The Benefits of Environmental Improvement: Estimates From Space-time Analysis

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Abstract. This paper develops estimates of environmental improvement based on a two-stage hedonic price analysis of the single family housing market in the Puget Sound region of Washington State. The analysis — which focuses specifically on several EPA-designated environmental hazards and involves 226,918 transactions for 177,303 unique properties that took place between January 2001 and September 2009 — involves four steps: (*i*) ten hedonic price functions are estimated year-by-year, one for each year of the 2000s; (*ii*) the hedonic estimates are used to compute the marginal implicit price of distance from air release, superfund, and toxic release sites; (*iii*) the marginal implicit prices, which vary through time, are used to estimate a series of implicit demand functions describing the relationship between the price of distance and the quantity consumed; and, finally (*iv*) the demand estimates are compared to those obtained in other research and then used evaluate the potential scale of benefits associated with some basic environmental improvement scenarios. Overall, the analysis provides further evidence that it is possible to develop a structural model of implicit demand within a single housing market and suggests that the benefits of environmental improvement are substantial.

1. Introduction

Environmental quality — a commodity that, over the past several decades, 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) — is not traded in conventional markets, so its value can only be estimated, never measured directly. Estimation, which requires knowledge of a demand function describing the relationship between price and the quantity consumed, is achieved through either stated or revealed preference approaches (Freeman 2003; Mäler and Vincent 2005). As the name implies, stated-preference approaches examine individuals' direct responses to hypothetical changes in environmental goods. The most common of these is the contingent valuation method, in which respondents are asked to state their willingness to pay or, as the case may be, to accept compensation for changes in the quality and/or quantity of the commodity of interest. These responses are then used to construct demand functions that, in turn, are used to estimate the benefits of marginal and non-marginal changes in consumption.[1] This compares to revealed preference approaches, which examine actual behavior within housing and labor markets to get at the value of environmental quality. The most common of these approaches is the hedonic price method — first implemented in a study of the automobile industry by Court (1939) and later formalized by Rosen (1974) — which has consistently shown that households pay higher (lower) housing prices and/or are compensated with lower (higher) wages in environmentally desirable (undesirable) locations. The so-called marginal implicit prices that come out of hedonic analysis can be used to construct implicit demand functions describing household willingness to pay for environmental quality. There is, however, a major barrier to doing this, which is information: the hedonic function is a composite of unique, individual demand and supply, so the implicit prices it yields are also composites and, for this reason, it is difficult to identify and estimate a structural demand function.

The two main ways around the information problem are the following. First, because hedonic equilibria are inherently nonlinear (Ekeland et al 2002, 2004) it is possible to use functional form restrictions in the first-stage hedonic price function to non-parametrically identify the second-stage demand function (see, for example, Chattopadhyay 1999; Noelwah et al 2010). Ultimately, the viability this strategy depends on the validity of assumptions about the exact nature of the relationships involved. Second, it is possible to use multiple markets and/or submarkets single market (Brown and Rosen 1982; Bartik 1987) to come up with varying

[1] See Carson and Hanemann (2005) for an extensive review of the contingent valuation method.

marginal implicit price estimates that help to identify the demand function (see, for example, Brasington and Hite 2005; Carruthers and Clark 2010). The bottom line for this strategy is that it requires that different consumers pay different prices for the same quantity/quality of a given environmental good — that is, the identical commodity must be priced differently from place-to-place or time-to-time.

This paper employs the latter strategy to develop estimates of environmental improvement based on a two-stage hedonic price analysis of the single-family housing market in the Puget Sound region of Washington State. The analysis — which focuses specifically on several EPA-designated environmental hazards and involves 226,918 transactions for 177,303 unique properties that took place between January 2001 and September 2009 — involves four steps: (*i*) ten hedonic price functions are estimated year-by-year, one for each year of the 2000s; (*ii*) the hedonic estimates are used to compute the marginal implicit price of distance from air release, superfund, and toxic release sites; (*iii*) the marginal implicit prices, which vary through time, are used to estimate a series of implicit demand functions describing the relationship between the price of distance and the quantity consumed; and, finally (*iv*) the demand estimates are compared to those obtained in other research and then used evaluate the potential scale of benefits associated with some basic environmental improvement scenarios. In the second stage demand functions, time — measured as the number of days since January 1, 2000 when the transaction occurred — is used as an instrument.

2. Background — the Two-stage Hedonic Model

Although the hedonic model actually has its foundations in the work of Adam Smith (1776) who discussed compensating wage differentials in the context of job characteristics,[2] the application of hedonic methods to housing markets was first explored by Ridker and Henning (1967) and Anderson and Crocker (1971), the model was first formalized by Rosen (1974) and later refined by Freeman (1979). Rosen envisioned a two-stage process. In the first stage, the sale price of sold homes are regressed on all of the attributes of the home, as well as the characteristics of the neighborhood and jurisdictions in which the home is located. This is shown in equation (1) below.

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

[2] Smith identified five different characteristics of jobs including: (1) the agreeableness, or disagreeableness of the job, (2) the difficulty to learn the job, (3) the extent to which there are interruptions in employment for the job, (4) the amount of trustworthiness required of the job, and (5) the likelihood of success in the job.

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. The implicit price for attribute, *k*, is derived as the partial derivative of (1) with respect to that attribute. Given that the hedonic function is in semi-log form, the implicit price is: $\hat{\pi}_{ik} = \hat{\alpha}_k \cdot p_i$.

Next, it is increasingly recognized that hedonic price models must address the problem of spatial dependence (Kim et al. 2003; Theebe 2004; Brasington and Hite 2005; Anselin and LeGallo 2006; Anselin and Lozano-Gracia 2008; Cohen and Coughlin 2008). On the supply side, proximate homes tend to be similar to each other, and, on the demand side, homebuyers regularly emulate one another's behavior. The result is a process of spatial interaction among market participants, which, at a minimum, suggests that the first stage hedonic price function shown in equation (1) should be modified to include a spatial lag of its dependent variable (Anselin 1988; Anselin and Bera 1998):

$$\tilde{p}_i = \beta_0 + \lambda \cdot W_{ij} \cdot \tilde{p} + \beta_1 \cdot z_{i1} + \beta_2 \cdot z_{i2} + ... + \beta_k \cdot z_{ik} + \upsilon_i . \qquad (2)$$

The notation in this equation is essentially the same as before, except that the βs stand in for the αs; υ_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 $n \times n$ weights matrix describing the connectivity of observations) giving the average sales price of nearby homes; and λ is an estimable spatial autoregressive parameter. Because the behavioral underpinning of equation (2) says that the sales prices of nearby homes influence each other, $W_{ij} \cdot \tilde{p}$ is endogenous to $\tilde{p}_i$ and the function cannot be properly estimated using ordinary least squares (OLS). A viable alternative is a spatial two stage least squares (S2SLS) estimator formalized by Kelejian and Prucha (1998), which, in a nutshell, involves regressing the spatially lagged variable on all explanatory variables plus spatial lags of those same variables to produce predicted values, and then using those predicted values in place of the actual values in equation (2). Like maximum likelihood estimation, S2SLS yields efficient, unbiased parameter estimates, even in the presence of spatial error dependence (Das et al. 2003).

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 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).

Moving on, once the hedonic function has been estimated and the implicit prices have been derived, an implicit demand function is estimated in the second stage, by regressing the quantity of a particular neighborhood (or housing) attribute on its marginal implicit price, as well as other determinants of demand:

$$q_{ik} = \gamma_0 + \delta_{ik} \cdot \hat{\pi}_{ik} + \gamma_1 \cdot x_{i1} + ... + \gamma_s \cdot x_{is} + \psi_i . \tag{3}$$

Within equation (3), q_{ik} the quantity of attribute k consumed at home i; $\hat{\pi}_{ik}$ represents the estimated marginal implicit price which is endogenous in this model; the xs represent various demand shifters; and δ_{ik} and the γs represent estimable parameters on the endogenous variable and explanatory variables, respectively; and ψ_i represents a stochastic error term.

