ASSESSING THE IMPACTS OF ENVIRONMENTAL CONTAMINATION ON COMMERCIAL AND INDUSTRIAL PROPERTIES

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Abstract

Using data for Atlanta, Georgia, hazardous waste sites are found to negatively affect the market values of nearby commercial and industrial properties. Estimates of the total value losses caused by many of the sites are sufficiently large relative to the cost of remediation to justify tax-increment financing as a clean-up option.

I. INTRODUCTION

In order to fully assess the effects and clean-up options of hazardous waste sites (HWS) located within urban areas, evidence is needed on the extent to which these sites reduce nearby property values. In urban areas, of particular interest is the potential effects of HWS on commercial and industrial property values. These land uses are much more likely to be located near HWS as compared to residential properties. A priori, a case can be made both against and in favor of the hypothesis that HWS produce spillover effects on commercial and industrial properties. On the one hand, the marginal investor's willingness to pay for a property may have little to do with its proximity to a HWS because experts in risk assessment argue that these sites generally pose only a small threat to human health and the environment (U.S. Environmental Protection Agency (EPA), 1987). On the other hand, it is not the actual risk, but the perceived risk that affects the willingness to pay. Potential buyers may fear that the contaminants on HWS may migrate to surrounding properties, evaporate and foul nearby air quality, or create a hazard to those who inadvertently cross property boundaries. Survey evidence suggests that these fears result in subjective probabilities that substantially exceed actual probabilities. In the past, survey respondents have ranked toxic waste sites as the number-one environmental problem in the U.S., ahead of nuclear accidents, pesticide residues, and the destruction of the ozone layer (Clymer, 1989).

Studies have found that badly contaminated properties, such as those appearing on the EPA's National Priority List (NPL), reduce the values of nearby single-family homes (Michaels and Smith, 1990, Kohlhase, 1991, and Kiel, 1995).[1] Each study investigates the price-distance relationship (a.k.a. gradient)

[1] Four studies have investigated the related issue of the effects of landfills on surrounding property values: Bleich et al. (1991), Reichert et al. (1991), Nelson et al. (1992) and Guntermann (1995). Similarly, Gwande and Jenkins-Smith (2001) investigate the effects of hazardous waste transportation on residential property values.

by measuring distance from the homes to the closest HWS and relies either wholly or partially on the NPL to determine the location of HWS. Each study also estimates separate gradients for before and after the HWS are announced by the government. Generally, proximity to a HWS is found to decrease housing prices after announcement of the contaminated status of the properties, but little to no negative effects of proximity are found prior to the announcement. The magnitude of the post-announcement effects are found to be substantial (Kiel and Kohlhase both find impacts of approximately $3,000 per mile) and geographically extensive (as far away as six miles in Kohlhase).

While these studies are important for understanding the impacts of HWS on residential property markets, they fail to address two major issues. First, as mentioned earlier, prior studies almost exclusively rely on the NPL to identify sites. However, the vast majority of HWS identified by the EPA and individual state's environmental authorities are not deemed severe enough by these agencies to be placed on the NPL. For example, of the 534 sites the state of Georgia lists as being severely contaminated, only 18 are NPL sites. More importantly, it is not clear whether the results obtained for single-family homes apply to other land uses such as commercial and industrial properties. In many respects, the latter effects are of greater interest. In addition to being more likely to be located near a HWS, commercial and industrial properties are more likely to incur spillover-induced changes in value large enough such that private cost-sharing and tax-increment financing emerge as clean-up options. Understanding the possibilities for creative financing of HWS cleanup is particularly important to policy makers as evidenced by a survey of 231 U.S. cities which for three years in a row ranked a lack of funding as the number one obstacle to HWS remediation and redevelopment (U.S. Conference of Mayors, 2000). In addition, growing concern over urban sprawl has heightened interest in increasing the proportion of commercial and industrial development that occurs within central cities. Fears of potential liabilities from possible migration of hazardous wastes, reluctance of lenders to provide capital for projects involving heightened liability risks, and lack of adequate insurance markets against such liabilities are all factors that may cause developers to favor suburban green-space over central cities. The extent to which properties are discounted as a result of their proximity to HWS gives an indication of the degree to which investors are reluctant to develop in areas surrounding these sites, and their impacts on the urban neighborhoods in which they are located.

The purposes of this paper are two-fold. First, we present evidence on the effects that properties appearing on various government lists of HWS have on the values of nearby commercial and industrial properties. Hedonic price models are estimated using property transactions data from Fulton County, Georgia, which is the central county of the Atlanta Metropolitan Statistical Area. The data are rich enough to implement an empirical approach that recognizes that HWS may emit externalities apart from those caused by the on-site discovery of toxic substances, because many HWS are industrial facilities that can be a source of air and noise pollution. This approach involves 1) estimating separate property price gradients for proximity to listed HWS both before and after the sites are listed, and 2) testing whether these gradients are statistically different from one another. Second, we use the estimated price gradients to examine tax-increment financing as an option for funding the clean-up of the contaminated sites. This involves estimating the aggregate loss in property values surrounding each site and comparing this loss to estimated clean-up costs.

The results show that post-announcement of their contaminated status, sites generate significant negative externality effects on all five of the commercial and industrial land uses we examine, indicating that prices decline with proximity to a contaminated site. In contrast, prior to their discovery by governmental authorities, the sites have only a statistically significant, negative affect on one of the five land uses we consider. In all cases, the post-announcement gradient is steeper than the pre-announcement gradient and these differences are generally significantly different from zero. The magnitudes of the total value losses we estimate based upon these results suggest that tax-increment financing is a viable option for funding the clean-up of many contaminated sites.

II. DATA

The study area is Fulton County, Georgia, which contains almost all of the geographical area of the City of Atlanta and inner-suburban areas lying immediately north and south of the central city. Fulton is a large county with a population of 816,000 and a land area of 529 square miles (Census, 2000). For Fulton County, a complete description and the most recent sales price for every commercial and industrial property appearing on the county tax rolls in 1998 were obtained and combined with three environmental data bases that identified HWS within the county in 1998. The property data are from a commercial vendor (Property Data Systems, Inc.), who purchased the complete tax roll from the county and researched deed transfer records to append to each property its most recent sales price. The three environmental databases are all in the public record and include the Georgia Environmental Protection Division's (EPD) Hazardous Site Inventory (HSI), the EPA's Comprehensive Environmental Response, Compensation, and Liability Information System (CERCLIS), and EPA's No Further Remedial Action Planned Reports (NFRAP).

HSI sites are a subset of suspected contaminated properties that have been screened by the EPD. Each property is scored based upon the Reportable Quantities Screening Method (RQSM).[2] If the score exceeds a threshold level the property is placed on the HSI, otherwise it does not appear on any list. The EPD first published the HSI on July 1, 1994 and since then it has been updated annually. In 1998, there were 31 HSI sites within Fulton County.

CERCLIS is EPA's list of hazardous waste sites. These sites have either been investigated, or are currently under investigation by the EPA for the release, or threatened release of hazardous substances. If severe contamination is found, a CERCLIS site may ultimately be placed on the NPL. In 1998, there were 23 CERCLIS sites in Fulton County, however none of these are listed as NPL sites. The majority of CERCLIS sites were first listed in the early 1980s. The EPA and the Georgia EPD use different screening methods to determine if a site should be placed on CERCLIS or HSI, respectively. As such, it is possible to have a site listed on CERCLIS but not on the HSI, and vice-versa. In Fulton County, there were 10 sites that appeared on both CERCLIS and HSI.

