Valuing Environmental Quality: A Space-based Strategy

John I. Carruthers ★ U.S. Department of Housing and Urban Development, Office of Policy Development and Research; University of Maryland, National Center for Smart Growth Research and Education (e-mail: *john.i.carruthers@hud.gov*)

David E. Clark Marquette University, Department of Economics (e-mail: *david.clark@marquette.edu*)

★ Corresponding author

U.S. Department of Housing and Urban Development working paper # REP 07-01; submitted in final form to the *Journal of Regional Science* May 2009

This paper and related research have been presented at the 2007 meetings of the Southern Regional Science Association in Charleston, South Carolina; the 2007 meetings of the European Regional Science Association in Paris, France; the 2007 meetings of the North American Regional Science Council in Savannah, Georgia; the 2008 joint congress of the Associated Collegiate Schools of Planning and the Associated European Schools of Planning in Chicago, Illinois; and at various seminars at the Department of Housing and Urban Development, the University of Maryland, and Marquette University. Special thanks to Robert Renner for his invaluable research assistance; Jim LeSage for his advice on the implementation and evaluation of GWR; and, especially, to the three anonymous referees for their helpful comments and feedback. John Carruthers dedicates his work on this project to Art Silvers.

Abstract. This paper develops and applies a space-based strategy for overcoming the general problem of deriving the implicit demand for non-market goods. It focuses specifically on evaluating one form of environmental quality, distance from EPA-designated environmental hazards, via the single-family housing market in the Puget Sound region of Washington State. A spatial two-stage hedonic price analysis is used to: (*i*) estimate the marginal implicit price of distance from air release sites, hazardous waste generators, hazardous waste handlers, superfund sites, and toxic release sites; and (*ii*) estimate a series of implicit demand functions describing the relationship between the price of distance and the quantity consumed. The analysis, which represents an important step forward in the valuation of environmental quality, reveals that the information needed to identify second-stage demand functions is hidden right in plain sight — hanging in the aether of the regional housing market.

1. Introduction

Over the past several decades, the demand for environmental quality has emerged as one of the most powerful forces acting on the economic landscape of the United States and other developed nations (see Kahn 2006). But, in spite of its great importance, the value of that commodity remains elusive because holistic measurement requires knowledge of a demand function that describes the relationship between price and the quantity consumed. The challenge that this presents begins with the fact that no distinct market for environmental quality exists, so it can only be approached indirectly — ideally, via preferences revealed in markets for larger, differentiated commodities like labor and housing. Although it is usually straightforward to estimate the marginal implicit prices of the various non-market goods embedded in such markets, the function used to do this, called a hedonic price function, is a market clearing function that results from interaction between the bid and offer functions of participants on either side of the market. Coming up with the value of non-marginal differences in consumption means extending hedonic price analysis to a second stage and estimating a demand function wherein price and quantity are endogenously determined. The barrier to this is one of information: because the underlying first-stage hedonic function is a composite of unique, individual demand and supply, the marginal implicit prices it yields are also composites and, for this reason, conventional econometric procedures cannot readily be used to identify the second-stage demand function the way they can for more traditional commodities.

This paper responds to the challenge with an analysis that leverages spatial heterogeneity in housing attribute prices to expose the demand for one aspect of environmental quality, distance from Environmental Protection Agency (EPA) designated environmental hazards. There are three specific objectives: (*i*) to define spatial heterogeneity in the context of housing markets and develop a strategy for using it to overcome the general problem of deriving the demand for non-market goods; (*ii*) to estimate the marginal implicit price of distance from air release sites, hazardous waste generators, hazardous waste handlers, superfund sites, and toxic release sites via the single-family housing market in the Puget Sound region of Washington State; and (*iii*) to estimate a series of implicit demand functions describing the relationship between the price of distance from environmental hazards and the quantity consumed. The analysis, which represents an important step forward in valuing environmental quality, reveals how the field of regional science's unifying epistemology — namely, that geographic space mediates socioeconomic processes — holds a workable solution to what has always been the albatross of two-stage hedonic price analysis.

2. Background Discussion

2.1 Hedonic Prices and Implicit Markets

Environmental quality is not traded in conventional markets so willingness to pay for it can only be estimated, never measured directly (Freeman 2003). Estimation is done either via stated preference approaches, such as contingent valuation, or revealed preference approaches, such as hedonic price analysis. In the latter case, competition for the right to occupy desirable locations — both among and within regions — generates implicit prices in labor and/or housing markets that correspond to spatial variation in environmental quality. And, since this process plays out across two different levels of geography, there are two corresponding levels of hedonic price analysis: (*i*) interregional, which deals with variation in wages (the price of labor) and housing prices among regions; and (*ii*) intraregional, which deals with variation in housing prices within regions.[1] Although the theory underpinning these two frameworks is more-or-less the same, the distinction is an important one because the appropriate spatial lens depends on the nature of the environmental commodity in question. For example, the value of sunshine is best measured by looking among regions, whereas the value of proximity to neighborhood parks is best measured by looking within them. Though both levels of analysis have long been used to evaluate environmental quality, it is specifically the intraregional level of analysis that is the focus of this paper (see Baranzini et al 2008 for a recent review).

Rosen (1974) formalized hedonic price analysis as a two-stage process. In the first stage, the transacted price of housing is regressed on all of the attributes that matter to it, including its features, its neighborhood characteristics, and its location:

$$\tilde{p}_i = \alpha_0 + \alpha_1 \cdot z_{i1} + \alpha_2 \cdot z_{i2} + ... + \alpha_k \cdot z_{ik} + \varepsilon_i . \quad (1)$$

In this equation, $\tilde{p}_i$ represents the natural logarithm of the sales price of home *i*; the zs represent measures of various housing attributes; the αs represent estimable parameters; and ε_i represents a stochastic error term. From this, the marginal implicit price of any attribute, *k*, for each home, *i*, is calculated as the product of the estimated parameter and the price of the home:[2] $\hat{\pi}_{ik} = \hat{\alpha}_k \cdot p_i$. Then, the total implicit expenditure is calculated as the product of the marginal implicit price and the quantity of that attribute: $\hat{\eta}_{ik} = \hat{\pi}_{ik} \cdot z_{ik}$. In the second stage of hedonic price analysis, quantities

[1] Carruthers and Mundy (2006) provide a survey of the two levels of hedonic price analysis.

[2] Because equation (1) in semi-log form, marginal implicit price is $\hat{\alpha}_k \cdot p_i$; if equation (1) were linear, the implicit price would be just $\hat{\alpha}_k$; and, if it were in log-log form, the marginal implicit price would be $\hat{\alpha}_k \cdot p_i / z_i$. The calculations that come later in the paper account for the log transform of the dependent variable and, where appropriate, explanatory variables.

of the attributes of interest are regressed on their estimated marginal implicit prices, which are endogenous, plus a set of relevant demand shifters:

$$\tilde{q}_{ik} = \beta_0 + \delta_{ik} \cdot \hat{\pi}_{ik} + \beta_1 \cdot x_{i1} + ... + \beta_s \cdot x_{is} + \upsilon_i. \quad (2)$$

Here, $\tilde{q}_{ik}$ represents the natural logarithm of the quantity of attribute *k* consumed via home *i*; $\hat{\pi}_{ik}$ represents its estimated marginal implicit price; the xs represent *s* number of demand shifters; δ_{ik} and the βs represent estimable parameters on the endogenous variable and explanatory variables, respectively; and υ_i represents a stochastic error term.

Because the second-stage implicit demand function contains an endogenous variable ($\hat{\pi}_{ik}$) it must be estimated via an appropriate econometric procedure. Rosen's (1974) original formalization suggested that the issue amounted to only a "garden variety identification problem" (page 50), so it could easily be resolved via an instrumental variables estimator, like two stage least squares (2SLS). Unfortunately, as demonstrated by Brown and Rosen (1982), the truth is not so convenient because, in hedonic price analysis, each revealed implicit price function results from a unique interaction between an individual demand function and an individual supply function. Like the hedonic price function it comes from, the implicit price function is really a reduced form composite of both unique, individual demand and unique, individual supply that does not contain the kind of information needed to identify a structural demand function. Though there are multiple ways of overcoming this problem — including by imposing certain functional form restrictions (Chattopadhyay 1999) — the most widely accepted strategy is to use spatially distinct housing market segments having different prices for the same attributes to identify a demand function for the entire market (Palmquist 1984; Bartik 1987; Epple 1987; Taylor 2008). Executing such a strategy requires that, all else being equal, different households are observed to pay different implicit prices for the same quantity of a given attribute — in other words, that implicit markets are spatially segmented and, for that reason, prices vary independently from characteristics influencing household demand.[3] While the parameter estimates of demand functions generated in this way are spatially invariant, it is the spatial variation in the underlying marginal implicit price estimates that are critical to identifying the structural equation.

Over the years, variations on the first stage of hedonic price analysis have been used to examine many general forms of environmental quality (see Boyle and Kiel 2001 and Kiel 2006 for in-depth reviews), plus a number of specific environmental hazards (for example, Kohlhase

[3] This paper contends that a space-based strategy — structured around Fotheringham et al's eeographically weighted regression (GWR) procedure — can be used to model the market segmentation that is needed to identify the underlying parameters of implicit demand functions. Yet another challenge lies in the difficulty of finding instrumental variables viable for implementing the necessary 2SLS estimation procedure. Each of the instruments used to estimate an implicit demand function in this analysis is subjected to rigorous validity testing.

1991; Kiel and McClain 1995; Clark et al 1997; Hite 1998; Clark and Allison 1999; Dale et al 1999; Hite et al 2001; Bae et al 2007; Brasington and Hite 2008). And, recently, there has been a revived interest in the second stage of hedonic price analysis, which has been used to evaluate the demand for air quality (Chattopadhyay 1999; Zabel and Kiel 2000), neighborhood and school quality (Cheshire and Sheppard 1995, 1998, 2004; Black 1999; Brasington 2000, 2003), and distance from environmental hazards similar to those that are of concern here (Brasington and Hite 2005). In addition to the growing commitment to second-stage analysis, there have been important advances in first-stage analysis, including gains made by studies that use spatial econometric methods to evaluate environmental quality (Kim et al 2003; Theebe 2004; Anselin and LeGallo 2006; Cohen et al 2008). Still other spatial analyses — beginning with work by Can (1990, 1992) — have found that there is a high degree of heterogeneity in housing attribute prices (Mulligan et al 2002; Fik et al 2003; Bitter et al 2007). This last category of research, which is addressed in the next section, points to a potential solution to the identification problem that has long plagued the second stage of hedonic price analysis.

2.2. Market Segmentation and Spatial Heterogeneity in Housing Attribute Prices

At about the same time that Rosen (1974) formalized the two stages of hedonic price analysis, Straszheim (1974) cautioned that, due to market segmentation, it is not always appropriate to assume that the implicit prices of housing attributes remain the same across geographic space — even within a single region. By this reasoning, the regional housing market is composed of an interconnected set of many localized submarkets having idiosyncratic differences in the structure of supply and/or demand and, consequently, unique schedules of attribute prices (Michaels and Smith 1990). But, in order for spatially distinct market segments to materialize, it must also be the case that buyers from one submarket do not normally participate in the other submarkets — for reasons having to do with barriers to entry, imperfect information,[4] and/or some other restriction on arbitrage opportunities. Under such circumstances, which are rather typical of complex regional housing markets, the implicit prices of housing attributes may vary from submarket-to-submarket, or even from household-to-household. In short, there is good reason to suspect upfront that there is considerable heterogeneity embedded in the regional housing market

[4] While the focus of the discussion is on heterogeneity, it is worth pointing out that some researchers have focused on how the nature of information influences housing markets: Kask and Maani (1992) find that both differences between the objective and subjective probabilities associated with the risk of environmental hazards and incomplete information about those probabilities affect the hedonic price function; Yavas and Yang (1995) find evidence of systematic inefficiencies due to incomplete information in the bargaining process; and Hite (1998) finds that the quality of information about environmental quality is what, in fact, determines whether or not it enters the hedonic price function in the first place.

and that, if so, it can be exposed and put to use for identifying second-stage implicit demand functions.