Since the estimated implicit price is an endogenous variable ($\hat{\pi}_{ik}$) it must be estimated using a simultaneous equations approach, and Rosen (1974) suggested that the endogeneity inherent in equation (2) was typical of all market demand and supply functions, and the demand function could be estimated using supply shifters as instruments. However, various authors including Brown and Rosen (1982) and Diamond and Smith (1983) have noted that one cannot simply map out the demand function using supply shifters because each revealed implicit price function results from a unique interaction between an individual, rather than a market demand function. That is, the hedonic price function that is used to derive the implicit price is really a reduced form function containing both a unique individual demand function and a unique, individual supply function, and it does not contain the kind of information needed to identify a structural demand function. While there are a number of different ways of overcoming this problem — for example Chattopadhyay 1999, Ekeland et al 2002, 2004, and Noelwah et al 2010 suggest functional form restrictions — the approach most widely used is to spatially identify unique housing market segments that have different implicit prices for the same attribute, and then use this independent variation in implicit prices to identify a market demand function. This approach was suggested by a number of different authors, including Palmquist (1984), Bartik (1987), and Epple (1987)).

While most of these multi-market approaches focus on more than one region (that is, multiple cities), housing economists have long believed that there are multiple housing markets within a single region. For example, Straszheim (1974) and Michaels and Smith (1990) suggested that implicit prices for housing attributes likely vary within a single region or city. In fact, in a recent paper, Carruthers and Clark (2010), show that the unique simultaneity inherent in the hedonic model can be addressed by examining spatial variation in the housing market within a single metropolitan area. Specifically, a geographically weighted regression (GWR) model is used to identify spatial variation in the implicit price function. That is, GWR models permit each observation to generate a unique set of parameters, and hence a unique implicit price function. Thus, the implicit price function waxes and wanes across space, with minor changes seen in relatively proximate properties and more significant changes seen in submarkets that are more distant.

Similarly, implicit price functions can also vary over time, with more significant shifts in the function occurring when there are wide swings in the business cycle. Indeed, the more income elastic are locational attributes, the larger should be the shift in the specific implicit price function resulting from a given change in income. The ongoing recession that (according to the National Bureau of Economic Research[3]) commenced in December 2007 was brought on by the implosion of a massive bubble[4] in the housing market and it has substantially eroded household income and access to credit. It has also generated a significant increase in unemployment at the national level, as well as for regional economies such as the Puget Sound region of Washington State[5]. The Federal Housing Finance Agency generates a constant quality housing cost index by metropolitan area, and the index, which is benchmarked to 100 in 1991Q and shown in Figure 1, rose to 156.11 in Q1 2000. Over the ensuing decade, the FHFA index[6] increased from 156.11 to 301.58 in Q2 2007, and then fell to 249.68 in the first quarter of 2010. This precipitous climb is also reflected in the well-known Case-Shiller housing price index, which is shown for the region from 1990 – 2010 in Figure 2. Overall, it is clear that the general economy has covered almost an entire business cycle over the time period[7], and in addition, there has been substantial variation in home prices in the Seattle metropolitan area. It is this variation that the following empirical analysis exploits to identify the implicit demand for environmental quality.

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[3] For information on NBER's recession dating procedure, see: *http://www.nber.org/cycles/recessions.html.*

[4] On December 15, 2008, the popular real estate website *Zillow.com* reported that, in that year alone, homes across the United States lost an estimated $2 trillion in value — an amount equal to about 20% of the nation's GDP. See: *http://zillowblog.com/2-trillion-in-home-values-lost-in-08/2008/12/.*

[5] Specifically, the seasonally adjusted national unemployment rate rose from 4.0% in December 2007 to 10.0% in December 2010. The Washington state seasonally adjusted unemployment rates increased from 4.7% to 9.2% over the same period, and the rate for the Seattle MSA rose from 4.1% to 8.9% over the period.

[6] The FHFA index is derived from housing transactions only and is seasonally adjusted.

[7] While the trough of the 2001 recession was dated November 2001, and the most recent recession began in December 2007, the National Bureau of Economic Analysis has not yet dated its trough.

3. Empirical Analysis

3.1 Research Design

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,[8] includes 226,918 transactions for 177,303 unique properties — all single-family home sales that took place between January 1, 2000 and September 30, 2009. The sales data, which is mapped year-by-year in Figure 3, was stripped of all non-arms-length transactions, like those with some type of deed other than a warrantee deed, and "bad" records, with missing information or some other problem. The transactions were then loaded into a geographic information system (GIS) wherein they were linked to parcel data, also from the King County Assessor. Once this was done, the data was matched with other relevant data from the 2000 Census of Population and Housing, the Environmental Protection Agency (EPA), and various regional sources, including school district boundaries, to create neighborhood level and distance-based metrics. Along the way, for each year of the study period, 2000 – 2009, a spatial weights matrix — W_{ij} from equation (2) — matching each transaction to its four nearest neighbors was generated and used to calculate spatial lags of all variables engaged in the analysis. Table 1 lists descriptive statistics for all non-lagged variables involved in the analysis.

The identification strategy involves three steps. In the first step, ten identical first-stage hedonic price functions, one for each year of the 2000s, are estimated.[9] The process of model construction led to the following nine categories of explanatory variables: (*i*) lot, measured as the square footage of the of the home's site, private access and whether or not the it is inaccessible to the public at large; (*ii*) structure, measured as the square footage of the home, its height in, its age in quadratic form, its number of bathrooms, its number of fireplaces, the proportion of its exterior composed of brick or stone, and weather or not it is a historic property; (*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,

[8] This information is publicly available but, for this research, it was obtained from *Metroscan*, a proprietary database that collects assessor's data from King County and elsewhere.

[9] In order to ensure the legitimacy of this initial step, Chow tests were used to formally test the hypothesis that the parameters vary from year to year. Following Brasington and Hite's (2005) approach, a model pooling the ten years was tested against models estimating the ten years separately — then, each individual year was tested against the other nine pooled together. A total of 11 separate Chow tests were constructed, and each overwhelmingly indicates that the parameters differe from year-to-year.

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, and the number of linear feet of waterfront its site has, if any; (*vi*) neighborhood, measured as the school district tax rate, school performance, calculated as the average percentage of students achieving success in several state aptitude tests,[10] plus, defined at the census tract level, median household income and density, calculated as housing units per acre; (*vii*) location, measured as distance from downtown Seattle, the average commute time to work in the census tract, and distance from the nearest arterial; (*viii*) environmental hazards, measured as the distance from the nearest air release site, hazardous waste generator, superfund site; and toxic release site; and (*ix*) time, measured as the number of days since January 1, 2001 when the home was sold.[11] Together, these 35 variables plus a spatial lag and an intercept form the vector $\boldsymbol{z}$ that explains the sales price of housing in King County's portion of the Puget Sound region. All models are estimated using a heteroskedasticity-consistent covariance matrix.

In the second step, the parameters from the hedonic price functions are used to calculate the marginal implicit price of distance from air release sites, superfund sites, and toxic release sites. Once calculated, the prices are adjusted for inflation, to 2010 dollars. The price estimates vary across geographic space due to the models' non-linear form — but, importantly, also though time because of variation owing to the business cycle. Note that what's required to identify the second-stage implicit demand model is that different consumers are observed to pay different prices for the same quantity of distance, which is the case across the years. The geographic variation in this case reflects the fact that households pay different marginal implicit prices for different values of distance, which is expected due to diminishing marginal utility: the first increment of distance away from an environmental hazard is valued greater than the *n*th increment.

Finally, in the third step, with the marginal implicit prices in hand, three demand functions are estimated, using all observations across all years. Each of the demand equations contains the three inflation-adjusted marginal implicit prices estimated via the first and second steps, plus a set of four demographic variables (measured at the census tract) that act as demand shifters: (*i*) median household income; (*ii*) the percentage of adults having a graduate degree; (*iii*)

[10] The aptitude tests are for mathematics, reading, science, and writing.

