOLQL	0.63	0.18	0.64	0.18	0.62	0.21	0.64	0.19	0.62	0.22	0.61	0.21	0.65	0.21
TAX RATE	30.32	3.48	30.52	4.59	34.33	7.06	31.43	4.61	30.42	5.18	34.13	4.04	34.34	5.19
OFFENSES	57.41	25.17	63.42	31.97	53.66	35.40	83.76	59.45	67.49	38.29	82.70	40.19	45.88	29.23
HAZARD	0.90	0.69	1.14	0.87	1.04	0.76	1.45	1.09	1.04	0.87	0.90	0.89	1.20	1.01
HAZARD^2	1.29	2.42	2.06	3.77	1.66	2.53	3.28	5.72	1.84	3.88	1.61	4.14	2.44	4.50
AIREMISN	3.76	44.76	6.67	166.64	3.07	70.61	3.07	43.77	4.50	56.61	6.86	54.61	9.81	84.38
ATTRATE_SD	93.16	2.47	93.65	2.05	93.23	3.34	93.18	2.76	92.85	3.43	94.19	1.48	93.56	1.88
DROPRTE_SD	4.58	2.29	5.31	3.02	6.45	6.66	6.10	4.25	6.78	5.43	7.20	5.33	4.77	3.79
PCTBA_CBG	0.17	0.11	0.19	0.11	0.16	0.10	0.21	0.13	0.14	0.09	0.15	0.10	0.12	0.07
PCTHS_CBG	34.16	12.46	30.04	11.54	31.89	10.48	29.64	13.39	32.01	10.74	33.02	11.11	41.74	9.47
PCTMAR_CBG	55.57	13.77	57.11	14.53	54.20	13.13	55.94	14.86	55.64	12.93	54.45	12.53	54.76	10.75
PCTURBAN_CBG	92.01	22.33	92.12	23.67	93.64	21.04	88.94	27.03	89.36	27.18	89.04	28.58	86.52	31.35
PTRATIO_SD	21.57	2.16	20.23	2.39	19.76	1.79	20.20	1.38	19.76	1.51	19.16	1.32	20.26	1.78
TCHPAY_SD	41,358	2,453	41,376	3,904	44,281	3,134	42,647	3,837	40,370	2,794	39,782	2,964	39,384	3,165
UNEMP_CBG	4.65	3.95	3.70	3.32	4.50	3.99	3.55	3.63	4.23	3.77	4.65	4.21	5.12	4.09
N	7,901		17,501		21,673		18,238		9,001		7,057		3,884	

It is also necessary to include other variables in the equation to act as demand shifters.[16] Even though there is no clear mention in the economics literature about which variables need to be included in a demand equation, it is understood that the price of the commodity, the prices of complements, the prices of substitutes, and income need to be included. Other variables have been traditionally used to identify demand equations. Precipitation, climate, and demographic variables are typical variables included in demand equations to act as shifters. The average rainfall in the MSA was then included as a demand shifter in all four demand equations.

3.6 Hedonic regression results

Hedonic price model

Results for the traditional hedonic price functions for Akron, Cincinnati, Cleveland, Columbus, Dayton, Toledo and Youngstown are presented in Table 3.3. Each of these models is estimated using Iterated Ordinary Least Squared (ITOLS) estimation. Most of the structural housing variables are significant and conform to expectations. Increasing the number of rooms, size of house and lot, as well as the number of full and half bathrooms, as expected, has a positive impact on house prices.

Also houses with garages and pools have higher selling prices. House age has a negative impact on house prices, though the estimated coefficients are small in magnitude. The impact of air conditioning and porches is mixed; coefficients in some MSAs are positive and others negative. The results for the environmental variables need

[16] Short term supply of characteristics considered fixed.

particular attention. First, we have the distance to the closest source of environmental risk. It is expected that house prices increase at a decreasing rate with respect to distance from the source of environmental risk. This implies a positive expected estimate for the linear distance measure and a negative estimate for the square of the distance. With the exception of insignificant estimates in Cincinnati, the estimated coefficients for the other six MSA conform to this expectation. Second, the total emissions into air by all industries are significant in just three areas. This result is somewhat expected since it is not possible to consistently determine whether a house is affected by air emissions unless there is some information on the spatial dispersion of the emissions. Many other environmental factors, i.e. wind direction and speed, as well as atmospheric humidity and precipitation, might be considered when effectively determining the price impact of any particular type of air emissions onto property values.