The last list we compile are NFRAP sites which are sites that were initially on the CERCLIS list but were subsequently "de-listed." De-listing occurs for one of three reasons: 1) no contamination is found, 2) contamination is found but quickly removed, or 3) contamination is found but is not judged serious enough to require federal superfund action or NPL consideration. For each NFRAP site the date it became a CERCLIS site and the date it became a NFRAP site (i.e., the de-listing date) are known. In

[2] The RQSM assigns numerical values to the following factors describing the released substance: toxicity, quantity, and physical state, how close the site is to nearby residents and drinking wells, the degree to which the release is contained, the accessibility of the site, whether or not the release has resulted in exposure to nearby residents, and the presence of on-site sensitive environments. A mathematical equation combines these numerical values to calculate a soil and groundwater score. If either of these scores is above their respective threshold level, the site is then placed on the HSI.

1998 there were 96 NFRAP sites in Fulton County.

To compute the proximity of each commercial and industrial property to a HWS, every property in Fulton County was spatially referenced with the use of a digitized tax map obtained from the county. The tax map contains the county parcel-id and latitude/longitude coordinates of the centroids of all properties on the tax roll. The key advantage of using this tax map to spatially reference the properties is that it is accurate to within three feet. The alternative spatial referencing method, address matching, provides only estimates of a property's location along a street segment and can thus produce substantial errors. With the use of ARCVIEW Geographic Information Systems (GIS), linear distances to the nearest HSI, CERCLIS, and NFRAP sites were computed for each property. Distances were also computed to transportation and employment nodes within the county and properties were assigned to census tracts so that neighborhood data could be appended to each property record.

The distances to the nearest HSI and CERCLIS sites are highly correlated (Pearson coefficient of correlation = 0.90), which is not surprising since 44 percent of the CERCLIS sites in Fulton County are also HSI sites. This high correlation precluded separately estimating the spillover effects of CERCLIS and HSI sites and so they were combined to form a single list ("List1") of HWS. Distance to the nearest CERCLIS <u>or</u> HSI site is therefore measured by List1. The listing date assigned to List1 sites is the earlier of either the CERCLIS or HSI listing date. The correlation between the distances to the nearest NFRAP ("List2") site and List1 site is only 0.46, making it possible to estimate separate gradients for List1 and List2 sites.

III. MODEL

The basic hedonic price model estimated to investigate the spillover effects of List1 and List2 sites can be expressed as follows:

$$
\begin{aligned}
P_{it} = {} & a + \sum_{t=1}^{T} b_t D_t + \sum_{j=1}^{J} c_j X_{jit} + d_1\, IDL1_i^{B} + d_2\, IDL1_i^{A} \\
& + e_1\, IDL2_i^{B} + e_2\, IDL2_i^{A} + e_3\, IDL2_i^{D} + w_{it}
\end{aligned}
\qquad \textbf{(1)}
$$

where P_{it} = transaction price of property i at time t, t = 1981 to 1998
D_t = dummy variables indicating the year the property was last sold,
X_j = j property characteristics, including location-oriented variables,
$IDL1^B$ = inverse of distance from property to List1 site (measured in quarter-mile increments) if sale occurred before the site was listed, otherwise 0,
$IDL1^A$ = inverse of distance from property to List1 site (measured in quarter-mile increments) if sale occurred after the site was listed, otherwise 0,
$IDL2^B$ = inverse of distance from property to List2 site (measured in quarter-mile increments) if sale occurred before the site was listed, otherwise 0,
$IDL2^A$ = inverse of distance from property to List2 site (measured in quarter-mile increments) if sale was after the site was placed on CERCLIS but before de-listing, otherwise 0,
$IDL2^D$ = inverse of distance from property to List2 site (measured in quarter-mile increments) if sale was after de-listing (i.e., after site was listed as NFRAP), otherwise 0,
w_{it} = random error.

Equation (1) assumes the price-distance relationship, or price-distance gradient, is described by the reciprocal transformation. Under this transformation, a negative estimated coefficient for the distance variable indicates that price will increase with distance at a decreasing rate approaching an asymptotically constant level. A priori, this is an attractive functional form because it is consistent with the general notion that spillover effects have a greater impact closer to their source but have no effect beyond a certain distance.[3] Equation (1) allows gradients to vary before and after listing in the case of List1, and in the case of List2 sites, to vary before CERCLIS listing, after CERCLIS listing but before delisting, and after delisting. The equation is estimated using sales over the period 1981 to 1998. The length of this period provided a reasonable number of sales for each of the five land uses before and after listing of the HWS.

The control variables (X_j) entering equation (1) are extensive. A complete listing of the variables, their definitions and their sources are available in the appendix. The variables generally fall into three categories: property characteristics that are provided by the tax roll; location-oriented variables that are created with GIS; and location-oriented variables assigned by census tract. Briefly, the property characteristics include the lot-size and the square footage, age, and a quality ranking of the building.[4] Also included are variables describing the exterior wall type, the parking type and adequacy, the type of street the property fronts, and a general location indicator (e.g., business cluster versus major strip). Location oriented variables include distances to the City of Atlanta's central business district, the nearest highway exit, Hartsfield International Airport, and the nearest subway station.[5] The tax jurisdiction of the property (there are 9 jurisdictions in Fulton County) is also recorded. Variables that vary by census tract include

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[3] In studies that have investigated the relationship between the sales prices of single-family residences and distance to a contaminated site, it has either been assumed that price increases with distance at a constant rate (Michaels and Smith, 1990, Kiel, 1995) or that price increases with distance at a declining rate -- thus, peaks and then decreases with additional distance (Kohlhase, 1991). Neither of these functional forms is consistent with the expectation that price increases with distance to a contaminated site at a declining rate, with the effect of distance disappearing completely beyond some distance. Support for the reciprocal transformation is provided by Li and Brown (1980), who find that the externality effects of industry on house prices decrease with distance at an increasing rate and disappear at a distance of 800 meters.

[4] Square footage is for all improvements on a property. Age is the age of the primary structure on the property. Quality rankings are assigned by the tax assessors.

[5] The effects of a number of the control variables are allowed to vary between the north and south sides of the Atlanta metropolitan area. This is based on Bollinger at al. (1998), who found that office rent gradients emanating from the center of the region differed significantly in slope depending on the location (north versus south) relative to the central business district.

population and employment densities, percent of the population that is non-white (obtained from the Atlanta Regional Commission), and the real median household income in the tract (obtained from Donnelly, Inc.). These variables vary by year. Lastly, the percent of land-area that is vacant in the tract in the census year (1980 or 1990) closest to the sale date is included (obtained from the Atlanta Regional Commission).

Equation (1) is estimated separately for five different land uses: apartment buildings, industrial facilities, office buildings, retail buildings, and vacant land. The vacant land category excludes all lots zoned for single-family homes. In preliminary regressions, all 65 control variables were included for each land use (except for the structural descriptors in the vacant land equation). As expected with this number of property descriptors in each equation, there were many variables with imprecise coefficient estimates. In the final regressions reported here, variables with t-statistics less than one were dropped from each equation. Dropping these variables reduced the standard errors of the coefficient estimates indicating proximity to a HWS, but had little effect on their magnitude, which suggests that greater efficiency was obtained without introducing bias. Between 30 and 46 variables remained in the regression models, depending on the land use.[6]

Two final estimation issues remain. The first concerns whether sales price observations should be restricted to only those properties which lie within some maximum distance from a listed site. Contaminated sites are expected to have highly localized impact areas given their possible spillover mechanisms (see Section I). Including sales price observations located outside the reasonable range of impact may cause imprecise estimates of the gradients because they add no useful information, but may introduce noise into the estimation. Our approach was, therefore, to continue to expand the assumed impact area surrounding

[6]Final specifications for each land use are reported in Tables A2 to A6 in the appendix.

a site using quarter mile increments until there was a decline in the precision of the estimated gradients. This occurred between 1.5 and 2.0 miles for each of the land uses. The second issue is whether a correction for heteroskedasticity is necessary. Because the null hypothesis of homoskedasticity is rejected for all land uses, White's (1980) heteroskedastic-consistent covariance matrix estimator is used to correct the estimated standard errors for an unknown form of heteroskedasticity. In addition to considering White's correction for heteroskedasticity, the possibility of spatially auto-correlated errors is also considered in the next section.