[11] Because the models are estimated year-by-year, this variable acts to capture annual the daily appreciation rate — and, ultimately depreciation rate. This same variable is used as an instrument in the second-stage models, which pool all ten years worth of transactions together.

the percentage of households having children; and (*iv*) the percentage of the population that is white. Going back to equation (3), note that, in each model, the own-price is an endogenous variable, so ordinary least squares estimation is not an option. Instead, each equation is estimated using two-stage least squares (2SLS), a technique that requires an instrumental variable, which must be both a good predictor of the marginal implicit price and uncorrelated with the structural models' error terms. The instrument used for this purpose is time, measured as days since January 1, 2009 – and it is subjected to two tests: (*i*) an F-test of the null hypothesis that its parameter is equal to zero in the first stage of the 2SLS routine; and (*ii*) a χ^2 test of the null hypothesis that the variable is uncorrelated with the error term of the structural model, also known as a test of over-identifying restrictions (see Wooldridge 2002 for overviews of both tests). The instrument must pass both tests in order for the econometric strategy — and, thus, the entire second-stage demand analysis — to be considered viable.

3.2 Econometric Estimates

The spatial two-stage least squares (Kelejian and Prucha 1998) estimates of each of the hedonic price functions are presented in Tables 1a – 1e. The models consistently do an outstanding job of explaining variation in the sales price of single-family housing — the adjusted R^2 values range from 0.80 to 0.86 — and nearly all of the parameters are statistically significant (the critical t-value for $p > 90\%$ in a two-tailed hypothesis test is 1.64) and appropriately signed. Note that evidence of the business cycle pictured in Figures 1 and 2 is visible in the parameters on the time variable. The rate of appreciation steadily escalates from 2000 – 2005, before it starts declining in 2006, falls out all together in 2007, and then reverses in 2008 and 2009, years that witnessed widespread depreciation. Finally, note that the parameters on distance from the three environmental hazards that are the object of this analysis (air release, superfund, and toxic release sites) are all positive and statistically significant. Distance from hazardous waste generators is included in the first-stage models, but not in the second-stage analysis because previous research (Carruthers and Clark 2010) has found little evidence that households exhibit much concern for the sites.

Next, the marginal implicit price ($\hat{\pi}_{ik}$) of distance from the three hazards is calculated as follows:

$$\hat{\pi}_{ik} = \hat{\beta}_k \cdot p_i / z_{ik},$$

which reflects the fact that both price and distance are expressed in natural log form in the estimated models. The results are displayed in Figures 4 – 6, which show surfaces that were interpolated from the inflation-adjusted marginal implicit price estimates based on the location of the transaction from each year. In the figures, it is clear to see that the estimated prices associated with the same distances vary from year-to-year — and result formally tested via the Chow tests described in the preceding section.

Finally, the 2SLS estimates of the second-stage implicit demand models are listed in Table 3. These models all register healthy adjusted R^2 values and, most important, the instrumental variable, time, passes both validity tests at well over a 99 percent level of confidence — note that the F-values are very high and the χ^2-values are all miniscule. Working down though the list of variables, and across models, the estimation results reveal the following. First, all of the own-price elasticities — –0.1437 for air release sites; –0.1890 for superfund sites; and –0.4315 for toxic release sites — indicate that the demand for distance is price inelastic: changes in price do not lead to large changes in consumption. Second, distance from air release and distance from superfund sites are evidently substitutes while distance from air release and distance toxic release sites are complements; the picture is less clear for the relationship between distance from superfund sites and distance from toxic release sites. Third, all three models indicate that distance from environmental hazards is a normal good, although the elasticities for superfund and toxic release sites are quite small. Fourth, having a graduate degree (except in the case of air release sites), having children, and being while are all associated with higher levels of consumption: these demographics are positively correlated with distance. In sum, the models perform very well and, in general, just as expected.

3.3 Benefit Estimates

Estimates of benefits can be derived from the second stage demand functions. Since the demand functions are derived as:

$$\tilde{q}_{ik} = \delta_0 + \delta_1 \hat{\pi}_{ik} + \sum_{j=2}^{n} \delta_j \cdot x_j + \varepsilon_{ik} \tag{6}$$

Where $\tilde{q}_{ik}$ is the natural log of the distance of home i from hazard *k*, $\hat{\pi}_{ik}$ is the implicit price; x_j are location specific demand shifters defined at the census tract level; the δ's represent parameters, and ε is the error term. Since the goal is to derive benefits, equation (6) is inverted and solved for $\hat{\pi}_{ik}$. Assuming x_j are defined at the census tract level, this gives the expected value of the inverse demand function as:

$$\hat{\pi}_{ik} = \beta_0 + \beta_1 \tilde{q}_{ik} \tag{7}$$

where $\beta_0 = 1/\delta_1 \cdot (\delta_0 + \sum_{j=2}^{n} \delta_j \cdot x_j)$ and $\beta_1 = 1/\delta_1$. Consumer surplus is by integrating equation (7) over some discrete improvement in distance from the hazard, $\Delta\tilde{q}_{ik}$.

There are several ways to simulate hazard mitigation. One approach would be to consider the benefits associated with the removal of each individual hazard[12]. Recall that distance is measured from a sold home to the closest hazard, so the mitigation of a particular site will influence only those properties in our sample for which that site was the closest. Thus, the geographic impact of a particular hazard mitigation project will depend on the density of hazards in the neighborhood. Other things equal, the larger are the number of hazards and the more evenly distributed they are across space, the smaller should be the number of homes for which a given site would be the closest. The benefits will also depend on the density of homes in a particular area. That is, for a given density of hazards in a region, the mitigation of those hazards that are located in more densely populated areas will generate larger benefits than those found in more sparsely populated areas. This is because the average benefits per household are then spread across more households. If benefits from the mitigation of each hazard are estimated, then cost-benefit ratios can be constructed to prioritize public policy efforts. Unfortunately, time constraints prevented precluded the precise derivation of individual benefits that could be then extrapolated to community-wide benefits in this version of the paper. However, that will be done in a subsequent version.

An alternative approach is to consider, for comparative purposes, the generic benefits associated with some absolute improvement in distance from the site (for example an additional 1000 feet), or some relative improvement in distance from the site (like an additional 10%). These estimates are as follows. The benefit to the average homeowner (based on the entire 10-year long sample of home sales in the region) from an additional 1000 feet of distance varies across hazards: \$6,123 for air release sites; \$7463 for superfund sites; and \$2,450 for toxic release sites. The second set of benefits is associated with a 10% improvement in distance. Hence, for those hazards that are less densely located throughout the region (Superfund sites), the improvement in relative terms is substantially larger more densely located sites (air release and toxic release sites). This type of simulation is more akin to the derivation of the benefits from an

[12] Since the hedonic approach derives a Marshallian demand function, rather than a utility invariant Hicksian demand function, deriving benefits by integrating the inverse demand function over the change in distance will give an estimate of Consumer Surplus (CS), rather than the ideal Compensating Variation (CV) or Equivalent Variation (EV) measures of utility change. However, Willig (1976) has shown that it is rare that CS differs significantly from CV or EV. Thus, we present CS in this paper.

average mitigation across hazard types, since the mitigation of a single Superfund site will move the average distance by a larger margin (given that there are only 5 of them in the region) than would the mitigation of an air release site. The average benefits from a 10% mitigation are: $6,530 for air release sites; $32,954 for superfund sites; and $3,307 for toxic release sites. These findings suggest that the mitigation of high profile hazards like superfund sites, are more prevalent in the region.

Finally, it is worth noting that the benefit estimates derived in the present analysis are nearly identical to those derived from the estimates presented in Carruthers and Clark (2010). In that case, the benefit to the average homeowner (based on 2004 data and a wholly different identification strategy) from an additional 1000 feet of distance varies across hazards: $6,720 for air release sites; $7,243 for superfund sites; and $7,239 for toxic release sites. Similarly, the average benefits from a 10% mitigation were: $7,092 for air release sites; $31,681 for superfund sites; and $9,736 for toxic release sites. Though it is important to note that both sets of estimates are very coarse — and for illustrative purposes only — it is encouraging that two very different identification strategies involving different data sets have produced such similar benefit estimates. It suggests that the methodology laid out here and in Carruthers and Clark (2010) is viable for a more detailed (and planned) welfare analysis.