Table 3.3 Hedonic results: Iterated Ordinary Least Square (ITOLS) estimation

	Akron		Cincinnati		Cleveland		Columbus		Dayton		Toledo		Youngstown	
Variable Name	Estimate	t-stat.	Estimate	t-stat.	Estimate	t-stat.	Estimate	t-stat.	Estimate	t-stat.	Estimate	t-stat.	Estimate	t-stat.
INTERCEPT	8.5019***	140.30	8.4322***	216.77	8.3085***	361.24	8.3262***	255.40	8.0003***	198.52	8.5874***	168.05	7.7708***	89.94
ROOMS	0.0081***	2.61	0.0094***	4.27	0.0146***	9.13	-0.008***	-3.64	0.0204***	7.03	0.0012	0.35	0.0085***	2.74
AIR	-0.1127***	-3.89	-0.0307***	-3.94	-0.0054	-1.06	0.0425***	8.17	0.0688***	11.86	-0.0063	-0.45	0.098***	6.24
FIREPLACE	0.0852***	13.11	0.1045***	22.23	0.0693***	17.77	0.0702***	16.33	0.0681***	12.38	0.0998***	14.06	0.0767***	8.92
AGE	-0.0042***	-21.00	-0.0032***	-32.00	-0.0024***	-24.00	-0.0007***	-7.00	-0.0025***	-25.00	-0.0034***	-34.00	-0.0051***	-25.50
LOT SIZE	0.0007***	7.00	0.0008***	20.00	0.0007***	17.50	0.0007***	17.50	0.0010***	10.00	0.0004***	4.00	0.0009***	9.00
HOUSE SIZE	0.2375***	23.75	0.3198***	57.11	0.2045***	49.88	0.3181***	50.49	0.2416***	32.21	0.2964***	30.88	0.2452***	22.70
GARAGE	0.0269*	1.94	0.1001***	20.43	0.1041***	23.13	0.0318***	5.68	0.0541***	8.07	0.0905***	9.84	0.0367***	3.34
FULLBATH	0.0966***	10.85	0.0291***	5.71	0.0475***	10.11	0.1218***	22.56	0.0765***	11.42	0.0774***	8.70	0.1001***	8.48
HALF BATH	0.0855***	11.10	0.0255***	5.10	0.0727***	17.31	0.0709***	13.90	0.0489***	8.15	0.0748***	9.59	0.068***	6.94
PORCH	-0.1407***	-4.37	0.0285***	8.64	-0.0029	-0.45	-0.044***	-9.17	0.0249***	3.72	-0.0184***	-4.38	0.0203***	3.69
PATIO	-0.3144	-1.55	0.0033	0.57	0.0012***	0.05	0.023*	1.72	-0.0166*	-1.73	0.0202***	2.43	-0.081	-0.89
POOL	0.0504**	1.98	0.0427***	3.09	0.0196	1.01	0.0157	0.79	0.0632***	3.55	0.0534*	1.80	0.047***	2.54
HAZARD	0.0320***	2.60	-0.0009	-0.15	0.0494***	6.86	0.028***	5.49	0.0287***	3.42	0.0997***	10.28	0.0595***	4.25
$HAZARD^2$	-0.0106***	-3.21	-0.0002	-0.14	0.0021	0.00	-0.0062***	-6.89	-0.0052***	-2.89	-0.0146***	-7.30	-0.0038	-1.27
AIREMISN	-0.00002	-0.20	-0.00001	-1.00	0.0001***	3.33	0.0001**	2.00	-0.0001***	-2.50	-0.0001	-1.00	-0.0001	-1.00
POVERTY	-0.3058***	-5.59	-0.1914***	-5.19	-0.3438***	-11.13	-0.3756***	-9.99	-0.2709***	-6.03	-0.4078***	-8.26	-0.2416***	-2.86
COMMUTE	0.0005	0.45	-0.0112***	-16.00	-0.0062***	-10.33	-0.0095***	-15.83	-0.0048***	-6.00	-0.0054***	-4.91	0.0007	0.50
TAX RATE	-0.0038***	-3.80	0.0039***	6.50	0.0010***	3.33	0.0019***	3.17	0.0008	1.00	-0.0061***	-6.10	0.0018	1.50
BLACK	-0.2882***	-12.92	-0.2394***	-17.10	-0.0869***	-8.69	-0.2449***	-17.13	-0.1347***	-8.47	-0.307***	-12.63	-0.3866***	-8.31
INCOME	0.0038***	12.67	0.0042***	21.00	0.0001	0.00	0.0045***	22.50	0.0026***	13.00	0.0035***	11.67	0.0037***	7.40
SCHOOLQL	0.2747***	7.01	0.0494***	2.39	0.4802***	30.59	0.12***	7.36	0.3947***	15.06	0.1711***	5.74	0.431***	9.21
OFFENSES	-0.0013***	-4.33	0.0004***	4.00	0.0001	1.00	-0.0001***	-2.50	0.0001	1.00	-0.0006***	-3.00	0.0008***	2.67
AGEDI	-0.0254	-0.35	0.3214***	8.44	0.0281	0.79	0.0198	0.55	0.1570***	3.79	0.307***	4.76	-0.0524	-0.68
INCDI	0.3508***	7.97	-0.0126	-0.48	0.1000***	4.26	-0.0966***	-3.99	0.1259***	4.17	-0.1044***	-2.26	0.2601***	4.05
EDUCDI	-0.197***	-4.28	-0.2902***	-9.27	-0.2204***	-8.16	-0.1055***	-3.37	-0.0687**	-2.06	-0.0758*	-1.76	-0.2365***	-3.39
RACEDI	0.0026	0.28	0.0527***	6.84	-0.0012	-0.18	0.0837***	9.30	0.0701***	12.52	-0.0503***	-3.81	0.043***	3.74
N		7,901		17,501		21,673		18,238		9,001		7,057		3,884
Adjusted R^2		0.7298		0.6773		0.6910		0.7033		0.7464		0.7381		0.7233