IV. RESULTS

The estimated coefficients for the variables indicating proximity to a List1 site are reported in Table 1. The results for the X_j control variables are reported in the appendix. Generally, the signs on the coefficients estimated for the X_j variables are as expected for each of the models estimated.

The apartment, office, and retail equations each explain over 49 percent of the variation in sales price within each of their respective categories (see Table 1). The industrial and vacant land equations perform less well, explaining 27 and 25 percent of the variation in sales price, respectively. The lower R-square for the industrial category likely reflects differences in the value of machinery included in the sales price, which is information not included in the property database. Variables missing for vacant land include the shape and slope of the lot -- variables that vary a great deal given Atlanta's terrain and that strongly effect the development potential of the lot. Because so few hedonic price equations for commercial and industrial property have been estimated, there is no benchmark that can be used to determine the explanatory success of the models estimated. Nevertheless, the R-squares of the models compare favorably to those obtained in the extensive literature that has estimated hedonic price models for single-family homes.

As reported in Table 1, the estimated coefficients for the variables indicating distance to sites not yet listed at the time of sale ("pre-listing distance" or $IDL1^B$) all have negative signs. Because distance enters the regression inversely, these negative coefficients indicate that an increase in the distance to a List1 site prior to the site's listing on CERCLIS or HSI causes price to rise, thus implying a positive price-distance gradient. However, while the pre-listing gradients are positive for the five land-uses, only the estimated coefficient for retail buildings is statistically significant (at the 10% level in a one-tailed test). In contrast, all five post-listing gradients are positively sloped and statistically significant at the 5% level. In all cases, the post-listing gradient is steeper than the pre-listing gradient. For apartment and office buildings, the difference between the pre- and post-listing gradient is statistically significant at the 5% level, while for the other land uses the difference is significant at the 15% level.[7]

To illustrate the magnitude of the spillover effects from List1 sites, the estimated post-listing distance coefficients are used to predict the prices of each type of land use at various distances from a List1 site, holding all other characteristics of the property constant at their sample means (see Table 2). The gradient is steepest for office buildings and flattest for industrial properties. For the average office building, increasing distance from a List1 site from 0.5 miles to 2.0 miles causes a 36% increase in price.[8] In contrast, the price of the average industrial property increases only 3% with this additional distance to a

[7]It is not surprising that the difference between the pre- and post-listing gradients is significant at only the 15% level for retail, industrial and vacant properties given the large standard errors associated with the pre-listing coefficients.

[8]A starting distance of 0.5 miles is used rather than a lesser distance because the distance is measured from the center of the contaminated site to the center of the property that sold. A 0.5 mile distance therefore implies a closer distance between property boundaries.

List1 site. The increase in price for apartments, vacant land, and retail are 23%, 16%, and 12%, respectively. Hence, except perhaps for industrial properties, the spillover effects from List1 sites are non-trivial in magnitude.

Table 3 reports the estimated distance coefficients for List2 sites. In contrast to the results obtained for List1 sites, the spillover effects from List2 sites are weaker and are generally not significant. None of the pre-discovery or post-delisting gradients are statistically significant. The post-discovery (but prior to delisting) coefficients are statistically significant for apartments and offices, with both coefficients indicating a positive price-distance gradient. In the case of apartment buildings, the post-discovery gradient is significantly different from the pre-discovery and post-delisting gradients, which suggests that listing of a site on CERCLIS creates a negative spillover effect on nearby properties, but the effect disappears once the site becomes de-listed. For office buildings, this also appears to be the case, however, the results are more equivocal than those for apartments because the difference between the post-discovery and post-delisting gradients are not statistically different (the same is true for pre-listing and post-discovery). It is noteworthy that apartment and office buildings are the land uses that yielded the strongest spillover effects from List1 sites; hence, there is consistency between the results obtained for List1 and List2 sites in terms of their relative effects across land uses.

The question arises as to why the sites on List2, even though they appear on CERCLIS at some point, are treated differently by the market than List1 sites. These results may be due to significant differences in the perceived hazardousness of List1 and List2 sites. If purchasers are aware that the property is listed, then it is reasonable to assume they also know the status of the EPD's or EPA's investigation of the site since this is easily obtainable public information. While the NFRAP sites would have appeared on CERCLIS after initial "discovery" of the site, the EPA records would indicate, in most cases, that no site assessments had taken place (the majority of NFRAP sites appeared to be de-listed at the time of their first assessment). Investors may place a low probability on a site's potential for causing future problems until assessments are completed. By contrast, sites that are "discovered" by the Georgia EPD are not placed on the HSI until after a site has been screened and found to be hazardous based on known releases. Recall that of the 44 sites on List1, 31 sites or 70% are HSI sites. Of the remaining 13 List1 sites (which are only on CERCLIS and not cross-listed with HSI), two-thirds of these sites were first listed in 1980 or 1981 and the EPA had assessed 70% of these sites by 1985. The fact that these sites had been assessed and remained listed for many years without being delisted may be a signal to investors that the site may have significant problems.

While the results reported in Tables 1 and 3 support the hypothesis that contaminated sites reduce the values of nearby property values, the estimated models that have generated these results are limited in two respects: they do not account for possible spatial autocorrelation, and they ignore possible property value impacts resulting from the density of contaminated sites in the vicinity of the property. Additional results that address each of these issues are discussed below.

As noted by Bell and Bockstael (2000), spatial autocorrelation is likely in a hedonic model of property values because property parcels located in proximity to one another will have similar unobservable characteristics. If errors are spatially dependent, the OLS estimator remains unbiased, but is not longer efficient. As a result, inference based on t-statistics will be misleading.

In order to test for spatial autocorrelation a spatial weights matrix must be specified that assumes a form for the underlying relationship among errors. Bell and Bockstael suggest that the distance-decay type of spatial weights matrix is most applicable to microeconomic data since it implies that more distant neighbors are less closely related. A common distance-decay matrix (and the one used by Bell and Bockstael) assumes that the elements of the spatial weights matrix are equal to the inverse of distance between properties raised to a power for distances less than some critical cutoff point. Beyond this critical distance cutoff, it is assumed that there is no dependence among errors. The specification of this spatial weights matrix requires that a power and cutoff distance be chosen. We choose a cutoff distance of 3 miles for two reasons. First, this is the smallest distance cutoff that guarantees that all observations have at least one neighbor and secondly, this distance seems sufficiently large to allow for almost any type of spatial dependence. For our choice of power, we alternatively used the values 1 and 2.

A Robust Lagrange multiplier test was used to test for spatial autocorrelation for all five of our hedonic models. This test is recommended by Anselin, et al. (1996) as it has good finite-sample properties and is robust to local mis-specification of the spatial dependence. The null hypothesis of no spatial autocorrelation could not be rejected at the 95 percent level of confidence for the office, industrial, and vacant land models. For the retail and apartment models, however, the null hypothesis is rejected at the 95 percent confidence level.

To address the spatial autocorrelation found for the retail and apartment models, a spatial error model was estimated based on the assumption of a spatial autoregressive process for the error term (SAR).[9] For List1 sites, the SAR models yielded results highly similar to those obtained with OLS. For

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[9]The software package SpaceStat Software for Spatial Data Analysis, Version 1.90 (Allen, Texas; SpaceStat (http://www.spacestat.com), 1998) was used to estimate the SAR models, and the models implemented assume homoskedastic errors. As noted above, this assumption is likely to be violated by our data. Nonetheless, the results obtained from estimating a spatial error model provides an indication of whether spatial autocorrelation substantially affects the conclusions we have drawn from our estimated OLS models.

retail, the estimated pre-listing distance coefficient is -30,314 (s = 26,133) in the SAR model versus -29,976 (s = 19,652) in the OLS model. The estimated post-listing coefficient is -80,029 (s = 49,401) versus -80,335 (s = 44,901). For apartments, the estimated pre-listing coefficient from the SAR model is -73,003 (s = 224,341) versus 63,518 (s = 110,190) in the OLS model. The estimated post-listing coefficient is -340,007 (s = 204,952) versus 331,532 (s = 122,952). Hence, based upon both the SAR and OLS results, we can conclude that contaminated sites have important spillover effects on the values of retail and apartment properties after the sites appear on either CERCLIS or the HSI.