One illustration of the potential for deriving demand parameters within an individual market is an analysis by Bajari and Kahn (2005, 2008) that uses a nonparametric estimation strategy to explain household willingness to pay for various housing attributes. The procedure involves three steps: (*i*) estimating a (nonparametric) first-stage hedonic price function; (*ii*) using the error term from that function to recover household-level preferences; and (3) estimating preferences as a function of household characteristics. Although the analysis does not estimate implicit demand functions[5] and, therefore, does not face the same type of endogeneity problem encountered here, it is nonetheless intriguing because it uses a random coefficients approach to derive estimates of the impact of individual preference shocks on willingness to pay. The results are used to draw conclusions about how housing demand influences nature of racial segregation in several regions and they reveal, among other things, that white households have stronger preferences than black households for low-density housing.

Beyond this, the realization that substantial heterogeneity may be embedded in individual regional housing markets has impacted hedonic research by motivating a number of analyses aimed at delineating and measuring differences among submarkets within regional housing markets (Goodman and Thibodeau 1998, 2003; Brasington 2000, 2001, 2002). In an early taxonomy, Goodman (1981) argued that heterogeneous demand functions are bound to interact with inelastic short-run supply functions to produce spatially distinct schedules of housing attribute prices that may not converge on a common regional value until the (unobservable) long-run, if ever. Another trend in hedonic price analysis is to allow for the possibility that housing attribute prices may not just be segmented, but are actually variable and even quite volatile, across regional housing markets. In other words, at any given spot, there exists a potentially unique housing attribute price schedule that can be estimated via spatial methods. This approach began with work by Can (1990, 1992), who applied Casetti's (1972) expansion method of model building by interacting an index of neighborhood quality with housing attributes to produce implicit price estimates that depend on location itself. Subsequent research has gone further still, by interacting Cartesian coordinates with housing attributes to generate a unique "location value

[5] Bajari and Kahn (2005) use the PUMS samples of the 1990 Census of Population and Housing to derive willingness to pay (WTP) functions for housing attributes, and, since they also know the characteristics of the household, they relate changes in WTP to those household characteristics. Their goal is to examine the role of household-level taste differences on WTP and they employ a random coefficients approach to derive household-specific taste shifters. However, they do not estimate an implicit demand function since WTP is not regressed on quantity. In contrast, the goal of the present analysis is to address the unique endogeneity issue that exists in the two-stage hedonic model so that implicit demand functions for environmental quality can be derived.

signature" (Fik et al 2003, page 643) for every home involved in the analysis.[6] Once estimated, location value signatures expose multiple housing attribute price surfaces within a single housing market — surfaces that are formed by otherwise unobserved factors. (Mulligan et al 2002; Fik et al 2003; Bitter et al 2007).

Critically, the heterogeneity that gives rise to these surfaces is non-stochastic because housing markets are subject to a great deal of spatial dependence (Kim et al 2003; Theebe 2004; Anselin and LeGallo 2006; Brasington and Hite 2005). On the supply side, proximate homes tend to be similar and, on the demand side, homebuyers regularly emulate one another's behavior. The result is a process of spatial interaction among market participants, which suggests that, at a minimum, equation (1) should be modified to include a spatial lag of its dependent variable (Anselin 1988; Anselin and Bera 1998):

$$\tilde{p}_i = \phi_0 + \lambda \cdot W_{ij} \cdot \tilde{p} + \phi_1 \cdot z_{i1} + \phi_2 \cdot z_{i2} + \ldots + \phi_k \cdot z_{ik} + \psi_i . \qquad (3)$$

The notation in this equation is essentially the same as before, except that the ϕs stand in for the αs; ψ_i replaces ε_i as the stochastic error term; $W_{ij} \cdot \tilde{p}$ represents the spatial lag of the dependent variable (W_{ij}, $j \neq i$, is a row-standardized $n \times n$ spatial weights matrix describing the geographic arrangement of transactions) giving the average sales price of proximate homes; and λ is an estimable spatial autoregressive parameter. Because equation (3) indicates that the sales prices of nearby homes influence each other, $W_{ij} \cdot \tilde{p}$ is endogenous to $\tilde{p}_i$ and, so, the function cannot be properly estimated using ordinary least squares (OLS). A viable alternative is a spatial two-stage least squares (S2SLS) strategy developed by Kelejian and Prucha (1998), which involves first regressing the spatially lagged dependent variable on all of the explanatory variables plus spatial lags of those same variables to produce predicted values, and then using the predicted values in place of the actual values in equation (3). Like the alternative, maximum likelihood estimation, S2SLS yields efficient, unbiased parameter estimates, even in the presence of spatial error dependence (Das et al 2003).

In practice, the spatial lag in equation (3) acts something like a flexible fixed effect, absorbing the type of spatial correlation in housing prices that arises from various forms of unobserved spatial heterogeneity.[7] But, while this helps to achieve proper first-stage estimates, it

[6] Clapp (2001) and others have developed similar, semi-parametric estimators for hedonic price models that also involve the use of a property's Cartesian coordinates. These approaches are a lot like the expansion method and geographically weighted regression (GWR) — the approach used in this paper — in the sense that they are designed to account for the influence of location in-and-of itself. The main difference is that these approaches estimate parameters on location-specific variables (Cartesian coordinates) whereas in GWR, parameters related to housing attributes vary by location.

[7] In an analysis of school quality, which varies by school district, Black (1999) used a fixed effects approach to capture unobserved factors associated with the neighborhood conditions that spill across the boundaries of school districts. The

does nothing to address the identification problem that arises in the second stage of hedonic price analysis. An alternative approach — Fotheringham et al's (2002) geographically weighted regression (GWR) procedure — opens the door to second-stage estimation:

$$\tilde{p}_i = \gamma_{i0} + \gamma_{i1} \cdot z_{i1} + \gamma_{i2} \cdot z_{i2} + ... + \gamma_{ik} \cdot z_{ik} + \tau_i. \tag{4}$$

The notation here is again the same as in equation (1), except that the γs represent estimable parameters specific to each home, i, located at spot $\{u, v\}$ and τ_i represents the stochastic error term. Just as before, the marginal implicit price of a given housing attribute is calculated as the product of the estimated location-specific parameter and the price of the home, or $\hat{\pi}_{ik} = \hat{\gamma}_{ik} \cdot p_i$, and the total implicit expenditure is calculated as the product of the marginal implicit price and the quantity of that attribute, or $\hat{\eta}_{ik} = \hat{\gamma}_{ik} \cdot z_{ik}$. The difference is that the estimates that go into the calculation, $\hat{\gamma}_{ik}$, differ from home-to-home, so the variable is the product a variable parameter and a variable, not a constant parameter and a variable.

Equation (4) is complicated to estimate and requires the use of software developed especially for that purpose (Fotheringham et al 2003) but, even so, the procedure is really just a logical extension of the familiar OLS estimator. In plain terms, GWR fits a separate OLS regression for each-and-every observation in the dataset and discounts information from other observations by distance via a spatial weights matrix, so that closer observations have a greater influence on the local solution. Also, each individual regression generally includes only a subset of the dataset, so the local sample size is something smaller than the total number of available observations. Put differently, GWR involves running the same regression over-and-over again — once for every observation in the dataset — but with a subset of all observations that is spatially centered on each individual observation, and in a way that discounts the value placed on included observations by how far they are from the spot where the regression is centered. The output of GWR is voluminous: a total of n observations $\cdot$ k parameters, so 100,000 parameters (plus corresponding standard errors and t-statistics) for a model having 10,000 observations, nine explanatory variables, and a constant.[8] See Fotheringham et al (2002) for an in-depth explanation and Kestens et al (2006), Bitter et al (2007), and Wheeler and Calder (2007) for applications of GWR to the first stage of hedonic price analysis.

spatially lagged dependent variable contained in equation (3) captures exactly this kind of unobserved heterogeneity, by making it explicit to the first-stage hedonic price function.

[8] On the face of it, GWR seems to produce many more parameters than there are observations — but this is not actually the case because the estimates are the accumulation of n separate regressions. In the example given in the text, the 100,000 parameters result from estimating the same 10 parameters 10,000 times and then pulling all of the estimates together.

Coming back to the matter at hand, GWR is a procedure for modeling spatial heterogeneity and, because of this, it is ideal for accommodating the kind of market segmentation identified by Straszheim (1974) and others. Although it may be possible to delineate certain kinds of submarkets upfront, either by way of assumption or by consulting with market participants, in practice, it seems unlikely that actual submarkets would ever follow rigid boundaries or that they would necessarily be congruent for all housing attributes. A more plausible supposition is that submarkets for housing attributes bleed across geographic space in various ways, waxing and waning in a manner relevant to the specific behavioral mechanisms that generate them. GWR models the heterogeneity of housing attribute prices — however organic and different from one another they may be — and retains it as a form of information that can, in turn, be used to estimate the demand for those attributes. This is fundamental because, if the marginal implicit prices estimated in the first stage of hedonic price analysis vary by location, then it follows that the housing market is spatially segmented in a way that allows the estimates from different locations to be pooled in the second stage to estimate a market-wide demand function. This space-based strategy is proposed as a general solution to the long-standing problem of deriving the implicit demand for non-market goods.

3. Empirical Analysis

3.1 Data, Setting, and Modeling Framework

The empirical analysis is set in King County, Washington, the location of Seattle and the heart of the Puget Sound region. The data, which originates mainly from the King County Assessor, includes 29,165 transactions for single-family homes that took place during 2004 — essentially all such arms-length transactions from that year. Once collected, the sales were entered into a geographic information system and linked to parcel data, also from the King County Assessor, plus spatial data from other relevant sources to create a variety of number of neighborhood- and distance-based metrics. Figure 1 displays surface trends interpolated[9] from the natural logarithm of the sales prices of the 29,165 homes and Table 1 lists the source of, and descriptive statistics for, all variables involved in the analysis.

In 2004, King County was home to over 1.75 million people living in more than 50 different jurisdictions. Within the region, there are many readily apparent submarkets but there is

[9] The surface trends were generated via an inverse distance weighting scheme, which is the simplest method of interpolating a surface from point data — it estimates values between observations *i* and *j* as a weighted average, where the weight given to each observation is determined by a standard distance decay function: $f(d_{ij}) = 1/d_{ij}^2$ (Longley et al 2001).

also considerable crossover between them because the region as a whole is well integrated and faces little of the kind of socioeconomic segregation that commonly bifurcates housing markets of large cities. This is not to say that income polarization and its attendant residential sorting do not exist in the Puget Sound, just that they do not exist at the same extremes as they do in many other American metropolitan areas. Instead, the region's housing market tends to be sorted more by preference: for example, some residents prefer the high-density, mixed-use neighborhoods of Seattle and others prefer the low-density, predominantly residential neighborhoods of the eastern suburbs and other outlying areas.[10] Moreover, the Puget Sound region in general, and Seattle — the so-called "Emerald City" — in particular, are famous worldwide for being among the nicest places to live and own housing in the United States. Views of the Cascade and Olympic mountain ranges are typical and so are views of the Sound, Lake Union, Lake Washington, the Ship Canal, and many other smaller water bodies. With its large and dynamic housing market and its many opportunities to consume environmental quality, King County is an ideal setting for evaluating the demand for that commodity.

As shown in each of the first-stage hedonic price functions — that is, in equations (1), (3), and (4) — the price of housing depends on a vector of housing attributes, say z, that describes the home itself, its neighborhood, and its location. In terms of model construction, the exact set of variables that fill out this vector depends, crucially, on the geographic scope of the analysis because different things matter within different spatial frames of reference. That is, constructing a model for a specific housing submarket is a different exercise than constructing a model for all of the regional market, which is what is of interest here.