The variables of primary interest are the segregation indices. The education dissimilarity index is the only one significant in all seven metro areas. The coefficient is negative as well, which implies that increasing the proportion of people with similar education levels in order to have an even distribution of education levels decreases property values.

The results in the regression of the remaining segregation indices are mixed. The age dissimilarity index is significant and positive only in Cincinnati, Dayton and Toledo. Increase in census block group age segregation increases property values in these areas. The income segregation index is significant in six out of the seven areas. Three of these areas results in negative estimates suggesting increased income segregation negatively impacts property values. The race dissimilarity index is of particular interest because of its attention in the segregation literature. The estimated coefficient for this variable is statistically significant in Cincinnati, Columbus, Dayton, Toledo and Youngstown. With the exception of Toledo, the estimated coefficients are positive, implying that increased racial segregation increases property values. This is particularly interesting since it indirectly supports one of the theories of self-segregation: that black people who self-segregate pay higher prices for properties located in predominantly black neighborhoods.

General spatial hedonic model

Table 3.4 presents estimates from the GSM hedonic functions. These models are estimated using a spatial econometrics program designed to run in Matlab® for estimating models that incorporate spatial effects.

Table 3.4 Hedonic results: General Spatial Model estimation

	Akron		Cincinnati		Cleveland		Columbus		Dayton		Toledo		Youngstown	
Variable Name	Estimate	t-stat.	Estimate	t-stat.	Estimate	t-stat.	Estimate	t-stat.	Estimate	t-stat.	Estimate	t-stat.	Estimate	t-stat.
INTERCEPT	8.3312***	1621.52	8.3389***	1839.39	8.1639***	562.57	8.2102***	992.21	7.7666***	341.68	8.3925***	740.94	7.8596***	1236.56
ROOMS	0.0100***	3.27	0.0101***	5.06	0.0151***	9.38	-0.0006	-0.27	0.0219***	7.71	0.0067**	2.13	0.0086***	2.88
AIR	-0.1055***	-3.54	-0.0141*	-1.65	0.0058	1.14	0.0500***	9.43	0.0662***	11.31	0.0175	1.21	0.0899***	5.83
FIREPLACE	0.0754***	11.70	0.0797***	17.66	0.0590***	15.36	0.0577***	14.09	0.0582***	10.53	0.0758***	11.21	0.0723***	8.48
AGE	-0.0041***	-24.97	-0.0032***	-28.32	-0.0024***	-27.48	-0.0013***	-12.85	-0.0023***	-18.79	-0.0030***	-21.39	-0.0051***	-22.05
LOT SIZE	0.0008***	8.73	0.0007***	19.41	0.0007***	15.47	0.0007***	16.29	0.0010***	16.65	0.0004***	6.31	0.0009***	9.21
HOUSE SIZE	0.2255***	22.71	0.2867***	52.39	0.1877***	45.45	0.2988***	49.50	0.2284***	30.24	0.2702***	29.71	0.2398***	22.31
GARAGE	0.0154	1.04	0.0757***	14.89	0.1025***	20.30	0.0377***	6.81	0.0507***	7.68	0.0865***	9.98	0.0330***	2.81
FULLBATH	0.0985***	11.27	0.0333***	6.86	0.0449***	9.85	0.1030***	20.07	0.0753***	11.28	0.0788***	9.60	0.0909***	7.83
HALF BATH	0.0789***	10.35	0.0309***	6.65	0.0635***	15.21	0.0601***	12.61	0.0472***	7.96	0.0605***	8.37	0.0642***	6.72
PORCH	-0.1246***	-3.85	0.0247***	7.82	0.0070	1.05	-0.0301***	-5.95	0.0214***	3.08	-0.0069*	-1.72	0.0205***	3.79
PATIO	-0.4051**	-2.07	0.0072	1.30	0.0023	0.10	0.0095	0.74	-0.0152	-1.53	0.0217***	2.82	-0.1167	-1.34