4 Summary and Conclusion

This paper has presented estimates of implicit demand for environmental improvement from a two-stage hedonic housing price model applied to the Puget Sound region of Washington State. Specifically, demand for three different types of environmental goods (air release sites, superfund sites, and toxic release sites) are derived from a single region, and these estimates are similar to those found by a previous analysis (Carruthers and Clark 2010). These estimates are then used to derive hypothetical benefits from hazard mitigation. Specifically, the benefit estimates were derived by simulating hypothetical changes in distance from the hazards. When the improvement in distance was uniform (1,000 feet) across hazard types, the typical benefits were relatively consistent. However, when the improvement was expressed relative to existing distances, substantial differences in estimated benefits emerged, with the reduction of high profile hazards like superfund sites, generating much larger average benefits than those that are more prevalent in a region.

These findings are only a preliminary first attempt at the derivation of community-wide benefits from hazard mitigation and much more work is needed before definitive conclusions can be drawn. First, the benefits from the mitigation of specific hazards have not considered. Given that the spatial distribution of both households and hazards is non-uniform, it is important to refine the simulations to consider precisely how the mitigation of a particular hazard site may impact a neighborhood by recognizing that most individual hazards have little impact on the entire region. Rather the benefits are more localized within the region. Second, the distribution of benefits across population groups has not considered. The environmental justice literature suggests that the costs of exposure to environmental hazards are borne disproportionately by those at the lower end of the income distribution. Since average benefits can be derived by census tract, it is possible to further explore this aspect of the distribution of benefits from environmental improvement. Third, whereas the estimation of the first-stage hedonic model employed spatial econometric approaches, the second-stage estimators did not. While such an approach will complicate the estimation of benefits, it may also improve the efficiency of the estimators, and potentially reduce any bias as well. These and other issues will be evaluated in a subsequent version of this paper.

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Table 1. Summary Statistics

	Mean	Std. Dev.	Min.	Max.
Sales Price	420,228.9	351,082.20	50,000.00	20,000,000.00
Lot				
Size	14,776.67	44,083.76	592.00	4,638,269.00
Private Access	0.05	0.22	0.00	1.00
Structure				
Size	2,058.74	895.45	500.00	14,030.00
Stories	1.40	0.50	1.00	4.00
Age	34.16	28.16	0.00	109.00
Age Squared	1,959.74	2,515.00	0.00	11,881.00
Baths	2.38	0.96	0.00	16.00
Fireplaces	1.04	0.57	0.00	7.00
Percent Brick	3.56	16.92	0.00	100.00
Historic Property	0.00	0.01	0.00	1.00
Grade				
Average	0.42	0.49	0.00	1.00
Good	0.26	0.44	0.00	1.00
Better	0.11	0.32	0.00	1.00
Very Good	0.05	0.22	0.00	1.00
Excellent	0.02	0.13	0.00	1.00
Luxury	0.00	0.07	0.00	1.00
Mansion	0.00	0.03	0.00	1.00
Condition				
Average	0.67	0.47	0.00	1.00
Good	0.27	0.44	0.00	1.00
Very Good	0.06	0.23	0.00	1.00
Amenities				
View	0.05	0.21	0.00	1.00
Nuisance	0.08	0.27	0.00	1.00
Waterfront Feet	1.10	13.97	0.00	1,860.00
Neighborhood				
Tax Rate	2.94	1.03	1.68	4.54
School Performance	0.68	0.08	0.39	0.87
Median HH Income	64.03	19.41	16.29	133.76
Density	2.64	2.23	0.00	26.40
Location				
Dist. from Seattle	66,664.74	36,755.24	1,888.93	196,516.50
Commute Time	26.31	4.30	16.30	45.90
Dist. from Arterial	1,149.67	1,424.29	0.00	23,602.50
Environmental Hazards				
Dist from Air Site	10,666.64	9,729.20	19.35	76,671.39
Dist from HWG	4,269.53	3,976.97	9.41	29,274.31
Dist. from Superfund Site	44,230.85	27,411.06	276.08	150,831.30
Dist. from TR Site	13,549.85	11,503.80	13.89	85,635.81
Time	1,662.90	911.27	1.00	3,541.00
Demographics				
% w/ Graduate Degree	0.13	0.08	0.00	0.43
% w/ Kids	0.35	0.12	0.03	0.65
% White	0.78	0.15	0.10	0.96
Estimated Marginal Implicit				
Price of Dist from Air Site	0.95	1.72	0.005	208.00
Price of Dist. from SF Site	0.50	0.62	0.01	38.09
Price of Dist. from TR Site	0.91	2.02	0.004	278.24

Table 2a. S2SLS Estimates of Hedonic Price Functions, 2000 - 2001

	2000		2001	
	Est.	t-value	Est.	t-value
Constant	11.248490	78.06	11.043150	73.21
Spatial Lag	0.210010	24.05	0.218838	23.42
Lot				
Size	0.000001	11.57	0.000001	5.09
Private Access	0.031030	4.25	0.023658	3.03
Structure				
Size	0.000157	35.42	0.000154	37.34
Stories	0.014833	3.43	0.020723	4.65
Age	–0.004754	–17.20	–0.005227	–17.37
Age Squared	0.000048	16.97	0.000054	18.28
Baths	0.010720	3.43	0.016727	5.01
Fireplaces	0.027634	7.77	0.040450	11.60
Percent Brick	0.000820	10.04	0.000953	10.61
Historic Property	–0.058674	–0.33	n/a	n/a
Grade				
Average	0.115715	22.48	0.089933	18.25
Good	0.213620	31.05	0.167790	25.22
Better	0.335026	36.02	0.283246	31.01
Very Good	0.449319	35.91	0.391586	31.87
Excellent	0.598003	32.02	0.519476	29.03
Luxury	0.790167	22.11	0.707707	15.78
Mansion	1.058218	8.54	0.833656	9.29
Condition				
Average	0.070560	1.44	0.156356	3.55
Good	0.098625	2.02	0.194558	4.42
Very Good	0.135599	2.74	0.212952	4.76
Amenities				
View	0.210576	17.65	0.211792	16.94
Nuisance	–0.042707	–7.15	–0.044611	–7.72
Waterfront Feet	0.001784	3.91	0.001231	2.51
Neighborhood				
School Tax Rate	–0.020476	–10.36	–0.020592	–10.83
School Performance	0.062077	2.59	0.113422	4.64
Median Income ($1000s)	0.001350	10.54	0.001270	9.95
Density	0.003412	3.12	0.001655	1.47
Location				
ln Dist. from Seattle	–0.201195	–41.83	–0.191513	–39.49
ln Commute Time	–0.172136	–12.31	–0.167790	–10.93
ln Dist. from Arterial	0.009017	6.03	0.011308	7.92
Environmental Hazards				
ln Dist from Air Site	0.010528	4.18	0.005892	2.29
ln Dist from HWG	0.006158	2.69	0.009338	4.08
ln Dist. from Superfund Site	0.034735	13.99	0.023429	8.72
ln Dist. from TR Site	0.014234	5.98	0.018512	7.73
Time	0.000122	9.08	0.000051	3.45
n		22,429		21,895
Adj. R Squared		0.85		0.83

Note: S2SLS is Kelejian and Prucha's (1998) spatial two-stage lease squares estimator; all models estimated using a heteroskedasticity-consistent covariance matrix.