With this in mind, the process of model construction led to the following nine categories of explanatory variables, some of which are captured by a lone variable: (*i*) lot size, measured as the square footage of the of the home's site; (*ii*) structure, measured as the square footage of living space, its age in linear and quadratic form, and its number of fireplaces; (*iii*) grade, a qualitative evaluation made by the assessor that rates the home as being of "below average," "average," "good," "better," "very good," "excellent," "luxury," or "mansion" quality; (*iv*) condition, another qualitative evaluation made by the assessor that rates the home as being in "below average," "average," "good," or "very good" shape; (*v*) amenities, measured as whether or not the home has a view of any kind, whether or not it is subject to some sort of a nuisance, like traffic noise, and the number of linear feet of waterfront its site has, if any; (*vi*) neighborhood, measured as the property tax rate, which is calculated as the ratio of the previous year's property tax bill to the assessed value, school quality, which is calculated as the average

[10] Charles Tiebout chose to live in Seattle itself, in a neighborhood adjacent to the University of Washington.

percentage of students achieving success in state aptitude tests for mathematics, reading, science, and writing, plus, defined at the census tract level, median household income and housing density, which is calculated as housing units per acre; (*vii*) location, measured as distance from downtown Seattle, the average commute time to work in the census tract, distance from the nearest arterial, whether or not the home is located outside of the Puget Sound's urban growth area, and distance from the nearest point on the growth area's boundary; (*viii*) environmental hazards, measured as the distance from the nearest air release site, hazardous waste generator, hazardous waste handler, superfund site; and toxic release site; and (*ix*) time, measured as the number of the month in which the home was sold.[11] Together, these 32 variables — plus a constant — form the vector of attributes that explains the sales price of single-family housing in King County's portion of the Puget Sound region.[12] The expected sign of each variable involved in the first-stage hedonic price functions is listed in the rightmost column of Table 1.

Last, before getting to the analysis, it is necessary to provide some basic details about the five EPA designated environmental hazards that are the center of this analysis: (*i*) air release sites (n = 287) are fixed sources of air pollution that are contained in the Aerometric Information Retrieval System; (*ii*) hazardous waste generators (n = 2,094) are waste-producing facilities that are contained in the Resource Conservation and Recovery Information System; (*iii*) hazardous waste handlers (n = 4,559) are waste-handling facilities (exclusive of hazardous waste generators) that are contained in the Resource Conservation and Recovery Information System; (*iv*) superfund sites (n = 5) are contaminated sites prioritized for cleanup that are contained in the Comprehensive Environmental Response, Compensation, and Liability Information System; and (*v*) toxic release sites (n = 281) are manufactures of toxic chemicals dangerous enough to pose severe environmental and, in certain cases, public health threats, that are contained in the Toxics Release Inventory.[13] All such sites — which range from everyday-type land uses, like drycleaners and gas stations, to highly stigmatized sites hosting heavy industrial activities[14] — located in King County or within five miles of its borders as of 2002, two years prior to the housing transactions, are included in the analysis. Distance is the most common way of measuring the presence of

---

[11] An alternative time specification — which yielded essentially identical results — employed monthly dummy variables. The continuous monthly variable was used because the Seattle region experienced monotonic growth in home prices during 2004.

[12] This specification is very similar, though not identical to, a specification developed independently by Bae at al (2007) for a hedonic analysis also focused on the central Puget Sound region.

[13] For an overview of each and access to the same data used here, see: *http://www.epa.gov/enviro/html/airs/index.html* for air release sites; *http://www.epa.gov/epaoswer/hazwaste/data/index.htm* for hazardous waste generators and hazardous waste handlers; *http://www.epa.gov/enviro/html/cerclis/index.html* for superfund sites; and *http://www.epa.gov/enviro/html/tris/index.html* for toxic release sites.

[14] Some toxic release sites are also air release sites but these categories were not made mutually exclusive in order to account for the compounding influence that the two types of designation may have. Also note that one of the superfund sites is the entire Duwamish River, which extends from Portage Bay into the industrial Southside of Seattle.

noxious land uses in hedonic price analysis and it is used here because of its ability to capture both the real and perceived levels of disamenity and/or risk associated with the hazards (see Clark and Allison 1999).

3.2 First-stage Hedonic Price Function — OLS and S2SLS Estimates

The purpose of this step of the analysis is to create a backdrop for the ensuing GWR estimation of the first-stage hedonic price function shown in equation (4) by estimating the more-familiar OLS and S2SLS variants shown in equations (1) and (3). Although the main substance of the analysis lies in the GWR estimates and the second-stage implicit demand functions they facilitate, the so-called "global" estimates outlined here provide a touchstone for what follows by helping to establish the specification and by demonstrating that the estimates do not vary wildly due to some kind of omitted spatial variable bias.

The left-hand panel of Table 2 lists OLS estimates corresponding to equation (1). Every explanatory variable carries its expected sign (if it was anticipated in advance) and all are statistically significant — most at well over a 99% level of confidence. Overall, the vector $\boldsymbol{z}$ influences the sales price of housing in the Puget Sound region according to the expectations expressed in Table 1. Furthermore, the adjusted R^2 is 0.83, indicating that the equation does an excellent job of explaining the cross-sectional variation in the sales price of single-family housing. Next, the right-hand panel of Table 2 lists the S2SLS estimates, corresponding to equation (3), wherein the spatial lag of the dependent variable is the average price paid in the four nearest transactions.[15] The autoregressive term is positive and highly significant, which shows that the sales prices of proximate homes are strongly correlated with one another, and its inclusion in the equation raises the adjusted R^2 slightly, to 0.85. The original 32 explanatory variables all have the same signs as before and, except for the variable indicating whether or not the home is located outside of the Puget Sound's urban growth area and distance from hazardous waste handlers, they all remain statistically significant at a 99% or greater confidence level. Most important, a comparison of the two models reveals that the OLS and S2SLS estimates, the latter of which account for unobserved neighborhood effects and other potentially omitted spatial variables, remain broadly consistent: the sign patterns on, and relative magnitudes of, the various explanatory variables are essentially the same. Even so, the Akaike Information Criterion (AIC) statistic, which provides a basis for discriminating among alternative models (Kennedy 1998), shows that the spatial variant of the hedonic price function is preferable to its aspatial counterpart.

[15] All spatially lagged variables were generated in *GeoDa* (see Anselin et al. 2006), and then imported into *EViews*, where the OLS, STSLS, and 2SLS equations described in this paper were estimated.

The next issue — the fine point of the entire matter — is to ascertain whether or not the global estimates in reality vary across geographic space.

3.3. First-stage Hedonic Price Function — GWR Estimates

As explained, GWR involves estimating the same regression repeatedly — once for every observation in the dataset — but with a subset of all observations that differs by location, and in a way that discounts the weight placed on included observations by their distance from the spot where the individual regression is centered. The technique, which is computationally intensive, produces output consisting of a huge total of $n \cdot k$ parameters — so, in this case, 962,445 (or 29,165 · 33) location-specific estimates. By placing greater weight on local activity and less weight on more distant activity in the first-stage hedonic function, GWR enables spatial heterogeneity in the Puget Sound's housing market to be observed and modeled directly, and thereby facilitates identification of second-stage implicit demand functions.[16]

Before discussing the estimates, a remaining aspect of the GWR procedure, the determination of the appropriate spatial bandwidth, requires some explanation because it can affect the results. Two options are available: (*i*) a fixed spatial bandwidth, which uses all observations, no matter how few or how many, located within a constant radius of the regression spot, so the sample size varies by location; and (*ii*) an adaptive spatial bandwidth, which uses a constant number of observations, no matter how close or how far away they are from the regression spot, so the sample size does not vary by location. Compounding this choice, the GWR software can be used to find a statistically "optimal" bandwidth or it will let the user supply a predetermined bandwidth. Various combinations of these alternatives were explored for the purposes of this research and, in the end, an adaptive spatial bandwidth encompassing a constant 70% of the dataset — so 20,416 location-specific observations were used to generate the estimates.[17]

The GWR estimation results, which correspond to equation (4), are displayed in Table 3. Only parameters having a corresponding t-value greater than or equal to 1.96 are considered statistically significant — that is, estimates significant at a minimum of a 95% level of

---

[16] As one anonymous referee pointed out, the strategy employed in this paper carries with it a certain risk: it assumes that the variation in the GWR estimates are the result market segmentation — not instead the result of one or more omitted spatial variables. The specification used in this paper is extensive (it includes numerous spatial variables) and, as explained in section 3.2, it is robust to other estimation strategies, including one that specifically accounts for localized spatial interaction, so the authors have confidence in the GWR estimates. That having been said, a matter for future research to address is the maintained assumption that the GWR estimates really do reflect systematic market segmentation, and not omitted variable bias.

[17] Models involving 50%, 60%, and 80% of all available transactions were also estimated for the purpose of comparison, and these were all similar to the model involving 70%.

confidence[18] — so each panel registers the percentage of significant location-specific parameters, plus the minimum, maximum, mean, median, and standard deviation of those parameters for all of the explanatory variables. The majority of the estimates are significant 100% of the time and, for the few that do not meet that mark, the rate of significance is still high. Distance from the nearest hazardous waste handler, the most innocuous of the five environmental hazards, registers the lowest rate of significance, 52%. The adjusted R^2 and AIC statistic of the GWR model are 0.83 and –3.46, respectively, and both statistics are comparable to those produced by the OLS and S2SLS versions of the model. Finally, Figure 2, a map of surface trends interpolated from the GWR error terms, shows that the error terms exhibit little or none of the kind of positive spatial autocorrelation commonly observed in the error terms of hedonic price functions estimated via OLS (Fotheringham et al 2002).

Because the parameters were estimated using a wide spatial bandwidth — again, the nearest 20,416 observations are included in each of the 29,165 location-specific regressions — they are quite smooth, but they nonetheless vary appreciably across geographic space. One variable that stands out in this regard is neighborhood density, which now breaks in both directions, from a minimum of –0.013430 to a maximum of 0.007248. Other things being equal, in some locations, density raises the price of housing and, in other locations, it lowers the price of housing — a finding that lines up well with other hedonic research that has uncovered distinct submarkets for urban form (Song and Knaap 2003; 2004). Figure 3, which shows surface trends interpolated from the location-specific density parameter estimates, illustrates that the pattern is systematic: it reflects the impact of households who value high-density, mixed-use neighborhoods bidding up the price of housing for that attribute in Seattle and its immediate vicinity and, conversely, the impact households who value low-density, predominantly residential neighborhoods bidding down the price of housing for that attribute in the region's eastern suburbs.[19] Although all of the other parameter estimates retain the same general sign pattern as their global counterparts, the descriptive statistics listed in Table 3 show that they are generally heterogeneous, especially in the case of variables that are spatial in nature, like commute time and distance from the five environmental hazards.

Table 4, which lists the mean values and standard deviations of the estimated marginal implicit price of, and total implicit expenditure on, each housing attribute, provides a more

[18] This is a conservative approach because the sign of most parameter estimates have was anticipated in advance and ended up having the anticipated sign — so, in fact, the t-value = 1.96 benchmark is at a 97.5% level of confidence.
[19] To the authors, who know the Puget Sound region well, this result serves as a conformation that the GWR parameter estimates reflect true patterns of spatial heterogeneity.

qualitative look at the estimation results.[20] (For these calculations, in cases where the location-specific parameter is not statistically significant, the marginal implicit price was taken to be zero because insignificance means, after all, that the variable has no influence on sales price.) To cite some interesting examples, the transactions reflect, on average, marginal implicit prices of about: $0.70 per square foot of lot size; $64 per square foot of living space; $53,500 for a view; $450 per percentage point of school quality; –$3,500 per additional minute of commute time; and $13 per foot of distance from the nearest arterial. This translates into, on average, total implicit expenditures of about: $8,400 on lot size; $163,000 on living space; $10,600 on views; $27,400 on school quality; –$84,400 on commute time; $4,100 on distance from the nearest arterial. Each of these examples seems reasonable.