POOL	0.0492**	1.99	0.0477***	3.73	0.0276	1.48	0.0252	1.37	0.0673***	3.93	0.0596**	2.23	0.0549***	3.06
HAZARD	0.0371***	2.56	0.0035	0.42	0.0570***	6.37	0.0367***	5.46	0.0351***	3.37	0.1129***	8.75	0.0636***	3.80
$HAZARD^2$	-0.0116***	-2.98	-0.0014	-0.79	-0.0108***	-4.20	-0.0075***	-6.14	-0.0053**	-2.40	-0.0172***	-6.47	-0.0059	-1.61
AIREMISN	-0.00005	-0.57	-0.00002	-1.01	0.0001**	2.15	0.0001*	1.73	-0.0001	-1.04	-0.0002***	-2.47	-0.0002***	-2.67
POVERTY	-0.2887***	-4.63	-0.1655***	-3.61	-0.2651***	-7.37	-0.2511***	-6.06	-0.2236***	-4.22	-0.3332***	-5.49	-0.2237**	-2.32
COMMUTE	0.0004	0.39	-0.0090***	-13.00	-0.0061***	-10.02	-0.0069***	-11.43	-0.0045***	-4.97	-0.0045***	-3.71	0.0009	0.61
TAX RATE	-0.0035***	-3.52	0.0046***	8.63	0.0013***	3.57	0.0028***	5.05	0.0037***	4.44	-0.0060***	-5.39	0.0018*	1.73
BLACK	-0.2784***	-10.67	-0.2231***	-12.20	-0.0914***	-7.41	-0.2309***	-12.95	-0.1326***	-6.66	-0.3246***	-10.02	-0.3590***	-6.48
INCOME	0.0031***	10.43	0.0042***	22.26	0.0036***	20.98	0.0042***	23.89	0.0028***	9.81	0.0037***	10.69	0.0037***	6.18
SCHOOLQL	0.3099***	8.70	0.0864***	4.41	0.4651***	25.15	0.1678***	8.71	0.4801***	17.80	0.1906***	5.65	0.3887***	9.90
OFFENSES	-0.0011***	-4.45	0.0003***	2.87	-0.00003	-0.35	-0.0001***	-2.49	0.00001	0.06	-0.0007***	-3.83	0.0003	1.05
AGEDI	-0.0395	-0.48	0.2973	5.93	0.0060	0.14	-0.0037	-0.08	0.1885***	3.74	0.3404***	4.06	-0.0904	-0.98
INCDI	0.3484***	6.83	-0.0070	-0.20	0.0955***	3.35	-0.0843***	-2.84	0.1153***	3.09	-0.0479	-0.80	0.3004***	3.95
EDUCDI	-0.2099***	-3.88	-0.2894***	-7.01	-0.2253***	-6.91	-0.1425***	-3.80	-0.0041	-0.10	-0.0830	-1.48	-0.2621***	-3.26
RACEDI	0.0046	0.21	0.0536***	3.47	0.0201*	1.78	0.1208***	8.17	0.0852***	4.91	-0.1123***	-4.76	0.0815***	2.64
RHO	0.0140***	6.03	0.0070***	3.75	0.0191***	13.16	0.0025*	1.80	0.0086***	7.59	0.0168***	7.15	-0.0037	-1.04
LAMBDA	0.1840***	29.10	0.3500***	96.76	0.2430***	24.44	0.3280***	59.04	0.2410***	13.12	0.3380***	39.35	0.2180***	25.42
N		7,901		17,501		21,673		18,238		9,001		7,057		3,884
Adjusted R^2		0.7420		0.7379		0.7601						0.7755		0.7367

Notes: *** 0.01 level of statistical significance; ** 0.05 level of statistical significance; * 0.10 level of statistical significance. Dependent variable is RENT, which is logged. Variables labeled with W refer to the estimated spatial lag α for the corresponding variable.

Similar to the hedonic price model results, increasing the number of rooms, the size of the house, the size of the lot, and the number of bathrooms and half bathrooms has a positive and significant effect on property values in all estimated equations. The absolute magnitude of the effects changed for some of these variables: most increased in size, but coefficient estimates are fairly consistent across models. With respect to age of the house, again the estimated coefficients are negative and statistically significant. The distance from the closest hazard variable is positive and significant in all areas, while the square of the distance is negative, yet not statistically significant in two out of the seven areas. The impact of air emissions did not change with this model. Coefficient estimates are statistically significant in four out of the seven MSAs. Two of these estimated coefficients are a positive sign; and the rest are negative.