Table 2b. S2SLS Estimates of Hedonic Price Functions, 2002 - 2003

	2002		2003	
	Est.	t-value	Est.	t-value
Constant	11.513830	76.59	11.303140	83.89
Spatial Lag	0.187698	21.03	0.195339	24.79
Lot				
Size	0.000001	3.52	0.000001	9.00
Private Access	0.016438	1.95	0.029704	4.17
Structure				
Size	0.000161	44.29	0.000163	50.02
Stories	0.023969	5.63	0.011259	2.94
Age	–0.004763	–16.85	–0.003902	–17.28
Age Squared	0.000048	18.07	0.000040	18.95
Baths	0.010436	3.61	0.010112	3.98
Fireplaces	0.033634	9.67	0.029154	10.63
Percent Brick	0.000736	8.71	0.000608	7.40
Historic Property	0.719596	1.62	0.240657	1.92
Grade				
Average	0.106007	21.79	0.092093	21.70
Good	0.184985	27.47	0.181189	32.18
Better	0.297488	32.06	0.300961	37.84
Very Good	0.408532	34.20	0.393867	34.85
Excellent	0.544118	31.90	0.495500	33.68
Luxury	0.738228	17.93	0.677511	20.77
Mansion	0.792421	9.62	0.606227	5.74
Condition				
Average	0.112382	4.01	0.146844	3.53
Good	0.153607	5.47	0.178865	4.29
Very Good	0.183906	6.40	0.213663	5.10
Amenities				
View	0.236460	20.93	0.196173	13.61
Nuisance	–0.035304	–6.27	–0.032176	–6.45
Waterfront Feet	0.001051	2.15	0.001457	1.78
Neighborhood				
School Tax Rate	–0.018931	–9.23	–0.022797	–13.22
School Performance	0.099588	4.16	0.101388	5.04
Median Income ($1000s)	0.001110	8.31	0.001060	10.37
Density	0.000031	0.03	0.001590	1.68
Location				
ln Dist. from Seattle	–0.209723	–43.65	–0.207061	–49.51
ln Commute Time	–0.173537	–12.09	–0.159588	–12.72
ln Dist. from Arterial	0.006439	3.83	0.008428	6.90
Environmental Hazards				
ln Dist from Air Site	0.011946	4.78	0.009372	4.26
ln Dist from HWG	0.012578	5.66	0.009736	5.02
ln Dist. from Superfund	0.033294	13.28	0.031817	15.27
ln Dist. from TR Site	0.015981	6.65	0.015313	7.51
Time	0.000123	9.16	0.000190	16.61
n		23,245		27,829
Adj. R Squared		0.83		0.85

Note: S2SLS is Kelejian and Prucha’s (1998) spatial two-stage lease squares estimator; all models estimated using a heteroskedasticity-consistent covariance matrix.

Table 2c. S2SLS Estimates of Hedonic Price Functions, 2004 - 2005

	2004		2005	
	Est.	t-value	Est.	t-value
Constant	10.764530	80.03	10.213330	74.50
Spatial Lag	0.210583	26.90	0.225749	28.12
Lot				
Size	0.000001	10.11	0.000001	4.91
Private Access	0.017529	2.70	0.020891	2.95
Structure				
Size	0.000156	49.14	0.000154	44.85
Stories	0.015470	4.25	0.015880	4.36
Age	–0.002740	–13.43	–0.003283	–14.51
Age Squared	0.000031	15.31	0.000035	16.28
Baths	0.015081	5.92	0.014685	5.59
Fireplaces	0.024923	9.27	0.027506	9.54
Percent Brick	0.000661	8.31	0.000723	9.81
Historic Property	n/a	n/a	0.334203	1.97
Grade				
Average	0.092266	21.52	0.089700	20.22
Good	0.184160	33.79	0.171765	28.98
Better	0.297974	40.95	0.279363	34.12
Very Good	0.393511	39.19	0.379190	34.59
Excellent	0.507297	33.16	0.445716	28.57
Luxury	0.690968	22.96	0.626863	23.69
Mansion	0.776150	6.22	0.634006	5.86
Condition				
Average	0.207691	5.20	0.063387	2.04
Good	0.243037	6.08	0.099716	3.21
Very Good	0.278211	6.86	0.134864	4.29
Amenities				
View	0.205097	19.51	0.209437	21.20
Nuisance	–0.031407	–6.82	–0.040353	–8.17
Waterfront Feet	0.001426	2.55	0.001898	4.84
Neighborhood				
School Tax Rate	–0.024031	–14.52	0.029715	–17.14
School Performance	0.152425	8.21	0.221031	10.64
Median Income ($1000s)	0.001040	11.27	0.001260	11.85
Density	0.002806	3.39	0.003256	3.63
Location				
ln Dist. from Seattle	–0.195904	–51.01	0.170887	–43.41
ln Commute Time	–0.153729	–13.04	–0.130357	–9.69
ln Dist. from Arterial	0.009092	8.09	0.003614	2.57
Environmental Hazards				
ln Dist from Air Site	0.011843	5.87	0.013955	6.51
ln Dist from HWG	0.007203	3.96	–0.000500	–0.22
ln Dist. from Superfund Site	0.030096	15.89	0.021050	10.39
ln Dist. from TR Site	0.010552	5.73	0.020616	9.24
Time	0.000280	25.90	0.000396	27.94
n		30,682		31,308
Adj. R Squared		0.86		0.80

Note: S2SLS is Kelejian and Prucha's (1998) spatial two-stage lease squares estimator; all models estimated using a heteroskedasticity-consistent covariance matrix.

Table 2d. S2SLS Estimates of Hedonic Price Functions, 2006 - 2007

	2006		2007	
	Est.	t-value	Est.	t-value
Constant	10.911480	71.62	11.831240	69.57
Spatial Lag	0.216208	24.31	0.211952	22.73
Lot				
Size	0.000001	8.80	0.000001	7.18
Private Access	0.020524	2.65	0.023705	2.91
Structure				
Size	0.000161	46.38	0.000163	42.91
Stories	0.022009	5.62	0.015604	3.19
Age	–0.002508	–11.10	–0.002262	–8.20
Age Squared	0.000025	12.07	0.000025	9.55
Baths	0.012849	4.99	0.022831	7.31
Fireplaces	0.022421	7.38	0.017632	4.92
Percent Brick	0.000598	6.74	0.000765	8.43
Historic Property	0.311288	1.37	n/a	n/a
Grade				
Average	0.065765	13.72	0.069698	11.71
Good	0.142631	22.32	0.138530	17.43
Better	0.234816	28.13	0.237247	22.94
Very Good	0.319394	28.45	0.322532	24.28
Excellent	0.423670	27.17	0.421373	22.89
Luxury	0.516084	18.73	0.485896	14.41
Mansion	0.607305	9.87	0.606709	9.73
Condition				
Average	0.072025	1.82	–0.027828	–0.63
Good	0.107112	2.72	0.005949	0.13
Very Good	0.146130	3.67	0.062067	1.39
Amenities				
View	0.214691	16.24	0.186326	16.68
Nuisance	–0.017857	–3.09	–0.012487	–1.84
Waterfront Feet	0.001374	1.70	0.003832	6.65
Neighborhood				
School Tax Rate	–0.026731	–13.75	–0.038061	–17.17
School Performance	0.150607	6.67	0.183394	7.00
Median Income ($1000s)	0.001350	11.14	0.001230	9.78
Density	0.003788	3.59	0.000401	0.37
Location				
ln Dist. from Seattle	–0.170392	–39.42	–0.186397	–36.05
ln Commute Time	–0.221530	–16.29	–0.212262	–13.83
ln Dist. from Arterial	0.009284	7.21	0.012553	7.36
Environmental Hazards				
ln Dist from Air Site	0.008898	3.60	0.009056	3.25
ln Dist from HWG	0.011383	5.40	0.008820	3.94
ln Dist. from Superfund Site	0.028793	13.60	0.030370	11.05
ln Dist. from TR Site	0.003616	1.66	0.009177	3.56
Time	0.000266	21.22	0.000006	0.40
n		27,410		21,327
Adj. R Squared		0.82		0.81

Note: S2SLS is Kelejian and Prucha’s (1998) spatial two-stage lease squares estimator; all models estimated using a heteroskedasticity-consistent covariance matrix.