Returning to Table 3, because sales price and the distances from the five environmental hazards are all expressed in natural log form, the distance parameters are elasticities. On average, these elasticities reveal that the influence of this form of environmental quality in the first-stage hedonic price function is ordered as follows: superfund sites (0.062731) > toxic release sites (0.018846) > air release sites (0.016356) > hazardous waste generators (0.014780) > hazardous waste handlers (0.006310). Table 4 shows the average estimated marginal implicit prices of distance from the hazards: $1.19 for an additional foot of distance from the nearest air release site; $3.04 for an additional foot of distance from the nearest hazardous waste generator; $0.99 for an additional foot of distance from the nearest hazardous waste handler; $0.90 for an additional foot of distance from the nearest superfund site; and $0.79 for an additional foot of distance from the nearest toxic release site.[21] The table also shows the average estimated total implicit expenditures on distance — that is, the average of implicit price times distance — from the hazards: $5,360 on distance from the nearest air release site; $5,758 on distance from the nearest hazardous waste generator; $1,070 on distance from the nearest hazardous waste handler; $24,686 on distance from the nearest superfund site; and $5,733 on distance from the nearest toxic release site.

Surface trends interpolated from the 29,165 location-specific marginal implicit prices of distance from the five environmental hazards are shown in Figures 4 – 8. These maps are of $\hat{\pi}_{ik}$,

[20] Marginal implicit expenditures are calculated as the product of the marginal implicit price and the quantity consumed. The reason for the calculation is that it enables evaluation of the overall implicit expenditure on the good in question. If the marginal implicit prices were simply summed up, they would incorrectly imply that a single unit of the good is consumed — that is, for example, each household is one mile from hazard. Since some locations consume more or less of an amenity than others, examining the expenditure enables an analysis based on how much of the amenity is being consumed

[21] These estimates are average prices per foot of distance across all distance consumed and that, because of diminishing marginal utility, the first foot of distance from an environmental hazard (or anything else) is far more expensive than, say, the 40,000th foot.

the values required for estimating the second-stage demand functions, and they illustrate exactly where and how the facilities have impacted King County's single-family housing market. In some parts of the region, which have been left white, air release sites, hazardous waste handlers, and toxic release sites have had no effect at all but, overall, the influence of the facilities is wide-ranging. A striking feature of the maps is that the marginal implicit prices of distance from the hazards are all spatially incongruent — the patterns of impact are completely different across the five types of facilities, and even from place-to-place within each type. This latter finding is consistent with an analysis of superfund sites by Kiel and Williams (2007), which found that the impact on housing markets varies greatly from site-to-site. Also, the patterns of impact illustrate why homes located far from the environmental hazards do not necessarily end up with large total implicit expenditures on distance: even though the amount of distance consumed is large for more distant homes, the marginal implicit price of distance at those locations is very small, so the product of the two can also be small.

Recall now that it is possible to estimate second-stage implicit demand functions for environmental quality if spatially segmented submarkets having separate hedonic price schedules for the identical attributes are available. A lone hedonic price function cannot be used to do this because it is a composite of unique, individual supply and demand and, so, does not contain the information needed to identify the second-stage function. Table 4 reveals that the marginal implicit price of, and total implicit expenditure on, many of the housing attributes included in the first-stage function have considerable range, but this, while promising, is not in-and-of-itself evidence of spatially segmented submarkets. What is needed in order to confirm the presence of segmentation is a test of the null hypothesis that there is no spatial heterogeneity in the underlying GWR parameter estimates. More specifically, the test — an analysis of variance (ANOVA) test crafted by Brundson et al (1999) — is:

$$\mathrm{H}_0: \frac{\partial \hat{\gamma}_i}{\partial u} = 0 \text{ and } \frac{\partial \hat{\gamma}_i}{\partial v} = 0 \quad \forall i$$

against

$$\mathrm{H}_\mathrm{A}: \frac{\partial \hat{\gamma}_i}{\partial u} \neq 0 \text{ and } \frac{\partial \hat{\gamma}_i}{\partial v} \neq 0 \quad \forall i$$

where, following the notation in equation (4), the $\hat{\gamma}$s represent estimated parameters specific to each home, i, located at spot $\{u, v\}$. The bottom panel of Table 3 lists the results of the ANOVA comparing the residuals from equation (1), the OLS model, to the residuals of equation (4), the GWR model. The pseudo F-statistic that the test yields is 48.05, a value far greater than the value needed to reject the null hypothesis of no spatial heterogeneity in the parameter estimates at a 99% level of confidence.[22]

Before moving on, a qualitative evaluation of the spatially segmented housing attribute submarkets confirmed by the ANOVA test is obtained by decomposing the variance of each of the total implicit expenditures ($\hat{\eta}_{ik}$) listed in Table 4 in a manner described by Ali et al (2007):

$$\begin{aligned}\mathrm{var}(\hat{\eta}_{ik}) = (\partial\hat{\eta}_{ik}/\partial z_k)^2\cdot\mathrm{var}(z_k) + (\partial\hat{\eta}_{ik}/\partial\hat{\pi}_{ik})^2\cdot\mathrm{var}(\hat{\pi}_{ik}) \\ + 2\cdot\mathrm{cov}(\hat{\pi}_{ik}, z_k)\cdot(\partial\hat{\eta}_{ik}/\partial z_k)\cdot(\partial\hat{\eta}_{ik}/\partial\hat{\pi}_{ik}).\end{aligned} \tag{5}$$

In this formula, the partial derivative in the first term is the mean of $\hat{\pi}_{ik}^2$; the partial derivative in the second term is the mean of z_k^2; and the partial derivatives in the third term are the means of $\hat{\pi}_{ik}$ and z_k. The terms themselves express the share of the variance in $\hat{\eta}_{ik}$ that is attributable to: (*i*) spatial variation in z_k, the attributes; (*ii*) spatial variation in $\hat{\pi}_{ik}$, the marginal implicit prices; and (*iii*) the covariance of $\hat{\pi}_{ik}$ and z_k.[23] The results of the spatial decomposition, listed in Table 5, are compelling because they show that, for attributes that are spatial in nature, most all of the variance in total implicit expenditure is owed to variation in the marginal implicit price, and not variation in the quantity consumed — especially for distance from the five environmental hazards. Because of this heterogeneity, formally tested by the ANOVA, the information needed to identify the second-stage implicit demand functions is available, hanging in the aether of the regional housing market.[24]

3.4 Second-stage Demand Functions — 2SLS Estimates

Like most other hedonic price analyses involving second-stage estimation, this research relies on spatial variation in housing attribute price schedules to address the identification problem. The key difference is that, instead of using different regions as distinct housing market segments, it leverages spatial heterogeneity in housing attribute prices within a single region to identify the second-stage demand functions. With the marginal implicit price estimates from the first-stage

[22] This test is conceptually the same as comparing two OLS models via an F-statistic derived from their sum of squared errors (SSE), and it is also similar to a Chow test, which can be used to compare constrained and unconstrained regressions when two or more spatially separated market areas, like metropolitan areas, are used (see Brasington and Hite 2005) instead of a single market area.

[23] Ali et al's (2007) analysis deals with a somewhat simpler situation wherein the term that is decomposed is the product of the GWR parameters and the explanatory variables. Since marginal implicit prices are the object of interest here, the actual values of the GWR-estimated housing attribute price schedules first had to be backed out of the log-transformed equations.

[24] The spatial decomposition also points to circumstances where this approach is less likely to work well. Specifically, when the majority of the variance is derived from differences in z_k rather than $\hat{\pi}_{ik}$, may yield inadequate spatial variation in the implicit price for second stage identification.

hedonic price function in hand, the remaining step is to estimate a series of second-stage implicit demand functions corresponding to equation (2).

The dependent variable of these equations is quantity — expressed as $\tilde{q}_{ik}$, the natural log of distance from each environmental hazard — and the explanatory variables are the estimated marginal implicit price of distance, $\hat{\pi}_{ik}$, plus a set of demand shifters.[25] Because price is endogenous to quantity, the demand functions must be estimated via two-stage least squares (2SLS) or some other instrumental variables procedure. The instruments used to do this are different from equation-to-equation — they are identified in Table 6, below the relevant set of estimates — but, in essence, one pertains to the home's location and the other to the home itself with the idea that, together, they distinguish the specific transaction and, hence, its individual housing attribute price schedule. In each case, the validity of the two relevant instruments was checked by testing: (*i*) the null hypothesis that they are uncorrelated with their structural model's error terms; and (*ii*) the null hypothesis that their estimated parameters are jointly equal to zero in the first-stage of the 2SLS routine. In order to pass these two tests, respectively, the instrumental variables must produce a χ^2 statistic of less than 3.84 and an F-statistic of greater than 3.00 — a failure of either test indicates that the instruments are not valid. (See Wooldridge 2000 for explanations of the χ^2-test of over-identifying restrictions and the F-test of multiple linear restrictions.)

The 2SLS estimates for the implicit markets for distance from air release sites, hazardous waste generators, hazardous waste handlers, superfund sites, and toxic release sites are listed in Table 6. Each of the equations register a respectable adjusted R^2 — the lowest, 0.33, is for the hazardous waste handler equation, where the marginal implicit price of distance is different from zero only 52% of the time — and all of the explanatory variables are statistically significant at least a 95% level of confidence. Further, the models' instruments passed both validity tests by a wide margin.[26] As a supplement to the estimation results, Table 7 lists the means of individually calculated (from the parameters in Table 6) price and income elasticities of demand for distance from the environmental hazards, across all transactions and across only those transactions located

[25] Additional marginal implicit prices may also be added to the equation in order to estimate cross-price elasticities of demand, but this is left to the next step of this research which implements a welfare analysis of site remediation (see Carruthers and Clark 2009).

[26] The instruments, listed below each equation in Table 6, are admittedly not obvious choices — they were selected via a process of trial and error from a set of possible instruments available in the dataset. The analysis employed a strategy of parsimony, which required at least two instruments to satisfy the over-identifying restriction requirement. While additional instruments can enhance the efficiency of the parameter estimates, the chosen instruments nonetheless meet all validity requirements and, as important, yield sensible results.

at less than 500 feet, between 500 and 1,000 feet, and greater than 1,000 feet from the relevant hazard. The following paragraphs summarize the findings.

The top panel of Table 7 shows price elasticities calculated across all transactions, which are the average values in the Puget Sound region: –0.2356 for air release sites; –0.3662 for hazardous waste generators; –0.0186 for hazardous waste handlers; –0.3761 for superfund sites; and –0.1855 for toxic release sites. These results are remarkably consistent with work done by Brasington and Hite (2005), who also found an inelastic price elasticity of demand (–0.12) for a similar measure of environmental quality, distance from the nearest Ohio Environmental Protection Agency designated environmental hazard. In general, it is reasonable to expect high profile environmental hazards to not only generate large implicit price responses in the first-stage hedonic price function but, also, to generate large distance responses in the second-stage demand functions. And, for this reason, it is interesting that all of the regional price elasticities of demand are less than one in absolute value, indicating that demand is inelastic. Overall, this finding suggests that household responses are relatively stronger in the first-stage hedonic price function than in the second-stage demand functions — households apparently will, on average, tolerate proximity, with sufficient compensation. However, a much different picture emerges in the lower three panels of Table 7, which partition the calculations by distance: transactions located at close range to environmental hazards exhibit very large elasticities; transactions located at a middle range exhibit moderate elasticities; and transactions located at a distant range exhibit small elasticities. Together, these findings show that the price response grows more intense with proximity: household behavior is very sensitive to variation in the marginal implicit price of distance at close ranges.

Next, Table 7 also shows income elasticities of demand for each of the five hazards. Note, though, that interpretations of these have to be tempered by the fact that the measure of income is calculated at the census tract level because household-level data corresponding to the single-family housing sales was not available. That said, as expected, all of the elasticities that come out of this calculation are positive, meaning that distance from environmental hazards is a normal good so, other things being equal, households spend more on it as their incomes rise. As to how readily, the ordinal ranking of income elasticities shows: hazardous waste generators > hazardous waste handlers > air release sites > toxic release sites > superfund sites. And, interestingly, unlike the price elasticities, the income elasticities do not change much when partitioned by distance from the sites.