One coefficient consistently of the expected sign is the percentage of people that live in poverty in a census block group. All coefficients in the seven equations are statistically significant and negative, implying that neighborhoods with greater percentages of people living in poverty have lower house prices.

In contrast to Brasington and Hite's (2005) results using 1990 data for Akron, Cincinnati, Cleveland, Columbus, Dayton and Toledo, the tax rate coefficients are positively and statistically related to house prices (except in Akron and Toledo).

The school quality coefficient estimates are interesting as well. Increasing the percentage of 9th graders that pass the Ohio proficiency test has a positive impact on property prices, just as suggested by local public goods theory.

3.7 Demand estimation results

The purpose of the second stage hedonics is to estimate demand functions for housing characteristics; in this case, the demand for neighborhood segregation. This allows us to calculate own price, cross price, and income elasticity measures as well as perform policy analysis, by calculating appropriate welfare measures. For example, changes in Consumer Surplus (CS) related to changes in certain independent variables included in the demand models are of interest. These measures, though, are sensitive to the specification of the demand system, as well as the method by which they are estimated.

We estimate the demand curves for age, income, education, and race neighborhood segregation using a number of statistical techniques: Table 3.7 presents estimates for the individual demand curves estimated using Iterated Ordinary Least Squares (ITOLS). Table 3.8 presents results for the four demand equations estimated as Iterated Seemingly Unrelated Regressions (ITSUR). Last, Table 3.9 presents single equation estimates using the general spatial model specification. The ITOLS and the ITSUR models are estimated imposing restrictions on the equality of the cross-price elasticities.[17] Table 3.6 presents variable definitions and sources for the selected demand variables. The ITOLS and ITSUR demand equations were estimated using an exponential specification and while the general spatial model was estimated using a semi-log specification.

[17] The statistical program used for estimating the general spatial model does not provide a routine to estimate SUR models, and attempts to write a program to estimate the model would not converge.

The fit of the ITOLS and ITSUR models for all four demand equations is poor. Accounting for contemporaneous correlations in the errors across equations does not seem to improve the overall performance of the models. The general spatial model performs considerably better in terms of adjusted R^2 compared to the ITOLS and ITSUR models.

The own-price coefficients in three out of the four demand equations are negative and statistically significant for the ITOLS and ITSUR estimates. This is consistent with demand theory. Inconsistent with demand theory, the own-price coefficient in the education segregation equation is positive and statistically significant. The coefficient on own price in the race segregation demand equation estimated with the general spatial model specification is positive, yet not statistically significant. Each equation includes own price plus the prices of the other indices. These prices are better interpreted as elasticities in a later section. Next we discuss results for the most important demand shifters.

The age segregation demand equation does not include the implicit price of taxes because it generated inconsistent results in the other demand variables. This equation, though, includes the percentage of young people at the census block group level. A negative sign for this variable indicates that increasing the percentage of young people in a census block group decreases the percentage of people less than the median age in the census tract needed to move in order to have an equal age distribution as the census tract. The coefficient in the general spatial model estimation is positive and statistically significant.

Table 3.5 Definitions and sources of second stage hedonics variables

Variable name	Definition (source)
PCTURBAN_CBG	Percentage of population in census block group living in urbanized area or urban cluster (1)
PCTMAR_CBG	Percentage of persons married with spouse present in census block group (1)
TCHPAY_SD	Average teacher salary for the district (3)
PTRATIO_SD	Pupil/teacher ratio (3)
ATTRATE_SD	Student attendance rate (3)
DROPRTE_SD	Dropout rate (3)
PCTHS_CBG2	Percentage of persons 25 years or older in census block group whose highest educational attainment is a high school diploma, including equivalency (1)
PCTBA_CBG2	Percentage of persons 25 years or older in census block group whose highest educational attainment a Bachelor's degree (1)
PCTNOHS_CBG2	Percentage of persons 25 years or older in census block group whose highest educational attainment is less than a high school degree or equivalent (1)
UNEMP_CBG2	Percentage of labor force in census block that is unemployed; labor force is sum of employed plus unemployed persons age 16 and over (1)
HU100_CBG	Number of housing units in the census block group in hundreds of units; a housing unit is a house, apartment, mobile home, a group of rooms, or a single room that serves as a separate living quarter (1)
PAGEDI	Price of age segregation derived from hedonic regressions
PINCDI	Price of income segregation derived from hedonic regressions
PEDUCDI	Price of education segregation derived from hedonic regressions
PRACEDI	Price of race segregation derived from hedonic regressions
PEFFMILLS	Price of tax segregation derived from hedonic regressions
PERCAPINC	Per capita income in dollars in census block group (1)
PCTYOUNG_CBG	Percent of persons in census block group who are between 0 and 4 years of age (1)
DENSITY_CBG	Number of persons per square mile in block group (1)
RAIN	Average rainfall in the MSA
BLUECOLL_CBG	Percentage of employed civilian population age 16+ in census block group with blue collar jobs (1)