The SAR and OLS model results are also similar for List2 sites, with one exception. The similarities are that for both models: 1) all the distance coefficients are statistically insignificant for retail, and 2) the pre-discovery and post-delisting coefficients are insignificant for apartments. The exception is that the post-discovery distance coefficient for apartment properties is less statistically significant in the SAR model (-193,603, s = 163,279) in comparison to the OLS model (-197,334, s = 107,124).

Turning to the effects of HWS density on property values, we explore whether density has an independent effect on property values. It may be that an increase in the total number of contaminated sites within a certain distance of the property reduces property values. Excluding measures of density could therefore result in omitted variable bias. In addition, if contaminated sites are spatially clustered, a decline in the property's distance to the nearest site will be correlated with the density of sites. If this is the case, ignoring density effects will upwardly bias our estimated gradients (i.e., they will appear steeper than they actually are).

To test for density effects, a count of the number of HSI and CERCLIS sites within 1.5 of each property sale (not including the closest site) is incorporated in the analysis. Analogous to the inclusion of pre- and post-listing distance variables, two count variables are created. The first is the number of List1 sites within 1.5 miles of a property that had not yet been listed at the time of sale (PRECOUNT), and the second is the number of List1 sites within 1.5 miles that had been listed at the time of sale (POSTCOUNT). Approximately 50% of the properties in our database has more than one List1 site within 1.5 miles. The exception is industrial properties where approximately 70% of the properties had more than one List1 site within 1.5 miles at the time of sale. The simple correlation coefficients between the post-listing inverse distance variable ($IDL1^A$) and POSTCOUNT indicate a positive, but weak correlation across land uses (the values range between 0.10 for XXX properties and 0.30 for industrial properties).

Equation (1) is re-estimated including the two count variables. Results indicate that the POSTCOUNT variable is negative and statistically significant for only the industrial and vacant land categories. In addition, the difference between the estimated PRECOUNT and POSTCOUNT coefficients is not significantly different from zero (at a 10% level in a one-tailed test) for any of the five land-uses. Importantly, the magnitude of all the estimated coefficients (both pre-listing and post-listing) for distance to the closest site and their levels of statistical significance are unchanged as compared to those reported in Table 1. Thus, it appears that in our application, the primary spillover effect of contaminated sites occurs through proximity to the closest site and density is less important.

V. PROPERTY VALUE LOSSES CAUSED BY CONTAMINATED SITES

To fully assess the impacts of HWS on the urban market we study, the estimated reduction in property value associated with being located near a List1 site is computed. The reduction in property value, ªP, for property i of land-use type j is given by:

$$\Delta \hat{P}_{ij} = \hat{P}_{ij}^{B} - \hat{P}_{ij}^{A} = (\hat{d}_{1j} - \hat{d}_{2j}) \frac{1}{DL1_{i}} . \tag{2}$$

In equation (2), the property value change associated with its proximity to a List1 site is equal to difference in the estimated price of the property before and after a contaminated site is listed on the HSI or CERCLIS. This price differential equals the difference in the estimated coefficients for $IDL1_i^B$ and $IDL1_i^A$ (defined in equation 1) weighted by the distance of property i to the nearest List1 site (DL1). The coefficients, d_1 and d_2, are specific to each of the five land-use types. The property value loss is computed for every property that is one of the five land-use types and is within a 1.5-mile radius of a List1 site, regardless of whether or not the property actually sold during our study period. The estimated value loss for properties within a particular land use category are summed to compute the total estimated property-value losses in Fulton County for each land use type.[10] The losses are substantial, with a minimum of $54 million for industrial properties and a maximum of $377 million for apartments (see Table 4). The magnitude of the property value losses for offices is $347 million, similar to that for apartments. Vacant properties also have substantial price impacts with losses of $231 million, while the losses for retail and industrial properties are approximately a quarter the size of the first three land-uses ($54 and $64 million, respectively).

To put these losses in context, they are compared to estimates of the total value of all properties located within a 1.5-mile radius of a List1 site. Our measure of value for each property is its 1997 fair-market value as estimated by the Fulton County tax assessors. Total estimated losses across all five land

[10] If a property is within 1.5 miles of more than one HSI or CERCLIS site, the value loss associated with the property is only computed based on proximity to the nearest site.

uses equals $1 billion, which is approximately 10% of the total fair-market value of all properties within a 1.5-mile radius of the 44 sites listed on CERCLIS or HSI in Fulton county.[11] This percentage should be interpreted as an upper-bound estimate since fair market values generally understate market prices because assessors' estimates of value lag behind changes in actual market prices.

Given the large total impacts of the contaminated sites in Fulton County, it may be feasible to utilize tax increment financing (TIF) to remediate some of these sites. In a TIF program, the local government would issue bonds in an amount sufficient to fund clean-up efforts at a contaminated site. The tax revenue to repay the bonds would come from the increased tax revenue associated with the incremental increases in property values surrounding the HWS post-cleanup. If TIF is to be feasible, the expected increases in property values surrounding a site post-remediation have to be of a magnitude sufficient to pay the annual debt service and to repay the bonds at their maturity. To determine if this will be the case for any of the sites in Fulton County, we sum the estimated property value changes (as given in equation (2)) for all properties located within 1.5 miles of a particular HSI or CERCLIS site and assume this would be the realized gain in property value should the site be cleaned. This assumption is valid if two conditions are satisfied. First, site cleanup must affect only a small part of the total real estate market for each land-use type. Otherwise, the hedonic equilibrium price schedule would shift and it would be indeterminant how

[11]The total fair market value is based on all non-residential land-uses within a 1.5 mile radius of a HWS. There were 13,230 properties within 1.5 miles of a HWS in our database, and of these, 10,270 are one of the five land-use types for which we estimate hedonic price functions. The land-uses for which we did not estimate gradients roughly fall into 3 major categories: auto-oriented (gradients were estimated in prior research, and never found to be significant), parking, and public land-uses such as schools, hospitals, and utilities. The total losses of $1 billion represents approximately 5% of the total tax assessed value of all non-residential land-uses in all of Fulton County (23,079 properties). While this may seem large relative to the losses within 1.5 miles (10% of total fair market value), it is not considering the 13,320 properties within 1.5 miles of a HWS represent approximately one-half of the total fair market value of non-residential properties in all of Fulton County.

property values would respond ex-post to HWS remediation. In the context of a TIF program targeting only a few contaminated sites, this is likely to be the case. Second, there must be no stigma effects associated with sites once they are cleaned. The results reported for NFRAP sites in the previous section suggest that this condition is satisfied for commercial and industrial properties. For the two land-uses which indicated a significant, negative impact of proximity to a NFRAP site while it was listed on CERCLIS, the negative effects were not present once the site had been delisted.

The estimated value gains for properties surrounding individual HWS sites in Fulton County are substantial. Three CERCLIS sites could each result in value gains for properties within 1.5 miles of the site of over $74 million should the sites be remediated. These sites are located within the Atlanta city limits, and the areas surrounding the sites are densely developed with commercial properties. Once these value gains are realized, the increased property tax revenues associated with remediation would be over $1.5 million per annum, per site.[12] There are 13 CERCLIS and HSI sites for which surrounding property values could increase by $25 to $50 million, implying property-tax increases of between $500,000 and $1 million per annum, per site, should the sites be remediated. There are twelve sites for which surrounding values could increase by $10 to $25 million and the remaining 16 CERCLIS and HSI sites would generate property value increases of less than $10 million should they be remediated.