Last, returning to Table 6, the remaining demand shifters illustrate how certain socioeconomic characteristics affect the quantity of distance from environmental hazards that households consume. The group shows that quantity is positively influenced by: the absence of racial minorities, measured as the percent of residents in the census tract that are white; and the presence of children, measured as the percent of households in the census tract with children. Education, measured as the percent of residents in the census tract that are college-educated, has a negative influence on quantity in the air release, hazardous waste handler, and toxic release equations, but a positive influence in the hazardous waste generation and superfund equations. The alternating sign pattern on education is somewhat surprising, but it may just reflect a greater level of awareness about the actual level of risk associated with the various hazards. In addition to playing their own part in the equations, the demand shifters generally have intuitive signs and magnitudes. This further validates the models' interpretation as implicit demand functions for distance from air release sites, hazardous waste generators, hazardous waste handlers, superfund sites, and toxic release sites.

4. Summary and Conclusion

This paper began by setting out three specific research objectives: (*i*) to define spatial heterogeneity in the context of housing markets and develop a strategy for using it to overcome the general problem of deriving the demand for non-market goods; (*ii*) to estimate the marginal implicit price of distance from air release sites, hazardous waste generators, hazardous waste handlers, superfund sites, and toxic release sites via the single-family housing market in the Puget Sound region of Washington State; and (*iii*) to estimate a series of implicit demand functions describing the relationship between the price of distance from environmental hazards and the quantity consumed. Having met these objectives, the few remaining comments focus on some implications and directions for future research.

Foremost, the strategy laid out here represents an important step forward in valuing non-market goods because it offers a workable solution to what has always been the albatross of two-stage hedonic price analysis. In practice, estimating demand functions with data from multiple regions is problematic because of the difficulty of obtaining identical datasets. In contrast, the approach developed here is more tractable in the sense that it requires data from only one region, but, that said, it does require a lot of data, plus a good degree of local knowledge. The importance of market knowledge on the part of the analyst should not be underappreciated because some danger lies in accepting the first-stage GWR parameter estimates at face value. The density parameter shown in Figure 3 is a prime example of what is at stake in terms of the risk of misinterpretation when using GWR. Knowing upfront that the influence of density cuts in both ways in the Puget Sound, and, also, that there exist clearly delineated housing market segments based on it was key to understanding the result. Had the region been less familiar, the density parameter would have raised questions instead of confirming expectations. Even still, it seems to the present authors that GWR analysis, if thoughtfully done, represents the very best of what the field of regional science has to offer — innovative solutions to the many untidy problems that emerge from how geographic space mediates socioeconomic processes.

Given its objectives, this paper has covered significant territory and often quite rapidly. The results presented in the tables and figures are an excellent starting point for a more detailed welfare analysis, and there may also be room for refinement and re-estimation of certain of the equations. According to the 2005 American Housing Survey, a great number of homes in the United States are affected by bothersome neighborhood conditions, including odors (~3.5 million homes), unpleasant noise (~16.9 million homes), the presence of undesirable land uses (~0.45 million homes), and more. In some circumstances, it may make economic sense to address these problems, but, for public policies aimed at doing so to be credible, they need to be based on sound benefit-cost analyses. And, in order to carry out these projects in the first place, analysts must have a way to estimate the demand for non-market goods — in all their myriad forms. The research presented in this paper was motivated by the need to better understand the value of environmental quality, and it is one of only a handful of intraregional hedonic analyses to have produced estimates of demand for that commodity. The space-based strategy it has developed is proposed as a general solution to the long-standing problem of estimating the implicit demand for non-market goods in the hope that, over time, it can be used to inform public policies aimed at community living conditions.

References

Ali K, Partridge MD, Olfert MR (2007) Can Geographically Weighted Regressions Improve Regional Analysis and Policy Making? *International Regional Science Review*, 30: 300 – 329.

Anselin L (1988) *Spatial Econometrics: Methods and Models*. Kluwer Academic Publishers, Boston, MA.

Anselin L, Bera AK (1998) Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics. In Ullah A, Giles DAE (eds.) *Handbook of Applied Economic Statistics*. Marcel Dekker, New York, NY.

Anselin L, Syabri I, Kho Y (2006) *GeoDa*: An introduction to spatial data analysis. *Geographical Analysis* 38: 5 – 22

Anselin L, Gallo, J (2006) Interpolation of Air Quality Measures in Hedonic House Price Models: Spatial Aspects. *Spatial Economic Analysis*, 1: 31 – 52.

Bajari P, Kahn ME (2004) Estimating Housing demand With an Application to Explaining Racial Segregation in Cities. *Journal of Business and Economic Statistics,* 23: 20 – 33.

Bajari P, Kahn ME (2008) Estimating Models of Consumer Demand with an Application to Urban Sprawl. In Baranzini A, Ramirez J, Schaerer, Thalmann P (eds.) (2008) *Hedonic Methods in Housing Markets: Pricing Environmental Amenities and Segregation*. Springer, New York, NY.

Bartik TJ (1987). The Estimation of Demand Parameters in Hedonic Price Models, *Journal of Political Economy*. 95, 81 – 88.

Bae CH, Sandlin G, Bassok A, Kim S (2007) The Exposure of Disadvantaged Populations in Freeway Air-pollution Sheds: A Case Study of the Seattle and Portland Regions. *Environment and Planning B*, 34: 154 – 170.

Baranzini A, Ramirez J, Schaerer, Thalmann P (eds.) (2008) *Hedonic Methods in Housing Markets: Pricing Environmental Amenities and Segregation*. Springer, New York, NY.

Bitter C, Mulligan GF, Dall'erba S (2007) Incorporating Spatial Variation in Housing Attribute Prices: A Comparison of Geographically Weighted Regression and the Spatial Expansion Method. *Journal of Geographical Systems*, 9: 7 – 27.

Black SE (1999) Do Better Schools Matter? Parental Valuation of Elementary Education. *Quarterly Journal of Economics*, 114: 577 – 599.

Boyle MA, Kiel KA (2001) A Survey of House Price Hedonic Studies of the Impact of Environmental Externalities. *Journal of Real Estate Literature*, 9: 117 – 144.

Brasington DM (2003) The Supply of Public School Quality. *Economics of Education Review,* 22: 367 – 377.

Brasington DM (2002) Edge Versus Center: Finding Common Ground in the Capitalization Debate. *Journal of Urban Economics*, 52: 524 – 541.

Brasington DM (2001) Capitalization and Community Size. *Journal of Urban Economics*, 50: 385 – 395.

Brasington DM (2000) Demand and Supply of Public School Quality on Metropolitan Areas: The Role of Private Schools. *Journal of Regional Science*, 40: 583 – 605.

Brasington DM, Hite D (2008) A Mixed Index Approach to Identifying Hedonic Price Models. *Regional Science and Urban Economics*, 38: 271 – 284.

Brasington DM, Hite D (2005) Demand for Environmental Quality: A Spatial Hedonic Analysis. *Regional Science and Urban Economics*, 35: 57 – 82.

Brown JN, Rosen HS (1982) On the Estimation of Structural Hedonic Price Models, *Econometrica*, 50: 765 – 768.

Brundson C, Fotheringham SA, Charlto M (1999) Some Notes on Parametric Significance Tests for Geographically Weighted Regression. *Journal of Regional Science*, 39: 497 – 524.

Can A (1992) Specification and Estimation of Hedonic Housing Price Models. *Regional Science and Urban Economics*, 22: 453 – 474.
Can A (1990) The Measurement of Neighborhood Dynamics in Urban House Prices. *Economic Geography*, 66: 254 – 272.
Carruthers JI, Clark DE (2009) The Benefits of Improving Environmental Quality: Evidence from Spatial Econometric Analysis. U.S. Department of Housing and Urban Development working paper # REP 09-05.
Carruthers JI, Mundy B (eds.) (2006) *Environmental Valuation: Interregional and Intraregional Perspectives*. Ashgate, Aldershot, UK.
Cassetti E (1972) Generating Models by the Spatial Expansion Method: Applications to Geographical Research. *Geographical Analysis*, 4: 81 – 92.
Chattopadhyay S (1999) Estimating the Demand for air Quality: New Evidence Based on the Chicago Housing Market. *Land Economics*, 75: 22 – 38.
Cheshire P, Sheppard S (2004) Capitalizing the Value of Free Schools: The Impact of Supply Characteristics and Uncertainty. *The Economic Journal*, 114: F397 – F424.
Cheshire P, Sheppard S (1998) Estimating the Demand for Housing, Land, and Neighborhood Characteristics. *Oxford Bulletin of Economics and Statistics*, 60: 357 – 382.
Cheshire P, Sheppard S (1995) On the Price of Land and the Value of Amenities. *Economica*, 62: 247 – 267.
Clapp JM (2001) A Semiparametric Method for Valuing Residential Locations: Applications to Automated Valuation. *Journal of Real Estate Finance and Economics*, 27: 303 – 320.
Clark DE, Allison T (1999) Spent Nuclear Fuel and Residential Property Values: The Influence of Proximity, Visual Cues and Public Information. *Papers in Regional Science,* 78: 403 – 421.
Clark DE, Michelbrink L, Allison T, Metz W (1997) Nuclear Power Plants and Residential Housing Prices: Evidence from Two California Plants. *Growth and Change*, 28: 496 – 519.
Cohen JP, Coughlin CC (2008) Spatial Hedonic Models of Airport Noise, Proximity, and Housing Prices. *Journal of Regional Science*, 48: 859 – 878.
Dale L, Murdoch J, Thayer M, Waddell P (1999). Do Property Values Rebound from Environmental Stigmas? Evidence from Dallas. *Land Economics,* 75: 311 – 326.
Das D, Kelejian HH, Prucha IR (2003) Finite Sample Properties of Estimators of Spatial Autoregressive Models with Autoregressive Disturbances. *Papers in Regional Science*, 82: 1 – 26.
Epple, D (1987) Hedonic Prices and Implicit Markets: Estimating Demand and Supply Functions for Differentiated Products. *Journal of Political Economy*, 95: 59 – 80.
Fik TJ, Ling DC, Mulligan GM (2003) Modeling Spatial Variation in Housing Prices: a Variable Interaction Approach. *Real Estate Economics*, 31: 623 – 646.
Fotheringham AS, Brunsdon C, Charlton ME (2003) *Geographically Weighted Regression, v. 3.0.1*. Spatial Analysis Research Group, Department of Geography, University of Newxastle upon Tyne.
Fotheringham AS, Brunsdon C, Charlton ME (2002). *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*. John Wiley, Chichester, UK.
Freeman, AM (2003) *The Measurement of Environmental and Resource Values*. Resources for the Future, Washington, DC.
Goodman AC (1981) Housing markets within Urban Areas: Definitions and Evidence. *Journal of Regional Science*, 21: 175 – 185.
Goodman AC, Thibodeau TG (2003) Housing Market Segmentation and Hedonic Prediction Accuracy. *Journal of Housing Economics*, 12: 181 – 201.
Goodman AC, Thibodeau TG (1998) Housing Market Segmentation. *Journal of Housing Economics*, 7: 121 – 143.

Hite D (1998) Information and Bargaining in Markets for Environmental Quality. *Land Economics*, 74: 303 – 316.

Hite D, Chern W, Hitzhuzen F, Randall A (2001) Property Value Impacts of an Environmental Disamenity: The Case of Landfills. *Journal of Real Estate Finance and Economics*, 22: 185 – 202.

Kahn ME (2006) *Green Cities: Urban Growth and the Environment*. The Brookings Institute, Washington, DC.

Kask SB, Maani SA (1992) Uncertainty, Information, and Hedonic Pricing. *Land Economics*, 68: 170 – 184.