Table 3.5 Definitions and sources of second stage hedonics variables (continued)

Variable name	Definition (source)
POLICERATIO	Number of police officers per 1000 residents in police district (2)
PCOMMUTE	Price of commuting time derived from hedonic regressions
XPUP_SD	Expenditure per pupil (3)
OWNEROCC_CBG	Percent of occupied housing units in census block group that are occupied by owners rather than renters (1)
PCTWHITE_CBG	Percentage of population in census block group that is white, non-Hispanic (1)
CL1VALPUP00	Per pupil value in 2000 of Class 1 (residential and agricultural) property, by school district (4)
CL2VALPUP00	Per pupil value in 2000 of Class 2 (mineral, industrial, commercial, and railroad real) property, by school district (4)

Sources:
(1) GeoLytics CensusCD 2000 Long Form Release 2.0
(2) GeoLytics CrimeReportsCD 1.0 of 2000
(3) Ohio Department of Education, Division of Information Management Services (1995);
(4) Ohio Department of Transportation

Table 3.6 Segregation demand estimation – Iterated Ordinary Least Squared Estimation

	Age		Income		Education		Race	
Variable Name	Estimate	t-stat.	Estimate	t-stat.	Estimate	t-stat.	Estimate	t-stat.
INTERCEPT	-2.2023***	-235.96	-1.4115***	-33.42	-1.7217***	-48.33	-1.9748***	-47.44
PAGEDI	-0.0000002	-0.11	0.00002***	11.99	-0.00001***	-7.37	-0.00001***	-5.24
PINCDI	0.00001***	11.99	-0.0001***	-21.01	0.00001***	7.99	-0.00003***	-11.58
PEDUCDI	0.00001***	7.37	-0.00003***	-7.99	0.00004***	13.61	-0.00004***	-13.63
PRACEDI	0.00001***	5.24	-0.00003***	-11.58	0.00001***	13.63	-0.0001***	-12.09
PEFFMILLS	-	-	0.0001	0.43	-0.0013***	-10.75	0.0004*	1.77
PERCAPINC	-0.000003***	-8.84	0.000003***	7.21	-0.00001***	-13.69	0.000002***	7.19
PCTYOUNG_CBG	-0.0176***	-20.12	-	-	-	-	-	-
DENSITY_CBG	-	-	-0.000002*	-1.76	0.00001***	8.72	0.000004***	4.98
RAIN	-	-	-0.0047***	-4.58	-0.0044***	-5.11	0.0034***	3.96
BLUECOLL_CBG	-	-	-0.0090***	-34.03	0.0028***	11.42	0.0035***	15.91
POLICERATIO	-	-	-0.0010***	-5.66	0.0004***	3.06	-0.0008***	-5.90
PCOMMUTE	-	-	0.0022***	10.76	-0.0011***	-8.86	0.0027***	17.43
XPUP_SD	-	-	0.00002***	4.94	-0.0000002	-0.07	-0.00001***	-3.05
OWNEROCC_CBG	-	-	0.0006***	4.19	-	-	0.0101***	67.29
PCTWHITE_CBG	-	-	-0.00004	-0.30	-	-	0.0013***	21.26
CL1VALPUP00	-	-	-0.0008***	-9.89	-0.0015***	-17.86	-0.0046***	-32.89
CL2VALPUP00	-	-	-0.0020***	-13.50	-0.0001	-0.60	-1.9748***	-47.44
N		85,255		85,255		85,255		85,255
Adjusted R^2		0.0079		0.0387		0.0485		0.1258

Table 3.7 Segregation demand estimation – Seemingly Unrelated Regression Estimation