Of course, the potential property value gains and associated tax-revenue increases must be compared to the potential costs of remediation. While information on cleanup costs at specific sites are not available, the Georgia EPD has completed investigation and cleanup at 113 HSI sites throughout

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[12]Commercial and industrial properties are taxed on 40% of their estimated fair market value at a millage rate of 5% in Fulton County. Thus, the expected increase in tax revenue from a TIF program to cleanup a site is 2% of the total expected increase in property value around that site.

Georgia at a total cost of $73.6 million, or $651,327 per site. The EPD estimates an average cleanup cost of less than $1 million per site for the remaining HSI sites in Georgia.[13] However, private parties have argued that average cleanup costs within Fulton County are likely to be much larger, on the order of $10 million per site.[14] With such a large range in the expected cleanup costs, three possible cost-of-cleanup scenarios are considered: $1, $5, and $10 million.[15] These bond issuances imply an annual debt service of either $60,000, $300,000 or $600,000, respectively (the municipal bond interest rate is assumed to equal 6%).[16]

The number of sites that are candidates for TIF programs under each of the three remediation cost scenarios are summarized in Table 5. The results are quite promising for implementing TIF programs in Fulton County. Assuming the highest remediation costs of $10 million per site, four sites are candidates for tax-increment financing of remediation with 15-year bonds, and two additional sites could be financed with 30-year bonds. If remediation costs are instead $5 million per site, nine sites could be financed with 15-year bonds and six additional sites could be financed with 30-year bonds. At costs closer to the Georgia EPD's estimates of remediation costs ($1 million per site), 27 sites, or 60% of the total number of sites in Fulton County would be candidates for remediation financing with 15-year bonds.[17]

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[13]"Cleaning Up Georgia's Hazardous Sites," Environmental Protection Division, Georgia Department of Natural Resources, Hazardous Sites Response Program, January, 2001.

[14]Costs estimates by private parties were reported to one of the authors in conversations with local regulatory authorities.

[15]These costs are assumed to include transactions costs of bond-issuance, which can be as much as $200,000 for the issuance of $1,000,000 in bonds.

[16]The average issue size of TIF bonds across U.S. municipalities is $6 million, which is considered small by financial markets (Johnson and Man, 2001, p.74-75).

[17]These calculations assume immediate increases in tax-assessments of the property's post clean-up and a 1-year time horizon for cleanup.

If only the CERCLIS and HSI sites within the City of Atlanta are considered, the chances that TIF could serve as a clean-up financing option are even better. Of the 26 sites located in the City of Atlanta, 8 of them, or 31% could be remediated with 15 year bonds assuming a clean-up cost of $5 million (see Table 5). The percentage of HWS that could be remediated with a 15 year bond if the cost is only $1 million per site is 81%.

V. CONCLUSIONS

In this research, hedonic property value models are estimated for commercial and industrial properties to assess the possible externality effects arising from sites known to have had hazardous waste releases. Our results suggest that properties surrounding these sites experience nontrivial reductions in property value. Significant price-distance gradients are found for all five of the commercial and industrial land-uses we consider. Property value losses in Fulton County, Georgia resulting from sites recorded as having environmental contamination on state and federal databases may be as large as $1 billion.

The magnitude of the spillover effects from hazardous waste sites estimated in this study are particularly interesting from a policy perspective. The property value changes estimated here would appear to be sufficiently large to justify private cost-sharing and tax-increment financing as clean-up options. This is especially true for the City of Atlanta, where hazardous waste sites are concentrated and surrounding property value losses per site are especially large. A TIF program in the City holds the promise of improving the City's poor financial position and may help the region in its struggle against worsening urban sprawl by stimulating economic development within the central city.

While our results are specific to Atlanta, and care should therefore be taken in applying them to other areas, they do suggest that property value losses from hazardous waste sites may be an important phenomenon in other metropolitan areas. There are many sites of the type that we consider within most of these areas and there is little reason to believe that Atlanta investors are atypical in their perceptions of the risks associated with these sites.

Table 1. Estimated coefficients for List1 sites.[a]

	Apartments Model 1	Offices Model 1	Retail Model 1	Industrial Model 1	Vacant Land Model 1
Pre-Listing Distance ($IDL1^B$)	-63,518 (110,190)	-1,109 (81,890)	-29,976** (19,652)	-9,462 (26,512)	-36,382 (83,113)
Post-Listing Distance ($IDL1^A$)	-331,532*** (122,952)	-1,033,108*** (404,692)	-80,335*** (44,901)	-42,838*** (24,038)	-168,067*** (95,922)
Difference†	-268,014*** (121,558)	-1,031,999*** (391,714)	-50,360* (47,400)	-33,376* (30,257)	-131,684* (120,621)
R-Squared	0.569	0.560	0.491	0.273	0.252
Obs.	1229	260	816	644	582

[a] Standard errors in parentheses.
* Significant at the 15% level in a one-tailed test.
** Significant at the 10% level in a one-tailed test.
*** Significant at the 5% level in a one-tailed test.
† This coefficient is from a separate regression in which $IDL1^B$ and $IDL1^A$ are combined into one variable, IDL1, and IDL1 is interacted with a dummy variable for whether or not the sale occured prior to the listing of the nearest contaminated site (POST). The coefficient reported is for the variable POST*IDL1 and is the difference between the coefficients for $IDL1^B$ and $IDL1^A$ and it is used to test for significant differences in these two coefficients.

Table 2. Predicted sales prices at various distances from List1 sites.

Distance from Contaminated site	Apartments	Offices	Retail	Industrial	Vacant Land
0.50 miles	533,039	1,063,412	251,459	501,845	400,399
0.75 miles	589,400	1,239,040	265,116	509,127	428,970
1.00 miles	615,922	1,321,689	271,542	512,555	442,415
1.25 miles	632,499	1,373,344	275,559	514,696	450,819
1.50 miles	643,439	1,407,437	278,210	516,110	456,365
1.75 miles	651,396	1,432,379	280,138	517,138	460,398
2.00 miles	657,364	1,450,828	281,584	517,909	463,424
% change in price from 0.5 to 2 miles	23	36	12	3	16

Table 3. Estimated coefficients for List2 sites.[a]

	Apartments	Offices	Retail	Industrial	Vacant Land
Pre-Listing	94,557	-563,838	4,331	-49,158	-147
($IDL2^B$)	(115,702)	(941,449)	(10,148)	(39,215)	(82,000)
Post-Discovery	-197,344***	-287,726**	1,195	-19,514	-13,528
($IDL2^A$)	(107,124)	(188,534)	(11,282)	(26,895)	(43,654)
Post-Delisting	52,487	-126,480	4,035	38,100	-40,918
($IDL2^D$)	(66,954)	(238,554)	(11,053)	(25,591)	(76,722)
R-Squared	0.569	0.560	0.491	0.273	0.252
Observations	1229	260	816	644	582

[a] Standard errors in parentheses.
** Significant at the 10% level in a one-tailed test.
*** Significant at the 5% level in a one-tailed test.

Table 4. Total Property Value Losses Due to HSI and CERCLIS sites in Fulton County.

	Apartments	Office	Retail	Industrial	Vacant	Total
# of Properties	2,823	703	2,167	1,868	2,709	10,270
Total Value Loss ($ millions)	377	347	63.5	54.3	231	1,073
Total Value Loss / Total Assessed Value	0.18	0.13	0.07	0.05	0.19	0.10

Table 5. Summary of the number of candidate HSI and CERCLIS sites for tax-increment financing of cleanup costs.[a]

	Remediation Costs		
Bond Duration	$1 million	$5 million	$10 million
5-year bond	15 sites (13)	4 sites (3)	1 site (1)
15-year bond	27 sites (21)	10 sites (8)	4 sites (3)
30-year bond	33 sites (25)	15 sites (13)	6 sites (5)

[a] There are 44 unique HSI and CERCLIS sites in Fulton County. The number of candidate sites that lie within the Atlanta City limits are reported in parentheses.