Kelejian HH, Prucha IR (1998) A Generalized Spatial Two Stage Least Squares Procedure for Estimating a Spatial Autoregressive Model with Autoregressive Disturbances. *Journal of Real Estate Finance and Economics*, 17: 99 – 121.

Kennedy P (1998) *A Guide to Econometrics*. The MIT Press, Cambridge, MA.

Kestins Y, Thériault M, Des Rosiers F (2006) Heterogeneity in Hedonic Modeling of House Prices: Looking at Buyers' Household Profiles. *Journal of Geographic Systems*, 8: 61 – 96.

Kiel KA (2006) Environmental Contamination and House Values. In Carruthers JI, Mundy B (eds.) *Environmental Valuation: Interregional and Intraregional Perspectives*. Ashgate, Aldershot, UK

Kiel KA, McClain KT (1995). House Prices during Siting Decision Stages: The Case of an Incinerator from Rumor through Operation. *Journal of Environmental Economics and Management,* 28, 241 – 255.

Kiel KA, Williams M (2007) The Impact of Superfund Sites on local Property Values: Are All Sites the Same? *Journal of urban Economics*, 61: 170 – 192.

Kim CW, Phipps TT, Anselin L (2003) Measuring the Benefits of Air Quality Improvement: A Spatial Hedonic Approach. *Journal of Environmental Economics and Management*, 45: 24 – 39.

Kohlhase J (1991) The Impact of Toxic Waste Sites on Housing Values. *Journal of Urban Economics*, 30: 1 – 26.

Longley PA, Goodchild MF, Maguire DJ, Rhind DW (2001) *Geographic Information Systems and Science*. John Wiley, Chichester, UK.

Michaels GR, Smith VK (1990) Market Segmentation and Valuing Amenities with Hedonic Models: The Case of Hazardous Waste Sites. *Journal of Urban Economics*, 28: 223 – 242.

Mulligan GM, Franklin R, Esparza AX (2002) Housing prices in Tucson, Arizona. *Urban Geography*, 23: 446 – 470.

Palmquist RB (1984) Estimating the Demand for the Characteristics of Housing. *Review of Economics and Statistics,* 66: 394 – 404.

Rosen, S (1974) Hedonic Prices and the Implicit Markets: Product Differentiation in Pure Competition, *Journal of Political Economy,* 82: 132 – 157.

Song Y, Knaap GJ (2003) New urbanism and housing values: A disaggregate assessment. *Journal of Urban Economics*, 54: 218 – 238.

Song Y, Knaap GJ (2004) Measuring the effects of mixed land uses on housing values. *Regional Science and Urban Economics*, 34: 663 – 680.

Straszheim M (1974) Hedonic Estimation of Housing Market Prices: A Further Comment. *Review of Economics and Statistics*, 56: 404 – 406.

Taylor LO (2008) Theoretical Foundations and Empirical Developments in Hedonic Modeling. In Baranzini A, Ramirez J, Schaerer, Thalmann P (eds.) (2008) *Hedonic Methods in Housing Markets: Pricing Environmental Amenities and Segregation*. Springer, New York, NY.

Theebe MAJ (2004) Planes, Trains, and Automobiles: The Impact of Traffic Noise on House Prices. *Journal of Real Estate Finance and Economics*, 28: 209 – 235.

Wheeler DC, Calder CA (2007) An Assessment of Coefficient Accuracy in Linear Regression Models With Spatially Varying Coefficients. *Journal of Geographical Systems*, 9: 145 – 166.

Wooldridge JM (2000) *Introductory Econometrics: A Modern Approach*. Thompson: USA.

Yavas A, Yang S (1995) The Strategic Role of Listing Price in Marketing Real Estate: Theory and Evidence. *Real Estate Economics*, 23: 347 – 368.

Zable JA, Kiel KA (2000) Estimating the Demand for Air Quality in U.S. Cities. *Land Economics*, 76: 174 – 194.

Table 1. Descriptive statistics

	Units	Min.	Max.	Mean	Med.	Std. Dev.	Exp. Sign
Sales Price [1]	Dollars	50,000.00	9,000,000.00	383,440.30	323,626.00	260,663.88	n/a
Lot							
Size [1]	Sq. feet	780.00	1,738,915.00	12,590.16	7,560.00	33,032.98	+
Elevation	Feet	–20.00	2,640.00	357.49	360.00	192.94	
Percent Brick [1]	Percent	0.00	100.00	3.81	0.00	17.58	n/a
Structure							
Living Space [1]	Sq. feet	360.00	12,750.00	2,207.73	2,130.00	886.09	+
Age [1]	Years	0.00	104	34.94	31.00	28.59	–
Age^2 [1]	Years	0.00	10,816.00	1,220.56	961.00	817.48	+
Fireplaces [1]	Count	0.00	6.00	1.19	1.00	0.71	+
Grade							
Average [1]	Binary	0.00	1.00	0.44	0.00	0.50	+
Good [1]	Binary	0.00	1.00	0.25	0.00	0.43	+
Better [1]	Binary	0.00	1.00	0.11	0.00	0.31	+
Very Good [1]	Binary	0.00	1.00	0.04	0.00	0.21	+
Excellent [1]	Binary	0.00	1.00	0.01	0.00	0.12	+
Luxury [1]	Binary	0.00	1.00	0.00	0.00	0.06	+
Mansion [1]	Binary	0.00	1.00	0.00	0.00	0.03	+
Condition							
Average [1]	Binary	0.00	1.00	0.71	1.00	0.45	+
Good [1]	Binary	0.00	1.00	0.24	0.00	0.43	+
Very Good [1]	Binary	0.00	1.00	0.04	0.00	0.20	+
Amenities							
View [1]	Binary	0.00	1.00	0.12	0.00	0.33	+
Nuisance [1]	Binary	0.00	1.00	0.13	0.00	0.34	–
Waterfront Feet [4]	Feet	0.00	1,600.00	0.92	0.00	13.93	+
Neighborhood							
Property Tax Rate [1]	Percent	0.32	2.99	1.16	1.17	0.15	–
School Quality [4]	Percent	37.88	83.60	55.77	53.75	11.67	+
Median Income [2]	Dollars	16.29	133.76	64.12	61.73	19.62	+
Density [2]	Units / Ac.	0.00	51.02	2.75	2.24	2.35	+/–
% College Educated [2]	Percent	1.13	43.63	18.76	18.70	7.17	n/a
% White [2]	Percent	1.72	59.18	28.13	25.61	11.82	n/a
% w/ Children [2]	Percent	10.66	96.65	78.78	83.19	15.12	n/a
Location							
Dist. from Seattle [4]	Feet	2,181.64	190,855.98	65,557.21	58,271.44	36,716.63	–
Commute Time [2]	Minutes	16.00	46.00	26.29	26.00	4.30	–
Dist. from Arterial [4]	Feet	0.14	21,292.92	1,161.09	712.76	1,399.70	+
Outside UGB [4]	Binary	0.00	1.00	0.06	0.00	0.23	+/–
Dist. from UGB [4]	Feet	27.62	88,040.18	25,088.06	21,435.22	19,666.14	+/–
Dist. from Subcenter [4]	Feet	1,195.03	131,731.37	52,793.56	53,045.32	21,212.90	n/a
Environmental Hazards							
Dist. from Air Site [2 and 4]	Feet	77.66	69,211.39	10,467.07	7,564.22	9,491.67	+
Dist. from HWG [2 and 4]	Feet	14.36	30,018.93	4,188.50	2,916.23	3,929.90	+
Dist. from HWH [2 and 4I]	Feet	4.92	19,005.26	2,207.47	1,683.23	1,877.89	+
Dist. from SF Site [2 and 4]	Feet	1,088.09	149,959.83	44,253.83	39,037.09	26,585.09	+
Dist. from TR Site [2 and 4]	Feet	44.43	81,959.90	13,336.76	10,526.59	11,285.17	+
Time	Months	1.00	12.00	6.75	7.00	3.11	+

Notes: the data sources are [1] King County Assessor; [2] U.S. Census of Population and Housing; [3] U.S. EPA; [4] author's calculations, based on regional data sources; n/a denotes not applicable to first stage estimation; median income is expressed in $ 1,000s.

Table 2. OLS and S2SLS Estimates of First-stage Hedonic Price Function

	OLS		S2SLS	
	Est. Parameter	t-value	Est. Parameter	t-value
Constant	14.024460 ***	243.10	11.506500 ***	82.31
Spatial Lag	-	-	0.171885 ***	19.96
Lot Size	0.000001 ***	7.48	0.000001 ***	7.90
Structure				
Size	0.000168 ***	64.97	0.000159 ***	63.55
Age	–0.004757 ***	–26.33	–0.004272 ***	–24.33
Age^2	0.000045 ***	22.97	0.000039 ***	20.12
Fireplaces	0.013785 ***	5.64	0.009446 ***	4.07
Grade				
Average	0.099544 ***	23.16	0.091563 ***	22.32
Good	0.214733 ***	40.70	0.190556 ***	36.91
Better	0.359716 ***	51.88	0.311497 ***	44.17
Very Good	0.496655 ***	53.08	0.426844 ***	44.23
Excellent	0.611455 ***	39.34	0.531379 ***	34.22
Luxury	0.855057 ***	23.94	0.759983 ***	22.00
Mansion	0.889018 ***	7.52	0.765276 ***	7.40
Condition				
Average	0.120423 ***	5.57	0.122644 ***	6.08
Good	0.161224 ***	7.45	0.163068 ***	8.07
Very Good	0.245634 ***	10.92	0.245750 ***	11.69
Amenities				
View	0.147851 ***	23.13	0.122340 ***	21.27
Nuisance	–0.026425 ***	–6.69	–0.028227 ***	–7.50
Waterfront Feet	0.001696 **	2.12	0.001670 **	2.26
Neighborhood				
Property Tax Rate	–0.310065 ***	–25.65	–0.251861 ***	–21.81
School Performance	0.001074 ***	6.43	0.0007131 ***	4.50
Median Income	0.002380 ***	23.35	0.001690 ***	16.90
Density	0.001876 *	1.92	0.002021 **	2.20
Location				
ln Dist. from Seattle	–0.219747 ***	–54.92	–0.178730 ***	–41.82
ln Commute Time	–0.200077 ***	–16.14	–0.157912 ***	–13.12
ln Dist. from Arterial	0.011131 ***	8.53	0.008788 ***	7.15
Outside UGB	0.015927 *	1.88	0.002257 n/s	0.28
ln Dist. from UGB	0.011901 ***	12.12	0.011720 ***	12.61
Environmental Hazards				
ln Dist. from Air Site	0.013267 ***	5.78	0.009219 ***	4.17
ln Dist. from HWG	0.015881 ***	7.83	0.011305 ***	5.90
ln Dist. from HWH	0.005435 ***	2.80	0.003017 *	1.64
ln Dist. from SF Site	0.055713 ***	27.58	0.045277 ***	22.75
ln Dist. from TR Site	0.014695 ***	7.09	0.014501 ***	7.28
Time	0.009646 ***	26.46	0.009640 ***	27.90
n		29,165		29,165
Adjusted R^2		0.83		0.85
AIC		–3.36		–3.47

Notes: all models were estimated using White-adjusted standard errors; all hypothesis tests are two-tailed; *** denotes at $p < 0.01$; ** denotes significant at $p < 0.05$; * denotes significant at $p < 0.10$; n/s denotes not significant.