	Age		Income		Education		Race	
Variable Name	Estimate	t-stat.	Estimate	t-stat.	Estimate	t-stat.	Estimate	t-stat.
INTERCEPT	-2.1924***	-242.92	-1.7370***	-41.34	-1.5671***	-44.93	-2.1728***	-52.13
PAGEDI	-0.00001***	-5.12	-0.000001	-0.59	-0.00001***	-8.26	-0.00001***	-10.59
PINCDI	-0.0000005	-0.59	-0.00002***	-5.00	-0.000001	-0.61	0.000003	1.16
PEDUCDI	0.00002***	8.26	0.000002	0.61	0.00004***	13.84	-0.00001***	-4.80
PRACEDI	0.00003***	10.59	0.000003	1.16	0.000003***	4.80	-0.0001***	-10.79
PEFFMILLS	-	-	-0.0022***	-15.52	-0.0011***	-9.63	-0.0006***	-2.86
PERCAPINC	-0.000002***	-7.59	0.000001***	2.92	-0.00001***	-14.41	0.000001***	3.94
PCTYOUNG_CBG	-0.0193***	-23.41	-	-	-	-	-	-
DENSITY_CBG	-	-	-0.000001	-0.69	0.00001***	7.22	0.000003***	4.57
RAIN	-	-	0.0023**	2.31	-0.0071***	-8.52	0.0059***	6.86
BLUECOLL_CBG	-	-	-0.0071***	-27.93	0.0032***	13.55	0.0045***	20.50
POLICERATIO	-	-	-0.0014***	-8.25	0.0003**	2.27	-0.0011***	-8.22
PCOMMUTE	-	-	-0.0016***	-8.99	-0.0015***	-13.18	0.0005***	3.51
XPUP_SD	-	-	-0.00001**	-2.38	-0.00002***	-5.90	-0.00002***	-6.18
OWNEROCC_CBG	-	-	0.0003***	2.48	-	-	-	-
PCTWHITE_CBG	-	-	0.0007***	6.50	-	-	0.0110***	72.06
CL1VALPUP00	-	-	-0.0012***	-15.56	-0.0011***	-14.08	0.0012***	18.72
CL2VALPUP00	-	-	-0.0018***	-12.12	-0.0003**	-2.18	-0.0043***	-31.50
N		85,255		85,255		85,255		85,255
Adjusted R^2		0.0086		0.030		0.0478		0.1210

Table 3.8 Segregation demand estimation – General spatial model estimation

	Age		Income		Education		Race	
Variable Name	Estimate	t-stat.	Estimate	t-stat.	Estimate	t-stat.	Estimate	t-stat.
INTERCEPT	-2.370***	-120.177	-3.222***	-7.82	-1.401***	-5.92	-2.172***	-5.78
PAGEDI	-0.000002	-0.846	0.0004***	19.54	0.0003***	20.11	0.0002***	9.33
PINCDI	-0.00001***	-4.255	-0.001***	-34.12	-0.001***	-32.69	-0.001***	-27.72
PEDUCDI	0.00009***	52.460	-0.001***	-28.58	-0.001***	-26.93	-0.001***	-24.77
PRACEDI	-0.00005***	-5.721	0.001***	8.71	0.0004***	9.22	0.0001	1.01
PEFFMILLS	-	-	-0.007***	-3.60	-0.005***	-3.86	-0.001	-0.27
PERCAPINC	0.002***	3.268	0.006**	2.25	0.002	1.45	0.012***	4.88
PCTYOUNG_CBG	0.008***	5.396	-	-	-	-	-	-
DENSITY_CBG	-	-	0.167***	29.24	0.087***	26.81	0.133***	24.30
RAIN	-	-	0.004	0.41	-0.007	-1.33	0.006	0.67
BLUECOLL_CBG	-	-	-0.024***	-12.59	-0.007***	-6.21	-0.012***	-6.41
POLICERATIO	-	-	-0.009***	-7.43	-0.005***	-7.57	-0.009***	-8.19
PCOMMUTE	-	-	0.064***	38.29	0.035***	36.27	0.047***	31.27
XPUP_SD	-	-	0.0001***	4.59	0.00001	0.82	0.00002	0.79
OWNEROCC_CBG	-	-	0.014***	16.37	-	-	-	-
PCTWHITE_CBG	-	-	0.008***	9.44	-	-	0.016***	19.89
CL1VALPUP00	-	-	0.000***	19.35	0.000***	28.73	0.000***	42.45
CL2VALPUP00	-	-	0.000***	-10.73	0.000***	-7.64	0.000***	-10.42
RHO	0.083***	24.586	0.122***	30.11	0.119***	28.73	0.212***	53.82
LAMBDA	0.365***	256.433	0.405***	208.82	0.405***	167.22	0.315***	152.88
N		85,255		85,255		85,255		85,255
Adjusted R^2		0.1954		0.2938		0.2984		0.2672

The sign on the coefficient of the per capita income included in all demand equations differs across equations. For the ITOLS and ITSUR results, all coefficients are statistically significant, but are positive for the income and race demand equations and negative for the age and education demand equations. In the general spatial model the coefficient for income is positive in all demand equations, but is not statistically significant in the education demand equation.