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APPENDIX

Table A.1. Description of variables used in hedonic price analysis.

Variable Name	Description
	Property Characteristics: Obtained from Property Data Systems, Inc.
saleprice	Most recent sales price of the property.
yr5-22	Dummy variables indicating the year in which the property sold for the years 1981 to 1998.
sqft (sqft2)	Square feet, in thousands of feet, of all improvements on a property (square feet squared).
numimp	Number of improvements on a property.
acre (acre2)	Acreage of the property (acreage squared).
age (age2)	The age of the primary improvement (age squared).
gradeab, gradec	Dummy variable indicating the structures on the property were scored by the tax assessors with an A or B rating, the two best possible ratings on a scale of A through E. Gradec indicates the property received a quality scoring of C. Gradeab and gradec are compared to grades D or E, the two categories left out of the models. D and E are combined due to small numbers of observations receiving an E score.
concrete	Dummy variable indicating whether the exterior wall of the primary structure is concrete.
glass	Dummy variable indicating whether or not the exterior wall of the primary structure was glass.
frame	Dummy variable indicating whether or not the exterior wall of the primary structure was frame.
extmisc	Dummy variable indicating whether or not the exterior wall of the primary structure was combined wall types.
brick	Dummy variable indicating whether or not the exterior wall of the primary structure was brick (category left out of the models).
pkadeq	Dummy variable indicating whether or not the property has adequate parking.
front2	Dummy variable indicating if the property fronts a major strip.
loccod2-loccod9	Dummy variables indicating the type of location for the property. Categories are: CBD or permanent CBD (loccod2), business cluster (loccod3), major strip (loccod4), secondary strip (loccod5), neighborhood or spot (loccod6), commercial/industrial park (loccod7), industrial site (loccod8), apartment/condominium (loccod9). The category not included in the model varies across land uses.

Variable Name	Description
ad1-ad3	Dummy variables indicating specific land-use codes within apartments and hotels. Categories are: non-high-rise apartments (ad1), hotels/motels (ad2), nursing/boarding homes (ad3).
rd1, rd2	Dummy variables indicating specific land-use codes within retail. Categories are eating and drinking establishments (rd1), and fast food (rd2).
od1	Dummy variable indicating land-use is a high-rise office.
manuf	Dummy variable indicating industrial land use is for manufacturing.
d1-d4	Dummy variables indicating specific land-use codes within industrial, other than manufacturing. Categories are: cold storage (d1), truck terminal (d1), mini warehouse (d1), prefab warehouse (d1). Category not included in the model is warehouse.
Location-Oriented Variables: **Created with ARCVIEW Geographic Information Systems**	
juris1-9	Dummy variables indicating the tax jurisdiction in which the property is located. Categories are: Alpharetta (juris1), Atlanta (juris2), College Park (juris3), East Point (juris4), Fairburn (juris5), Fulton County unincorporated (juris6), Hapeville (juris7), Palmetto (juris8), Roswell (juris9). Category not included in the model varies by land-use type. Sales included in our models did not occur in every jurisdiction for each land use.
north	Dummy variable equal to one of the property is located north of the central-point of the central business district.
cbd (ncbd)	Distance to the center-point of the central business district. The center is the central public rail transit station (5-points MARTA station) in downtown Atlanta (distance to the center-point of the central business district interacted with the dummy variable 'north').
marta1	Dummy variable equal to one if a property was within one mile of a MARTA station at the time of sale.
exit (nexit)	Distance to the nearest highway exit (distance to the nearest highway exit interacted with the dummy variable 'north').
harts (harts2)	Distance to Hartsfield International Airport (distance to the airport squared).

Variable Name	Description
Census-tract Variables: Obtained from the Atlanta Regional Commission (ARC) and Donnelly, Inc.	
rmedinc [from Donnelly, Inc.]	Real median income, by year, of the census tract in which the property is located. Real median income for years 1981-1989 and 1991-1996 are estimated based on census data from 1980 and 1990. Estimates for 1997 were not available and so sales in 1997 are assigned values from 1996.
popden (npopden) [from ARC]	Population density (persons per acre of land), by year, of the census tract in which the property is located. Population densities in non-census years are assigned in the same manner as described for rmedinc (population density interacted with dummy variable 'north').
empden (from ARC)	Employment density (workers in all sectors per acre of land), by year, of the census tract in which the property is located. Employment densities in non-census years are assigned in the same manner as described for rmedinc.
minority (nminority) [from ARC]	Percent non-white in the census tract in which the property is located. Racial compositions in non-census years are estimated by ARC by conducting field surveys (minority interacted with the dummy variable 'north').
vacant (from ARC)	Percent of the land-area that is vacant in the census year closest to the sale date in the census tract in which the property is located.
Proximity to Listed Sites Variables: Created with ARCVIEW Geographic Information Systems	
IDL2B	Inverse of distance from property to List2 site (measured in quarter-mile increments) if sale occurred before the site was listed, otherwise 0.
IDL2A	Inverse of distance from property to List2 site (measured in quarter-mile increments) if sale was after the site was placed on CERCLIS but before de-listing, otherwise 0.
IDL2D	Inverse of distance from property to List2 site (measured in quarter-mile increments) if sale was after de-listing (i.e., after site was listed as NFRAP), otherwise 0.
IDL1B	Inverse of distance from property to List1 site (measured in quarter-mile increments) if sale occurred before the site was listed, otherwise 0.
IDL1A	Inverse of distance from property to List1 site (measured in quarter-mile increments) if sale occurred after the site was listed, otherwise 0.

Table A.2. Hedonic model for apartments.

Dependent variable = saleprice
Number of obs = 1229
Prob > F = 0.0000
R-squared = 0.5691

Variable	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
constant	66821.36	1485653	0.04	0.964	-2847990	2981632
yr6	-460621	262062	-1.76	0.079	-974779.5	53537.51
yr7	-275240.6	166425.3	-1.65	0.098	-601762.6	51281.41
yr8	286564.8	148199.1	1.93	0.053	-4197.915	577327.4
yr11	671322.9	538183.8	1.25	0.213	-384579.1	1727225
yr17	-60249.6	123822	-0.49	0.627	-303185	182685.8
yr21	191325.7	126084.8	1.52	0.129	-56049.33	438700.7
yr22	324016.4	156522.3	2.07	0.039	16923.85	631109
sqft	48446.11	17556.2	2.76	0.006	14001.31	82890.91
sqft2	-30.03152	11.58094	-2.59	0.010	-52.75301	-7.310025
numimp	-214417.3	182385.7	-1.18	0.240	-572253.1	143418.5
acre	406362.4	221661.4	1.83	0.067	-28531.25	841256
acre2	-5244.856	4965.984	-1.06	0.291	-14987.98	4498.271
age	24925.92	26439.02	0.94	0.346	-26946.71	76798.56
age2	-230.0982	212.4779	-1.08	0.279	-646.9742	186.7777
gradeab	1414677	569933.6	2.48	0.013	296482.9	2532872
concrete	376071.4	345302.8	1.09	0.276	-301403.5	1053546
glass	-2826689	1104151	-2.56	0.011	-4993004	-660374.2
frame	-86871.12	105315.4	-0.82	0.410	-293497.1	119754.8
pkadeq	57108.99	77467.73	0.74	0.461	-94880.59	209098.6
loccod2	1317843	1331736	0.99	0.323	-1294987	3930673
loccod3	5251213	4612475	1.14	0.255	-3798338	1.43e+07
loccod4	666520.4	1159898	0.57	0.566	-1609169	2942209
loccod5	948394	1149255	0.83	0.409	-1306413	3203201
loccod6	832341.1	1154098	0.72	0.471	-1431969	3096651
loccod7	-317939.9	1267232	-0.25	0.802	-2804215	2168335
loccod9	860891	1137624	0.76	0.449	-1371097	3092879
ad1	-126507.8	112433.8	-1.13	0.261	-347099.8	94084.27
ad2	1854362	727941.7	2.55	0.011	426160	3282564
ad3	-259787.7	204262	-1.27	0.204	-660544.2	140968.9
juris4	181334.2	245061.4	0.74	0.459	-299469.7	662138.2
juris5	1425321	698737.9	2.04	0.042	54416.63	2796226
north	104496.1	472082.3	0.22	0.825	-821716.6	1030709
marta1	-197582.5	123498.8	-1.60	0.110	-439883.8	44718.76
nexit	-737435.3	239572.3	-3.08	0.002	-1207470	-267400.8
harts	-412928.1	111512.2	-3.70	0.000	-631712.1	-194144.1
harts2	39841.31	10278.45	3.88	0.000	19675.26	60007.36
rmedinc	-38.56709	18.54357	-2.08	0.038	-74.94907	-2.185106
npopden	43204.58	25043.72	1.73	0.085	-5930.514	92339.68
vacant	-25470.58	8825.014	-2.89	0.004	-42785.02	-8156.137
nmin	-32177.62	330555.4	-0.10	0.922	-680718.3	616363.1
empden	-14754.58	7169.63	-2.06	0.040	-28821.2	-687.957
IDL1B	**-63518.04**	**110190.2**	**-0.58**	**0.564**	**-279708.3**	**152672.2**
IDL1A	**-331531.8**	**122951.7**	**-2.70**	**0.007**	**-572759.8**	**-90303.8**
IDL2B	**94556.65**	**115702.1**	**0.82**	**0.414**	**-132447.8**	**321561.1**
IDL2A	**-197344.5**	**107123.9**	**-1.84**	**0.066**	**-407518.8**	**12829.79**
IDL2D	**52487.34**	**66953.77**	**0.78**	**0.433**	**-78874.14**	**183848.8**