Table 3. GWR Estimates of First-stage Hedonic Price Function

	Est. Parameters w/ t-value ≥ 1.96					
	Pct.	Min.	Max.	Mean	Med.	Std. Dev.
Constant	100%	12.934200	15.022930	14.035734	14.065230	0.518073
Lot Size	100%	0.000001	0.000003	0.000002	0.000002	0.000001
Structure						
Size	100%	0.000157	0.000170	0.000164	0.000165	0.000003
Age	100%	–0.006139	–0.003145	–0.004633	–0.004953	0.000759
Age^2	100%	0.000032	0.000064	0.000043	0.000043	0.000007
Fireplaces	100%	0.009770	0.025852	0.015115	0.013870	0.004149
Grade						
Average	100%	0.052672	0.110494	0.090252	0.094257	0.014858
Good	100%	0.161429	0.238759	0.207246	0.210151	0.020681
Better	100%	0.311483	0.399205	0.358701	0.362428	0.023446
Very Good	100%	0.443996	0.570643	0.503014	0.504260	0.033575
Excellent	100%	0.548801	0.695969	0.622102	0.628828	0.036310
Luxury	100%	0.763465	1.034255	0.832570	0.818349	0.039997
Mansion	100%	0.568349	1.124774	0.862671	0.884431	0.188754
Condition						
Average	85%	0.033365	0.197207	0.116507	0.117058	0.039385
Good	94%	0.038647	0.242701	0.147630	0.152155	0.047948
Very Good	100%	0.118119	0.328626	0.224447	0.230261	0.051779
Amenities						
View	100%	0.114954	0.163121	0.138761	0.136622	0.010441
Nuisance	69%	–0.045912	–0.009888	–0.031308	–0.033447	0.012706
Waterfront Feet	100%	0.000601	0.010182	0.004838	0.004119	0.003204
Neighborhood						
Property Tax Rate	100%	–0.449045	–0.108765	–0.285579	–0.300377	0.822333
School Performance	73%	0.040687	0.294293	0.172156	0.192934	0.058232
Median Income	100%	0.001340	0.003220	0.002319	0.002280	0.000548
Density	74%	–0.013430	0.007248	–0.000400	0.003253	0.006429
Location						
ln Dist. from Seattle	100%	–0.306197	–0.168900	–0.227372	–0.219436	0.031720
ln Commute Time	100%	–0.323754	–0.101852	–0.210556	–0.190880	0.055599
ln Dist. from Arterial	100%	0.005794	0.014971	0.010285	0.010678	0.002506
Outside UGB	89%	–0.154739	0.056363	–0.047142	–0.047843	0.054555
ln Dist. from UGB	94%	0.003383	0.035998	0.016473	0.012561	0.009277
Environmental Hazards						
ln Dist. from Air Site	79%	–0.008454	0.026178	0.016356	0.016385	0.005803
ln Dist. from HWG	100%	0.010639	0.021478	0.014780	0.014065	0.002953
ln Dist. from HWH	52%	–0.007666	0.010748	0.006310	0.006331	0.002376
ln Dist. from SF Site	100%	0.041832	0.095047	0.062731	0.065954	0.011162
ln Dist. from TR Site	82%	–0.010813	0.034760	0.018846	0.020163	0.006685
Time	100%	0.009167	0.010923	0.009837	0.009780	0.000361
n						29,165
Overall Adj. R^2						0.83
AIC						–3.46

ANOVA — Comparing GWR to OLS

	um of Squared Errors	Degrees of Freedom	Mean Square	F-value	p-value
OLS Residuals	1,011.40	34.00			
GWR Improvement	96.70	63.96	1.51		
GWR Residuals	914.60	29,067.04	0.03	48.05	0.00

Notes: these estimates are based on an adaptive spatial bandwidth encompassing a constant 70% of the dataset, 20,416 location-specific observations; the ANOVA test (Brundson et al 1999) rejects the null hypothesis that there is no heterogeneity in the GWR parameter estimates.

Table 4. Dollar Value of Estimated Marginal Implicit Prices and Total Implicit Expenditures

	Marginal Implicit Prices		Total Implicit Expenditures	
	Mean	St. Dev.	Mean	St. Dev.
Lot Size	$0.70	$0.71	$8,406.09	$24,045.46
Structure				
Living Space	$62.90	$42.59	$163,023.33	$228,717.77
Age	–$1,754.78	$1,119.61	–$52,829.16	$59,456.95
Age^2	$16.64	$11.04	$29,046.86	$48,481.47
Fireplaces	$5,986.93	$4,886.82	$8,405.18	$24,045.37
Grade				
Average	$33,629.99	$22,383.97	$163,022.93	$228,721.68
Good	$78,047.71	$51,495.51	–$52,827.48	$59,457.27
Better	$136,915.94	$94,771.48	$29,046.82	$48,482.30
Very Good	$191,825.20	$131,978.54	$16,718.13	$89,303.25
Excellent	$237,531.71	$163,550.24	$9,603.87	$90,478.65
Luxury	$316,905.80	$211,132.04	$5,543.95	$108,670.02
Mansion	$319,482.08	$198,249.97	$1,496.33	$62,842.21
Condition				
Average	$34,365.95	$30,250.69	$23,237.98	$29,176.70
Good	$49,606.83	$39,402.43	$12,575.74	$28,470.64
Very Good	$82,851.13	$56,868.62	$4,407.38	$28,766.29
Amenities				
View	$53,636.64	$36,924.70	$10,558.82	$37,511.25
Nuisance	–$9,380.29	$12,141.71	–$1,524.71	$5,789.46
Waterfront Feet	$1,993.79	$2,476.74	$4,948.66	$106,889.19
Neighborhood				
Property Tax Rate	–$106,445.45	$78,875.29	–$120,727.44	$78,361.76
School Quality	$448.77	$456.95	$27,362.81	$31,912.01
Median Income	$0.91	$0.75	$62,128.94	$71,100.73
Density	–$344.13	$2,798.84	$2,142.21	$9,502.09
Location				
ln Dist. from Seattle	–$2.31	$4.01	–$88,314.46	$62,552.81
ln Commute Time	–$3,490.57	$3,670.97	–$84,441.60	$71,453.49
ln Dist. from Art.	$12.53	$109.66	$4,124.37	$3,325.41
Outside UGB	–$18,461.47	$28,900.34	$46.08	$2,697.81
ln Dist. from UGB	$1.25	$6.08	$6,091.82	$7,061.20
Environmental Hazards				
ln Dist. from Air	$1.19	$2.11	$5,360.65	$5,507.51
ln Dist. from HWG	$3.04	$5.81	$5,758.58	$4,717.62
ln Dist. from HWH	$0.99	$3.91	$1,070.25	$1,640.65
ln Dist. from SF	$0.90	$1.14	$24,686.45	$18,605.04
ln Dist. from TR	$0.79	$1.37	$5,722.16	$5,607.65
Time	$3,792.71	$2,694.17	$25,939.31	$24,353.00

Table 5. Spatial Decomposition of Total Implicit Expenditures

	Variance (z_k)	Variance ($\hat{\pi}_{ik}$)	Covariance (z_k , $\hat{\pi}_{ik}$)
Lot Size	63.55%	36.84%	–0.39%
Structure			
Size	21.07%	47.74%	31.19%
Age	70.04%	50.52%	–20.55%
Age^2	72.86%	36.33%	–9.19%
Fireplaces	31.74%	48.56%	19.71%
Grade			
Average	74.11%	40.40%	–14.52%
Good	70.47%	28.59%	0.94%
Better	69.85%	25.42%	4.72%
Very Good	71.59%	24.07%	4.34%
Excellent	73.44%	23.98%	2.58%
Luxury	75.32%	23.24%	1.44%
Mansion	77.88%	21.67%	0.45%
Condition			
Average	42.11%	63.61%	–5.71%
Good	65.29%	33.19%	1.52%
Very Good	73.98%	24.69%	1.33%
Amenities			
View	67.60%	24.83%	7.58%
Nuisance	57.22%	41.19%	1.59%
Waterfront Feet	61.91%	37.73%	0.36%
Neighborhood			
Property Tax Rate	4.61%	104.94%	–9.55%
School Performance	6.57%	79.69%	13.74%
Median Income	15.39%	72.80%	11.82%
Density	31.26%	72.90%	–4.16%
Location			
ln Dist. from Seattle	0.53%	103.69%	–4.22%
ln Commute Time	0.49%	104.42%	–4.91%
ln Dist. from Arterial	2.80%	97.87%	–0.68%
Outside UGB	58.26%	43.84%	–2.10%
ln Dist. from UGB	2.25%	100.61%	–2.85%
Environmental Hazards			
ln Dist. from Air Site	1.28%	105.33%	–6.60%
ln Dist. from HWG	1.57%	104.86%	–6.43%
ln Dist. from HWH	1.21%	100.46%	–1.67%
ln Dist. from SF Site	0.90%	106.90%	–7.81%
ln Dist. from TR Site	1.11%	104.32%	–5.44%
Time	33.31%	63.85%	2.84%

Table 6. 2SLS Estimates of Second-stage Implicit Demand Models

	Dist. from Air Release Site		Dist. from HWG		Dist. from HWH		Dist. from Superfund Site		Dist. from Toxic Release Site	
	Est. Parameter	t-value	Est. Parameter	t-value	Est. Parameter	t-value	Est. Parameter	t-value	Est. Parameter	t-value
Constant	7.603317 ***	353.95	6.742505 ***	296.41	6.023883 ***	302.44	9.066443 ***	135.24	7.829389 ***	313.51
Marginal Implicit Price	–0.197285 ***	–34.27	–0.120608 ***	–31.72	–0.018835 ***	–3.50	–0.416738 ***	–17.23	–0.233590 ***	–25.21
Median Household Income	0.005101 ***	12.83	0.013400 ***	22.89	0.007330 ***	12.27	0.001240 *	1.84	0.002550 ***	5.90
College Educated	–0.017299 ***	–18.96	0.004696 ***	4.20	–0.013220 ***	–12.21	0.011848 ***	20.13	–0.019962 ***	–21.97
White	0.011569 ***	42.10	0.004837 ***	19.63	0.008077 ***	25.11	0.025054 ***	35.22	0.014210 ***	43.73
w/ Children	0.022220 ***	34.17	0.009684 ***	11.28	0.022172 ***	29.84	0.009986 ***	8.11	0.022552 ***	37.30
n	29,165		29,165		29,165		29,165		29,165	
Adjusted R^2		0.57		0.44		0.33		0.64		0.50
AIC		–1.15		–0.86		–0.85		–1.57		–1.07
	Instruments									
	ln Dist. from Seattle ☆ Fireplaces ☆		ln Dist. from Seattle ☆ % Brick ☆		ln Dist. from Subcenter ☆ % Brick ☆		ln. Elevation ☆ % Brick ☆		ln Dist. from Subcenter ☆ Nuisance ☆	
χ^2-value		0.15		1.49		0.09		1.02		2.01
F-value		382.32		244.55		111.59		129.34		245.05

Notes: all models were estimated using White-adjusted standard errors; all hypothesis tests are two-tailed; *** denotes at $p < 0.01$; ** denotes significant at $p < 0.05$; * denotes significant at $p < 0.10$; n/s denotes not significant; all models have one over-identifying restriction, so the critical value to reject the null hypothesis that the instrumental variables are exogenous $p < 0.05$ is 3.84; ☆ denotes valid instrument; distance from subcenter is the distance, in feet, to Bellevue, Everett, or Tacoma, whichever is closer; elevation is the level, in feet, above sea-level; percent brick is the percentage of the home's exterior composed of brick.