3.8 Discussion

The main hypothesis of this essay is that people sort into neighborhoods looking for combinations of amenities, such as parks and better schools, provided by local governments, but at the same time they look for similar peer group characteristics. A demand curve is a representation of the willingness of consumers to acquire units of a good or service at a series of prices in a given period of time, *ceteris paribus*. In this essay, we relate a household's desire to sort into racially, income, age, and educationally segregated neighborhoods as a function of their implicit prices and other demand shifters. Increases in the segregation index are related to decreases in the implicit prices. In order to better understand how these neighborhood characteristics affect the decision to sort into a particular neighborhood, we calculate own-price elasticities, cross-price elasticities, and income elasticities for age, income, education and race segregation. Table 3.10 presents the own-price elasticities of demand and cross-price elasticities of demand calculated with the estimated ITSUR models. Both the ITOLS and the ITSUR are similar, but differ consistently from the general spatial models. We select the ITSUR for the elasticity calculations because we suspect that the errors might be contemporaneously correlated across equations and therefore the ITSUR estimates would control for these correlations. Further, some of the estimates from the general spatial model are inconsistent with demand theory. Results for the education demand equation are left out as well. Collinearity and identification problems might be causing a positive sign for the own-price coefficient; we therefore avoid interpreting results from these estimates.

All three own-price elasticities are small in magnitude, suggesting that small percentage changes in the marginal willingness to pay for age, income, education, and race segregation have a less than proportionate impact on the percentage of people that need to move across census block groups in order to make the age, income, education, or race distribution even with respect to the census tract. This result has considerable importance for policy making: policies that intend to increase neighborhood integration along any of the dimensions studied in this essay need to substantially reduce the willingness to pay for segregation in order to achieve a considerable impact on the level of neighborhood integration.

Table 3.9 Price elasticities of demand

	AGEDI	INCDI	RACEDI
PAGEDI	-0.01		
PINCDI	-0.0005	-0.01	
PRACEDI	0.03	0.002	-0.04

The cross-price elasticity of demand between age and income neighborhood segregation is negative and small. This suggests that neighborhood age segregation and income segregation are weak complements; increasing the willingness to pay to live with others of similar age or income decreases the demand for income or age neighborhood segregation.

Neighborhood age segregation is a substitute for race segregation, thus increasing the implicit price for neighborhood age segregation increases the demand for racially segregated neighborhoods. This suggests that people who are willing to pay more to live in an area with people of similar age are will demand to live in more racially integrated neighborhoods. The same results apply between income and race neighborhood segregation.

The income elasticity of demand for the age segregation demand equation is -2.23. This implies that neighborhood age segregation is inferior; increases in income decrease the demand for age segregation. This may suggest that poor people tend to be in neighborhoods that are more homogenous with respect to age. The opposite effect is found in the other demand equations. The income elasticity of demand in the income equation is 0.55 and 0.59 in the race demand equation. This suggests that neighborhood income and race segregation are normal neighborhood characteristics; increases in income increase the demand for these characteristics.

We also calculate consumer surplus changes from increases in three out of the four dissimilarity indices. We discarded calculations from the education demand curve because of the positive coefficient for own-price. Even though the urban economics literature emphasizes the negative socioeconomic impact of neighborhood segregation, primarily segregation of African Americans, the purpose of this essay is to address segregation as a characteristic that households choose to select when sorting into a particular neighborhood. Though increasing integration in any of the dimensions studied in this essay might be a policy target, we are interested in how much households would be willing to pay to move to a different location from their actual one that is segregated in any of the dimensions studied here. In this fashion, we compute consumer surplus changes for a 10% increase in the current or actual age, income and race dissimilarity index levels; that is, a 10% more segregated neighborhoods. The estimated average surplus gain from the age segregation demand equation is $571.59; from the income segregation demand equation is $477.09; and $246.77 for the race segregation demand equation.

3.9 Conclusion

This essay estimates four demand equations for age, income, education and race neighborhood segregation. The main motivation of the essay is to provide some insight into the possible causes of neighborhood sorting. It is hypothesized that people sort into neighborhoods looking for certain characteristics in terms of the peers with whom they will live. That is, it is expected that families with children, for example, look for amenities such as high school quality, safety, and low environmental risk, among others, as well as neighborhoods that are segregated by either age, income, education, and race. The same thing occurs for people of the same racial background or income level. In this essay we estimate the demand for this neighborhood characteristic and calculate elasticities so as to shed light into the complementarities and substitutions among them.

This essay has considerable policy implications. It has been argued in the literature that neighborhoods that predominate of a particular race (e.g. African Americans) have a negative impact on the individual performance of this group. This result has sparked concerns about policies that would reduce the gap between whites and African Americans socioeconomic outcomes, for example, by formulating policies that favor neighborhood integration. It is of interest to research whether segregation in other dimensions, i.e. age, income and education as researched in this essay, has a negative or positive impact on the performance of the segregated groups.

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