Table 2e. S2SLS Estimates of Hedonic Price Functions, 2008 - 2009

	2008		2009 (Q1 -	
	Est.	t-value	Est.	t-value
Constant	13.560170	63.86	12.571640	43.96
Spatial Lag	0.159774	13.04	0.177870	11.71
Lot				
Size	0.000001	8.91	0.000001	4.38
Private Access	0.009379	0.81	0.032189	2.37
Structure				
Size	0.000163	29.81	0.000145	16.48
Stories	0.014707	2.50	0.004997	0.61
Age	–0.001837	–5.78	–0.003300	–7.70
Age Squared	0.000025	8.43	0.000036	8.70
Baths	0.028299	6.80	0.031713	5.47
Fireplaces	0.019396	3.97	0.022067	3.44
Percent Brick	0.000448	4.07	0.000630	3.80
Historic Property	n/a	n/a	0.110401	1.67
Grade				
Average	0.080055	10.10	0.119560	10.58
Good	0.177176	18.46	0.218118	15.21
Better	0.282110	22.90	0.338700	18.93
Very Good	0.397459	24.36	0.434299	18.65
Excellent	0.510163	20.81	0.451911	13.04
Luxury	0.691360	15.39	0.609174	9.08
Mansion	0.393071	2.39	0.523165	2.75
Condition				
Average	0.119220	3.01	0.242441	3.96
Good	0.155157	3.92	0.288879	4.72
Very Good	0.206694	5.10	0.341468	5.48
Amenities				
View	0.231084	16.00	0.251016	12.81
Nuisance	–0.025966	–3.22	–0.058585	–4.81
Waterfront Feet	0.003331	5.24	0.003107	3.86
Neighborhood				
School Tax Rate	–0.035736	–12.57	–0.038907	–10.88
School Performance	0.228001	6.28	0.287660	6.05
Median Income ($1000s)	0.001290	7.73	0.001300	6.06
Density	0.001093	0.75	0.002326	1.11
Location				
ln Dist. from Seattle	–0.216167	–31.03	–0.242288	–26.43
ln Commute Time	–0.233709	–11.06	–0.185325	–6.84
ln Dist. from Arterial	0.013113	6.54	0.011674	3.98
Environmental Hazards				
ln Dist from Air Site	0.012265	3.17	0.008120	1.65
ln Dist from HWG	0.003575	1.05	0.010061	2.43
ln Dist. from Superfund Site	0.037266	10.48	0.032810	6.93
ln Dist. from TR Site	0.012354	3.70	0.019939	4.39
Time	–0.000335	–16.58	–0.000121	–3.14
n		12,922		7,871
Adj. R Squared		0.83		0.82

Note: S2SLS is Kelejian and Prucha's (1998) spatial two-stage lease squares estimator; all models estimated using a heteroskedasticity-consistent covariance matrix.

Table 3. 2SLS Estimates of Second-stage Implicit Demand Functions

	ln Dist from Air Release Site		ln Dist. from Superfund Site		ln Dist. from TR Site	
	Est.	t-value	Est.	t-value	Est.	t-value
Constant	4.329364	163.68	7.119139	364.84	7.063127	303.60
Price and Cross-price Elasticities						
ln Price of Dist from Air Site	–0.143717	–24.59	0.121506	59.92	–0.120741	–39.45
ln Price of Dist. from Superfund Site	0.137528	65.00	–0.188993	–23.22	0.001835	1.06
ln Price of Dist. from TR Site	–0.217964	–79.25	–0.086655	–55.73	–0.431522	–84.49
Demographic Factors						
ln Median Income (1000s)	0.814830	99.32	0.211271	28.82	0.097947	12.36
% w/ Graduate Degree	–2.044648	–63.28	0.844737	44.44	1.492587	78.94
% w/ Kids	1.917294	110.90	1.373597	73.54	0.953211	60.30
% White	0.954185	101.97	2.159097	107.64	1.078964	99.68
n		226,918		226,918		226,918
Adj. R Squared		0.65		0.62		0.70
	Instrument: Time Since January 1, 2000					
F-value		13767.21		8315.06		10371.75
c^2-value		–3.78E-09		3.50E-09		3.75E-09