Table 7. Estimated Price and Income Elasticities of Demand for Distance from Environmental Hazards

Average — All Transactions		
	Price Elasticity	Income Elasticity
Dist. from Air Site	–0.2356	0.3277
Dist. from HWG	–0.3662	0.8592
Dist. from HWH	–0.0186	0.4700
Dist. from SF Site	–0.3761	0.0795
Dist. from TR Site	–0.1855	0.1635
Average — Transactions < 500 Feet from Hazard		
	Price Elasticity	Income Elasticity
Dist. from Air Site	–3.4596	0.2551
Dist. from HWG	–2.6502	0.6838
Dist. from HWH	–0.0990	0.3924
Dist. from SF Site	–15.0729	0.0383
Dist. from TR Site	–3.1517	0.1206
Average — Transactions 500 – 1,000 Feet from Hazard		
	Price Elasticity	Income Elasticity
Dist. from Air Site	–1.5578	0.2427
Dist. from HWG	–0.9982	0.6930
Dist. from HWH	–0.0317	0.4004
Dist. from SF Site	–8.0391	0.0383
Dist. from TR Site	–1.1807	0.1175
Average — Transactions >1,000 Feet from Hazard		
	Price Elasticity	Income Elasticity
Dist. from Air Site	–0.2126	0.3287
Dist. from HWG	–0.2487	0.8785
Dist. from HWH	–0.0098	0.4898
Dist. from SF Site	–0.3738	0.0795
Dist. from TR Site	–0.1736	0.1639

Notes: All elasticities we calculated at the mean values of the regressors after filtering observations by relevant conditions; n/a denotes not applicable; n/s denotes not significant in demand equation.

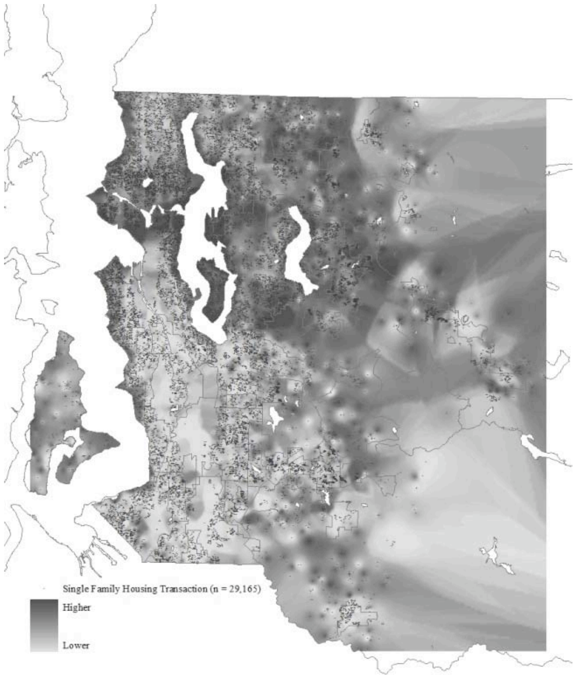

Figure 1. Natural Log of Sales Price of Single-family Homes, 2004

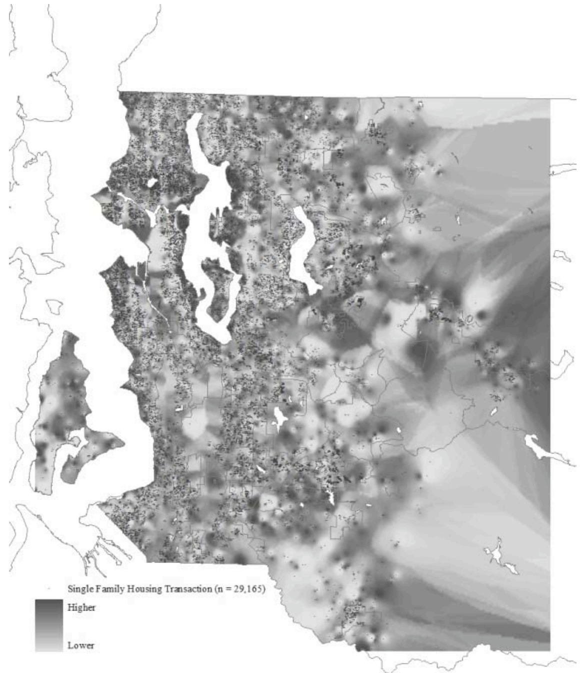

Figure 2. GWR Error Terms

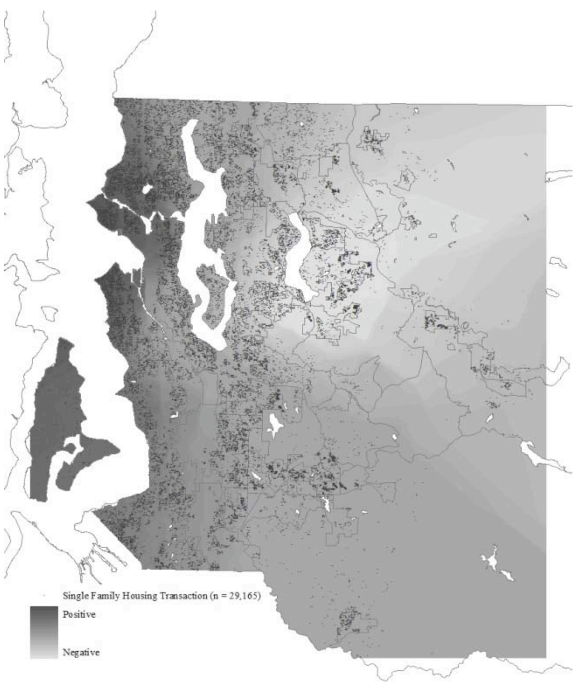

Figure 3. Estimated Influence of Density in the First Stage Hedonic Price Function

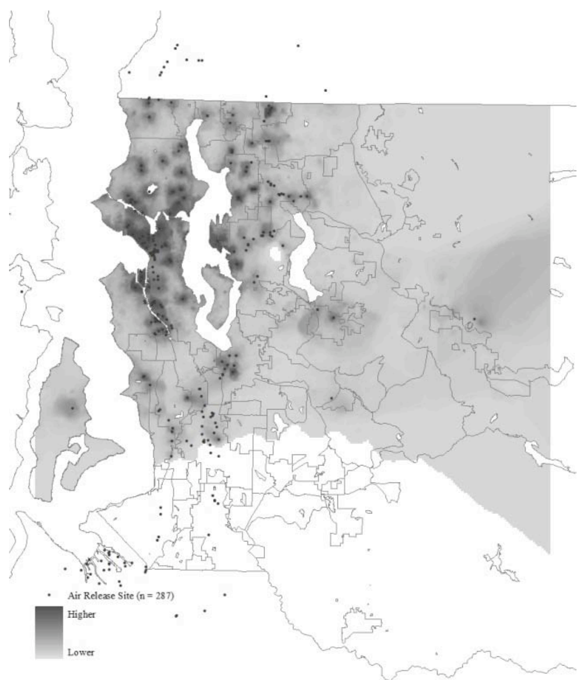

Figure 4. Dollar Value of Estimated Marginal Implicit Price of Distance from Air Release Site

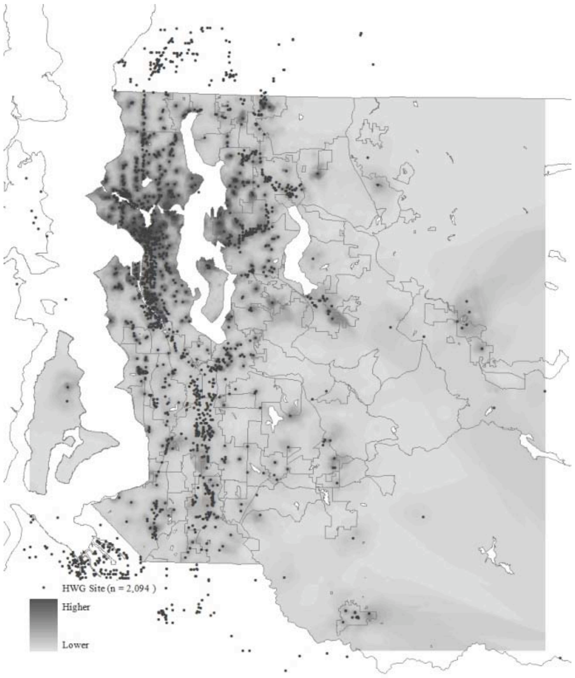

Figure 5. Dollar Value of Estimated Marginal Implicit Price of Distance from HWG Site

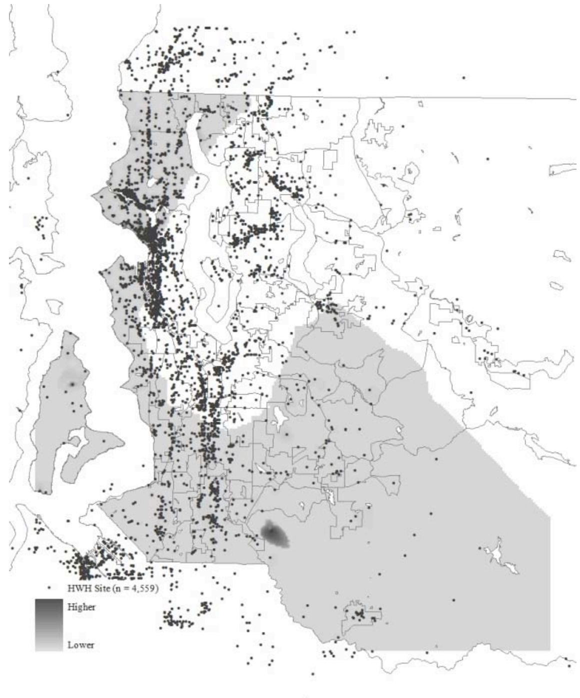

Figure 6. Dollar Value of Estimated Marginal Implicit Price of Distance from HWH Site

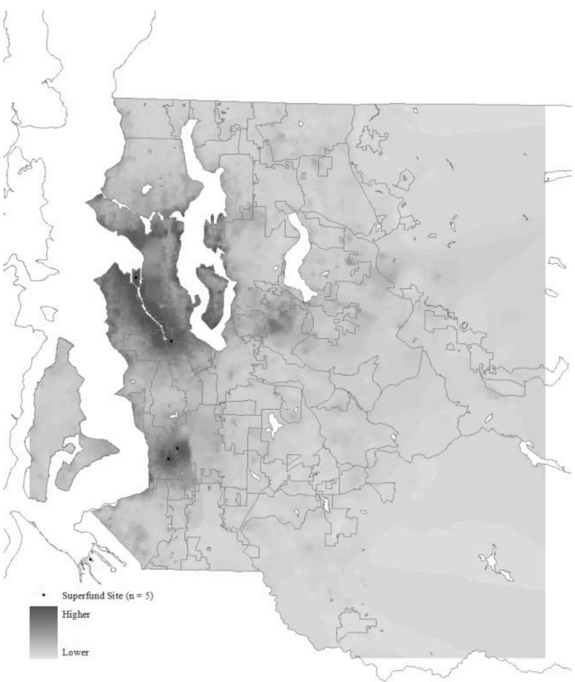

Figure 7. Dollar Value of Estimated Marginal Implicit Price of Distance from Superfund Site

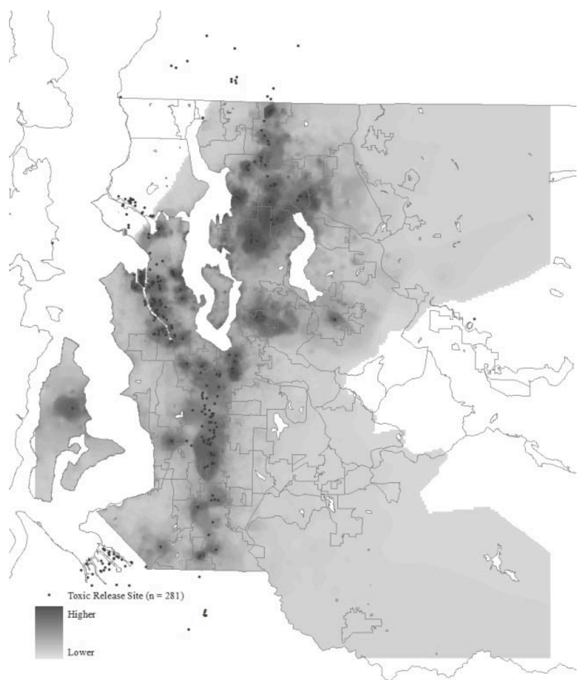

Figure 8. Dollar Value of Estimated Marginal Implicit Price ($\hat{\pi}_{ik}$) of Distance from Toxic Release Site