Table A.3. Hedonic model for offices.

Dependent variable = saleprice
Number of obs = 260
Prob > F = 0.0000
R-squared = 0.5598

Variable	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
constant	-2116310	940768.8	-2.25	0.025	-3969980	-262641
yr7	956311.9	391023	2.45	0.015	185849.1	1726775
yr9	673992.4	364558.8	1.85	0.066	-44325.91	1392311
yr10	876186.1	306860.6	2.86	0.005	271554.9	1480817
yr11	1075741	382935.7	2.81	0.005	321213.5	1830269
yr12	1035500	406288.2	2.55	0.011	234959.5	1836041
yr13	1720168	404294.3	4.25	0.000	923555.9	2516780
yr18	1596513	431912.1	3.70	0.000	745483.4	2447543
yr19	504166.7	478625.7	1.05	0.293	-438906.4	1447240
yr20	1127149	633678.7	1.78	0.077	-121437.2	2375735
yr21	1653700	451360.5	3.66	0.000	764349.1	2543050
sqft	28735.37	11487.25	2.50	0.013	6101.151	51369.59
sqft2	-88.80679	25.6311	-3.46	0.001	-139.3097	-38.30384
numimp	469044.3	297841.1	1.57	0.117	-117815	1055904
acre2	25250.13	12318.63	2.05	0.042	977.7895	49522.48
concrete	1344741	400959.7	3.35	0.001	554698.8	2134782
glass	1177030	936532.6	1.26	0.210	-668292.5	3022352
extmisc	-259036.3	275447.4	-0.94	0.348	-801771.6	283699
pkadeq	660221.7	404911.2	1.63	0.104	-137606.1	1458049
front2	858262.6	321625.4	2.67	0.008	224539.3	1491986
od1	1643865	552083.9	2.98	0.003	556051.2	2731678
north	144835.9	303715.4	0.48	0.634	-453598	743269.9
exit	-220424.5	262791.9	-0.84	0.402	-738223.7	297374.7
harts	13291.55	35560.54	0.37	0.709	-56776.13	83359.24
rmedinc	10.98132	13.02215	0.84	0.400	-14.67724	36.63987
empden	5414.601	5515.33	0.98	0.327	-5452.681	16281.88
IDL1B	**-1109.123**	**81889.63**	**-0.01**	**0.989**	**-162462.6**	**160244.3**
IDL1A	**-1033108**	**404691.6**	**-2.55**	**0.011**	**-1830503**	**-235712.9**
IDL2B	**-563838**	**941448.8**	**-0.60**	**0.550**	**-2418847**	**1291171**
IDL2A	**-287726**	**188533.7**	**-1.53**	**0.128**	**-659208.6**	**83756.54**
IDL2D	**-126480**	**238554.2**	**-0.53**	**0.596**	**-596521.7**	**343561.8**

Table A.4. Hedonic model for retail properties.

Dependent variable = saleprice
Number of obs = 816
Prob > F = 0.0000
R-squared = 0.4911

Variable	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
constant	373920.7	185101	2.02	0.044	10559.62	737281.7
yr6	-145851.6	49783.64	-2.93	0.003	-243578.9	-48124.22
yr12	94542.51	41681.43	2.27	0.024	12720.13	176364.9
yr13	307672.9	127082.7	2.42	0.016	58204.2	557141.5
yr17	53512.6	60050.8	0.89	0.373	-64369.61	171394.8
yr19	327662.5	149584.6	2.19	0.029	34021.69	621303.2
yr20	77586.23	43763.29	1.77	0.077	-8322.919	163495.4
yr21	111040.7	53121.12	2.09	0.037	6761.707	215319.6
sqft	10737.91	9222.434	1.16	0.245	-7366.107	28841.94
sqft2	126.5986	93.58175	1.35	0.177	-57.10624	310.3035
numimp	-107957.4	46795.53	-2.31	0.021	-199819	-16095.87
acre	246514.8	123623.8	1.99	0.046	3836.117	489193.5
age	-7415.055	2890.372	-2.57	0.010	-13088.98	-1741.135
age2	48.69974	22.85151	2.13	0.033	3.841283	93.5582
gradeab	290660.4	157492.1	1.85	0.065	-18503.07	599823.9
gradec	-46144.25	35983.53	-1.28	0.200	-116781.4	24492.91
front2	161680.6	83511.06	1.94	0.053	-2255.086	325616.3
loccod3	174437.3	137123.4	1.27	0.204	-94741.68	443616.4
loccod5	40061.72	43309.17	0.93	0.355	-44955.98	125079.4
loccod6	56971.37	66240.73	0.86	0.390	-73061.95	187004.7
loccod8	-68589.81	159057.6	-0.43	0.666	-380826.4	243646.8
loccod9	233146.6	238562.5	0.98	0.329	-235161.5	701454.7
rd1	123558.1	120514.9	1.03	0.306	-113017.8	360133.9
rd2	-321875.9	118426.9	-2.72	0.007	-554352.7	-89399.02
juris2	-148622.9	80329.59	-1.85	0.065	-306313.3	9067.377
juris3	270840.7	80532.9	3.36	0.001	112751.3	428930.2
juris7	235399.9	93015.38	2.53	0.012	52806.84	417993
north	182002.3	113558.9	1.60	0.109	-40918.65	404923.2
cbd	-72213.46	25362.17	-2.85	0.005	-122000.5	-22426.47
ncbd	42480.52	19948.55	2.13	0.034	3320.694	81640.34
marta1	-107446.6	45260.5	-2.37	0.018	-196294.8	-18598.32
nexit	-260242	101690.2	-2.56	0.011	-459864.2	-60619.89
harts	67844.82	32961.64	2.06	0.040	3139.744	132549.9
harts2	-3395.982	1705.195	-1.99	0.047	-6743.351	-48.61266
rmedinc	4.763451	2.984638	1.60	0.111	-1.095517	10.62242
popden	6666.81	6407.658	1.04	0.298	-5911.688	19245.31
empden	2568.791	828.578	3.10	0.002	942.2581	4195.324
minority	-219006.7	62544.03	-3.50	0.000	-341783.3	-96230.19
vacant	6255.841	3769.45	1.66	0.097	-1143.745	13655.43
IDL1B	**-29975.99**	**19652.27**	**-1.53**	**0.128**	**-68554.21**	**8602.224**
IDL1A	**-80335.88**	**44900.76**	**-1.79**	**0.074**	**-168477.9**	**7806.192**
IDL2B	**4330.66**	**10147.59**	**0.43**	**0.670**	**-15589.49**	**24250.81**
IDL2A	**1195.476**	**11282.13**	**0.11**	**0.916**	**-20951.82**	**23342.77**
IDL2D	**4135.552**	**11052.96**	**0.37**	**0.708**	**-17561.87**	**25832.98**

Table A.5. Hedonic model for industrial properties.