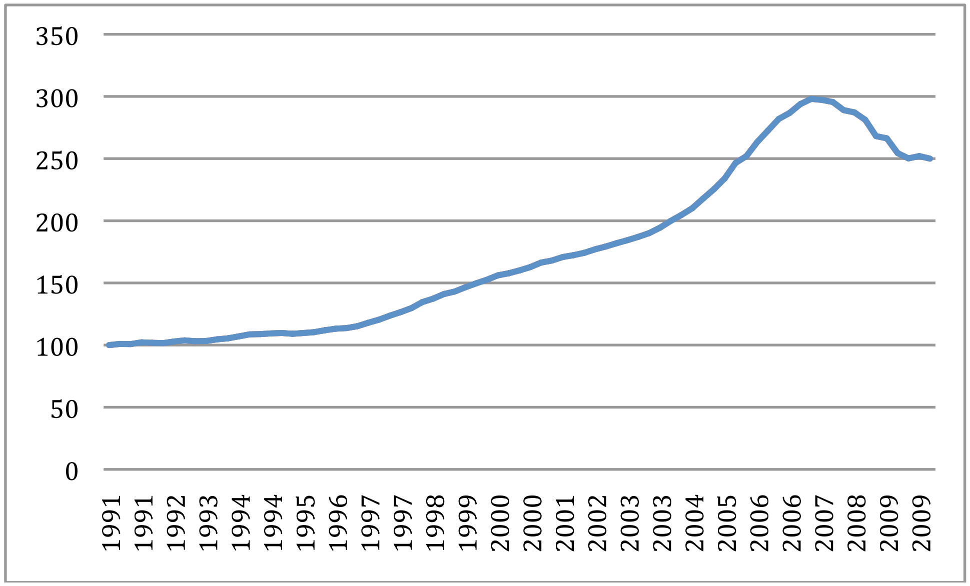

Figure 1. FHFA Housing Price Index - Seattle-Bellevue-Everett MSA

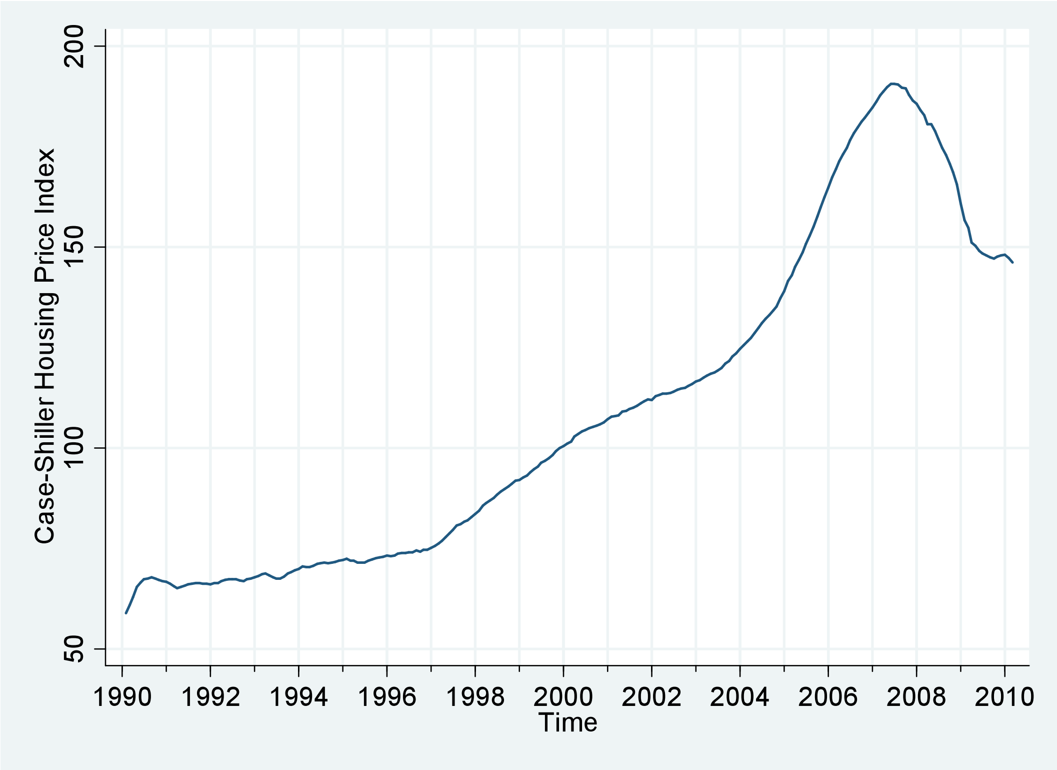

Figure 2. Case-Shiller Housing Price Index for Seattle, 1990 - 2010

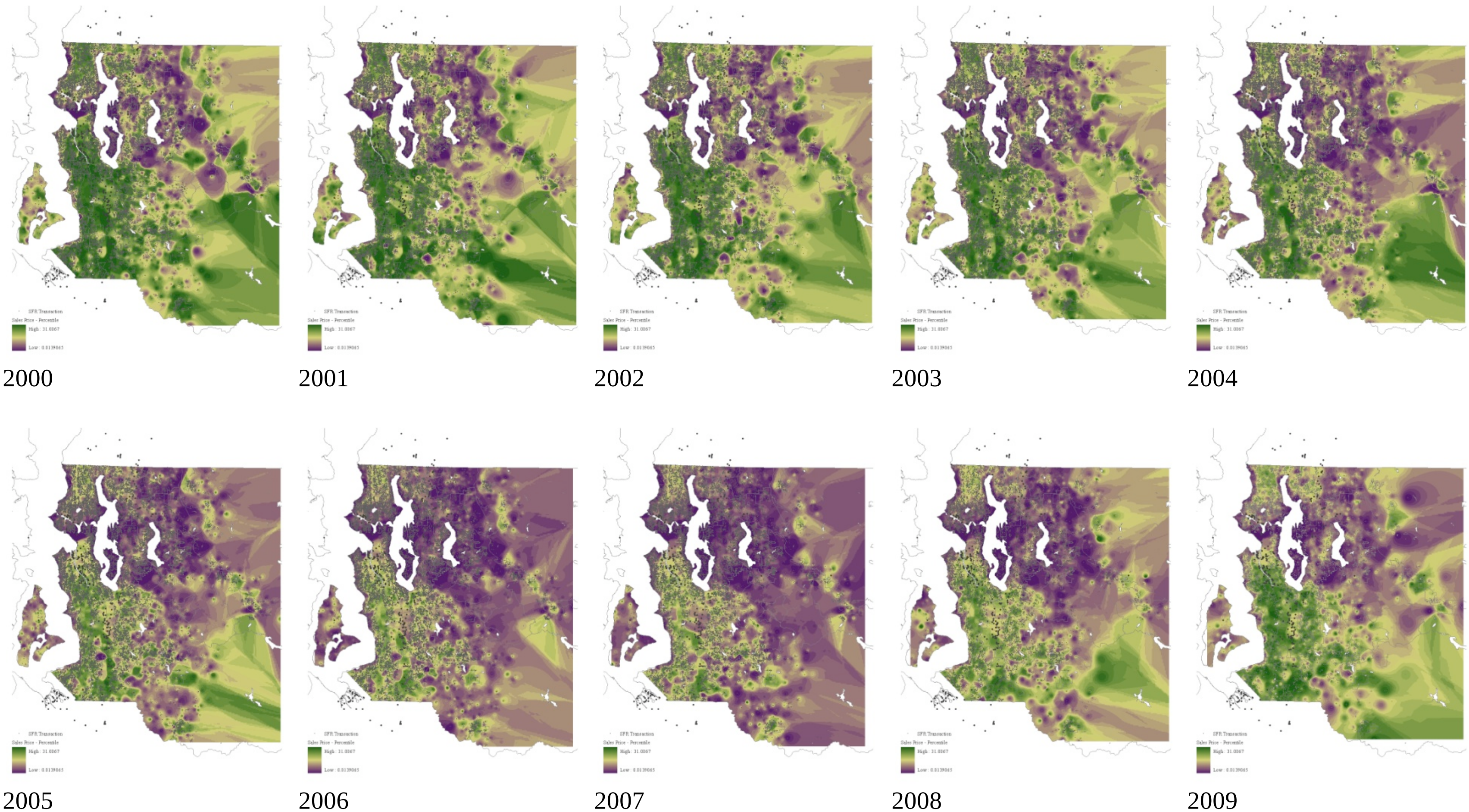

Figure 3. Inflation-adjusted Sales Price ($2010) of Single Family Homes, 2000 - 2009

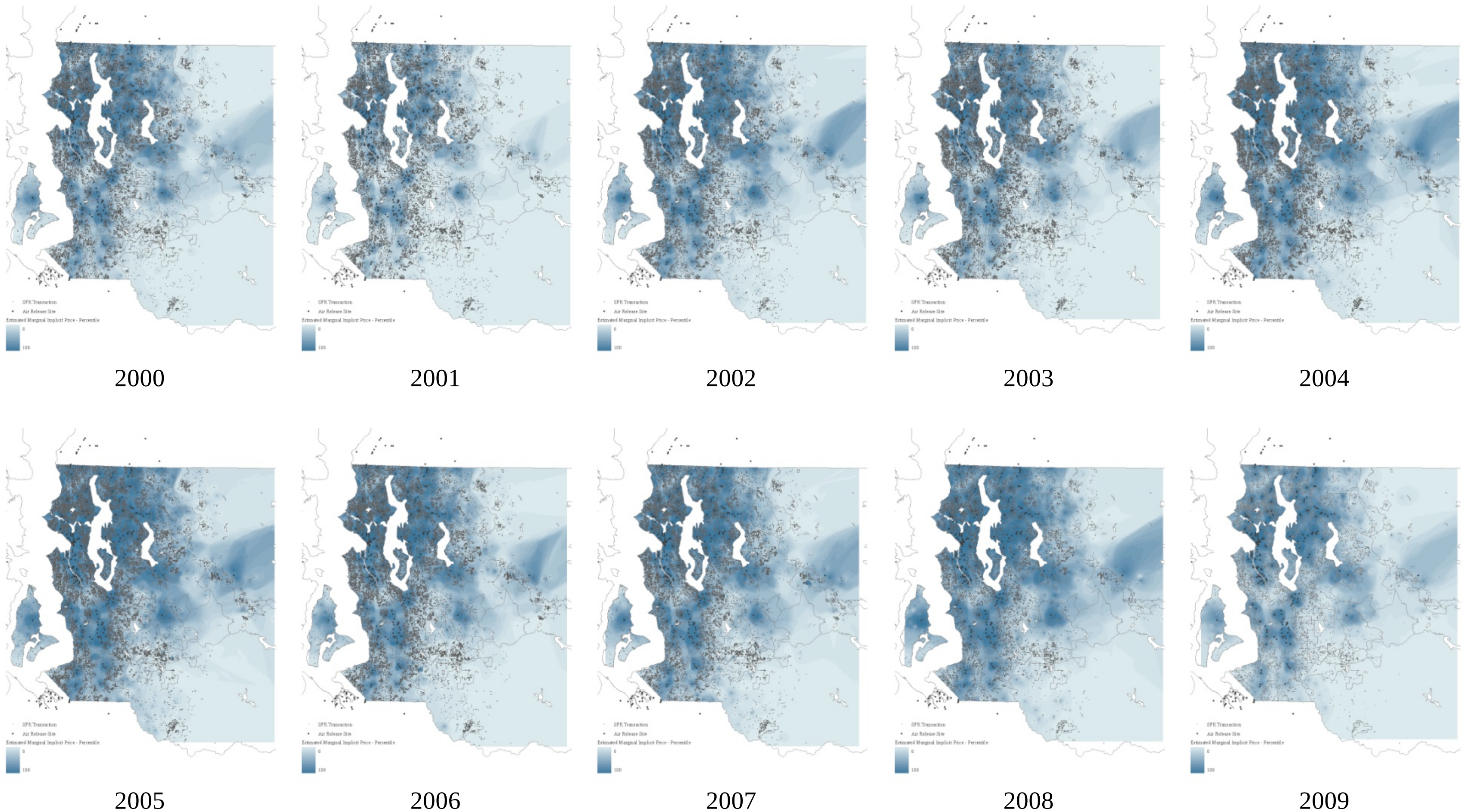

Figure 4. Estimated Marginal Implicit Price ($2010) of Distance from Air Release Sites, 2000 – 2009

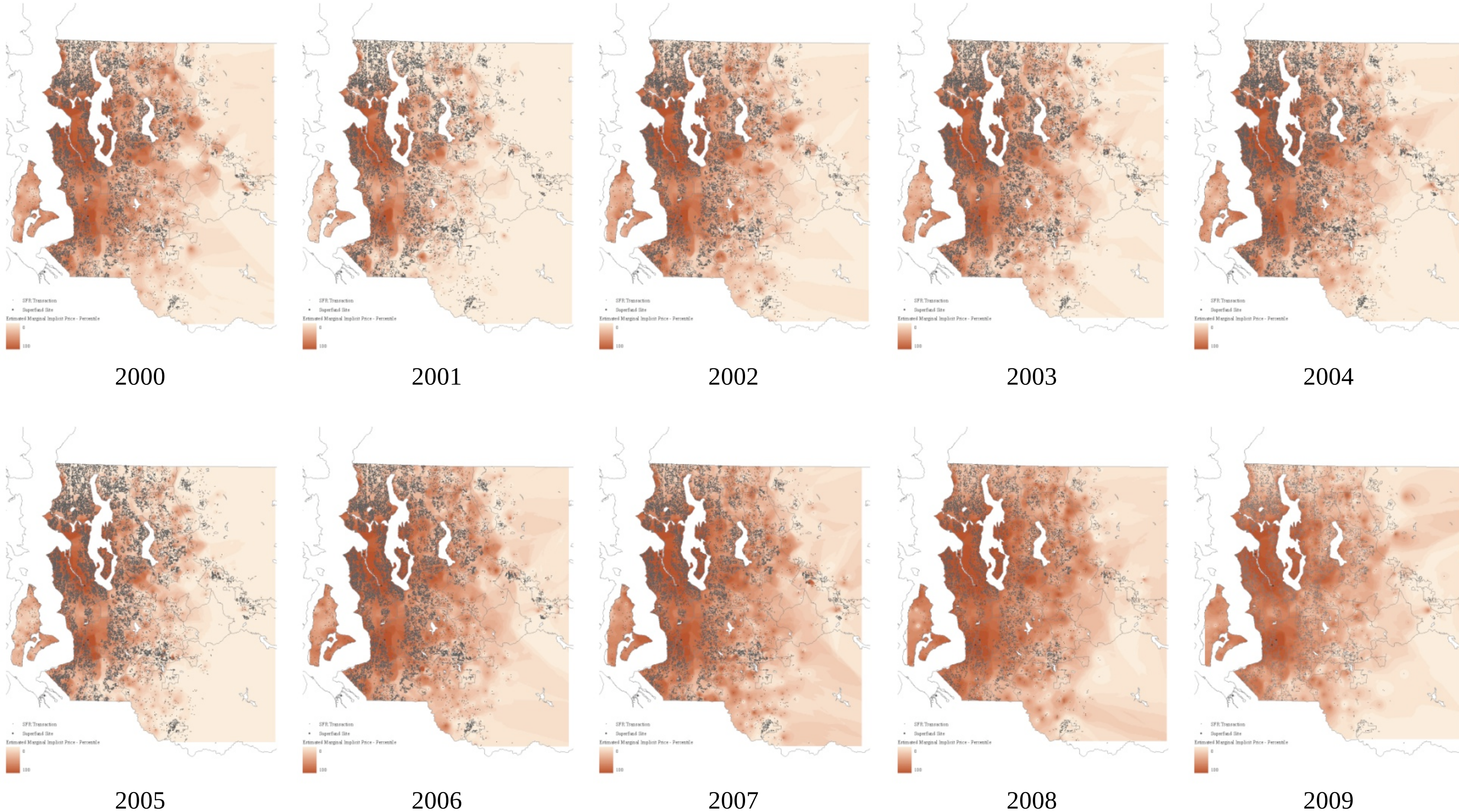

Figure 5. Estimated Marginal Implicit Price ($2010) of Distance from Superfund Sites, 2000 – 2009

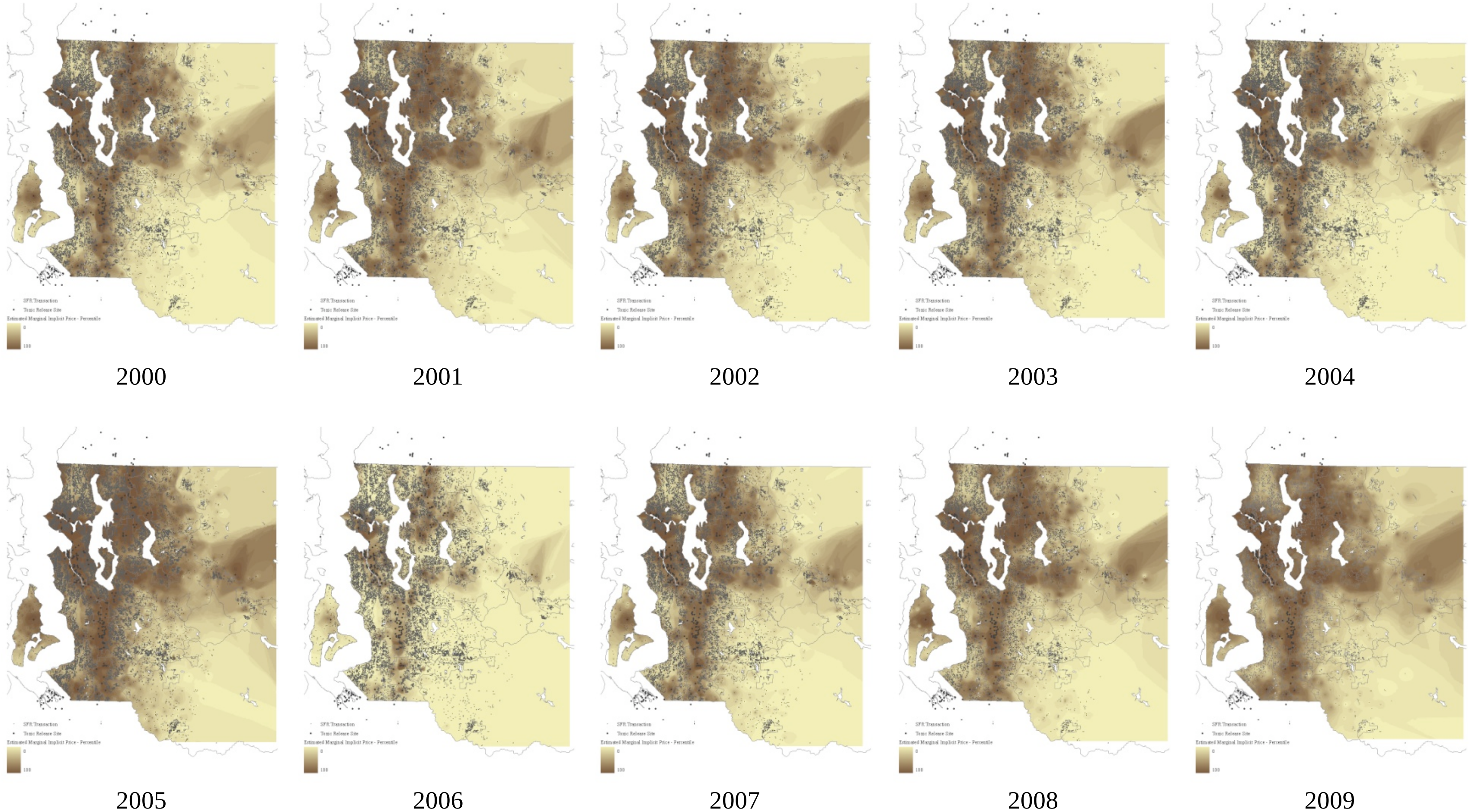

Figure 6. Estimated Marginal Implicit Price ($2010) of Distance from Toxic Release Sites, 2000 – 2009