Dependent variable = saleprice
Number of obs = 644
Prob > F = 0.0000
R-squared = 0.2728

Variable	**Coef.**	**Robust Std. Err.**	**t**	**P>|t|**	**[95% Conf.**	**Interval]**
constant	2426769	427413	5.68	0.000	1587362	3266177
yr6	327266.4	236441.9	1.38	0.167	-137087.9	791620.7
yr9	175929.9	80309.66	2.19	0.029	18207.66	333652
yr10	225214.3	135287.3	1.66	0.096	-40479.98	490908.6
yr12	144813.7	90279.78	1.60	0.109	-32489.08	322116.4
yr13	216076.9	94846.58	2.28	0.023	29805.3	402348.6
yr14	135842.6	72122.22	1.88	0.060	-5800.033	277485.3
yr15	169929.7	101690.8	1.67	0.095	-29783.54	369642.9
yr19	481408.4	202358.7	2.38	0.018	83990.97	878825.8
yr20	271333.5	86380.32	3.14	0.002	101689	440978
yr22	155272.2	73488.97	2.11	0.035	10945.36	299599.1
sqft	8623.553	1832.713	4.71	0.000	5024.241	12222.87
numimp	-104070.2	37021.67	-2.81	0.005	-176778	-31362.42
acre	63442.63	22778.62	2.79	0.006	18707.11	108178.2
acre2	-2699.586	470.7791	-5.73	0.000	-3624.161	-1775.011
age2	-2.48626	10.24725	-0.24	0.808	-22.61109	17.63857
gradeab	493198.1	458551.8	1.08	0.283	-407363.5	1393760
gradec	152499.3	82975.94	1.84	0.067	-10459.29	315457.8
concrete	196317.1	161613.4	1.21	0.225	-121079.5	513713.7
glass	1356428	895830.5	1.51	0.131	-402916	3115773
loccod2	-1874896	182011.9	-10.30	0.000	-2232354	-1517439
loccod4	-1857076	231308.1	-8.03	0.000	-2311348	-1402804
loccod5	-1957897	216469.2	-9.04	0.000	-2383026	-1532767
loccod6	-1973435	157586.4	-12.52	0.000	-2282923	-1663947
loccod7	-2057724	162864.5	-12.63	0.000	-2377578	-1737871
loccod8	-2030472	163161.7	-12.44	0.000	-2350910	-1710035
indd1	1363546	847397.3	1.61	0.108	-300679.7	3027771
indd3	791573.4	269483.2	2.94	0.003	262328.5	1320818
manuf	-88931.14	69254.66	-1.28	0.200	-224942.1	47079.84
juris4	-472363.8	291726	-1.62	0.106	-1045292	100564.2
juris5	-2075392	519273.2	-4.00	0.000	-3095206	-1055578
juris6	-1162517	402323	-2.89	0.004	-1952649	-372384.2
juris7	-482782.9	408487.1	-1.18	0.238	-1285021	319455.4
nmin	745754	505089	1.48	0.140	-246203.2	1737711
north	-705480.5	449302.7	-1.57	0.117	-1587878	176916.6
exit	171683	88183.75	1.95	0.052	-1503.294	344869.3
popden	32800.39	19764.2	1.66	0.098	-6015.031	71615.8
minority	-1190392	516110.7	-2.31	0.021	-2203995	-176789.2
vacant	14878.26	4344.878	3.42	0.001	6345.247	23411.28
IDL1B	**-9462.421**	**26512.27**	**-0.36**	**0.721**	**-61530.54**	**42605.69**
IDL1A	**-42838.41**	**24028.29**	**-1.78**	**0.075**	**-90028.18**	**4351.361**
IDL2B	**-49157.98**	**39215.43**	**-1.25**	**0.210**	**-126174.2**	**27858.2**
IDL2A	**-19513.86**	**26894.84**	**-0.73**	**0.468**	**-72333.33**	**33305.61**
IDL2D	**38100.03**	**25591.57**	**1.49**	**0.137**	**-12159.9**	**88359.97**

Table A.6. Hedonic model for vacant properties.

```
Dependent variable =  saleprice
Number of obs      =  582
Prob > F           =  0.0130
R-squared          =  0.2522
```

Variable	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
constant	663643.8	386518.5	1.72	0.087	-95592.31	1422880
yr6	109852	131322.7	0.84	0.403	-148104.5	367808.6
yr10	67842.85	83455.3	0.81	0.417	-96087.92	231773.6
yr11	155453.4	203642.8	0.76	0.446	-244561	555467.9
yr12	271016.5	200834.8	1.35	0.178	-123482	665515.1
yr15	-457536.7	262417.4	-1.74	0.082	-973001.8	57928.33
yr19	896846.6	397381.3	2.26	0.024	116272.7	1677420
yr20	1267989	559303.7	2.27	0.024	169352.2	2366626
acre	54468.96	31609.29	1.72	0.085	-7620.995	116558.9
acre2	-779.4781	345.2091	-2.26	0.024	-1457.57	-101.3858
front3	-257093.1	142436.1	-1.80	0.072	-536879.5	22693.42
loccod2	554232	373523.6	1.48	0.138	-179478.3	1287942
loccod4	199574.7	234824.8	0.85	0.396	-261690.3	660839.7
loccod5	180788	200909.6	0.90	0.369	-213857.7	575433.6
loccod6	274697.2	218403.2	1.26	0.209	-154310.9	703705.3
loccod7	417440.2	250725.4	1.66	0.096	-75058.32	909938.7
loccod8	6352.212	263656.6	0.02	0.981	-511547.1	524251.5
loccod9	1063324	467480.6	2.27	0.023	145054.2	1981593
juris3	658475.2	368132.1	1.79	0.074	-64644.6	1381595
juris5	249963.4	262790.3	0.95	0.342	-266234.1	766160.8
juris6	1943628	802946.7	2.42	0.016	366404.6	3520852
cbd	-67466.14	32270.17	-2.09	0.037	-130854.2	-4078.034
marta1	-293524.6	170130.4	-1.73	0.085	-627710.8	40661.5
exit	13091.73	98071.89	0.13	0.894	-179550.3	205733.8
popden	-5622.191	14781.71	-0.38	0.704	-34657.83	23413.45
npopden	-7740.881	12078.08	-0.64	0.522	-31465.78	15984.02
minority	-1019761	287118.5	-3.55	0.000	-1583746	-455775.9
empden	20208.26	9696.338	2.08	0.038	1161.798	39254.72
IDL1B	**-36382.68**	**83113.04**	**-0.44**	**0.662**	**-199641.1**	**126875.8**
IDL1A	**-168066.8**	**95922.37**	**-1.75**	**0.080**	**-356486.6**	**20352.92**
IDL2B	**-147.578**	**82000.63**	**-0.00**	**0.999**	**-161221**	**160925.8**
IDL2A	**-13528.13**	**43654.32**	**-0.31**	**0.757**	**-99278.07**	**72221.81**
IDL2D	**-40918.24**	**76722.21**	**-0.53**	**0.594**	**-191623.2**	**109786.8**