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THE EFFECTS OF ENVIRONMENTAL CONTAMINATION ON COMMERCIAL AND INDUSTRIAL PROPERTY VALUES: DO PERCEPTIONS MATTER?

BY

PETER EDWARD GRIGELIS

A Dissertation Submitted in Partial Fulfillment
of the Requirements for the Degree
of
Doctor of Philosophy
in the
Andrew Young School of Policy Studies
of
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ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

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ABSTRACT

THE EFFECTS OF ENVIRONMENTAL CONTAMINATION ON COMMERCIAL AND INDUSTRIAL PROPERTY VALUES: DO PERCEPTIONS MATTER?

BY

PETER EDWARD GRIGELIS

2005

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The effects of severely contaminated properties (e.g. NPL sites) on residential property values are well documented. However, most contaminated sites are not so severe to warrant placement on the NPL, and little is known about the impacts to commercial and industrial property markets. Furthermore, perceptions may be developed about different types of land-uses as a result of information made public about sites placed on lists. If perceptions matter, then properties with no known contamination may be viewed as undesirable neighbors in a way similar to listed sites. Therefore, property value impacts could be even more substantial as compared to only the impacts of known contaminated sites.

The economic impacts of known and perceived environmental contamination are quantified by estimating two sets of hedonic property value models using data on commercial and industrial property sales for Fulton County, Georgia. Sites listed on the

EPA's CERCLIS and NFRAP reports and the Georgia EPD's HSI and NonHSI reports are utilized to estimate the impacts of known environmental contamination. The impacts from perceived contamination are estimated utilizing a set of properties that are identified by an ordered probit model that computes the probability commercial and industrial properties may be contaminated. The probability of contamination model is built on factors that are assumed to be key signals to investors in forming their perceptions about the likelihood commercial and industrial properties may be contaminated.

Property value losses due to known contamination were estimated at slightly over $1 billion and potential losses from perceived contamination were near $663 million. Although estimated property value impacts are not equivalent to expected gains that may result from the remediation of all contaminated sites, the magnitude of the estimated losses suggests that significant gains can be achieved if property values recover by only a fraction. Policies could be implemented that prioritize site remediation to target minority and/or economically depressed areas to help spur economic development. Potential increases in the tax base would result in greater property tax revenues for the provision of public services for the community and new economic development could help provide access to new jobs for local residents.

CHAPTER 1

INTRODUCTION

The objective of this research is to investigate how real and perceived environmentally contaminated properties affect commercial and industrial (CI) property markets. The effects of severely contaminated properties, such as National Priority List (NPL) sites, on residential property values are well documented in previous research (e.g. Michaels and Smith, 1990, Kohlhase, 1991, Kiel, 1995, Kiel and Zabel, 2001). However, most contaminated sites are not so severe as to warrant placement on the NPL and little is known about the possible economic impacts of these less contaminated sites on neighborhoods. Furthermore, the placement of contaminated sites on lists, such as the Environmental Protection Agency's (EPA) Comprehensive Environmental Response, Compensation, and Liability Information System (CERCLIS)[1], is a way of signaling to the general public that these properties may now represent potential dangers. Perceptions may be developed about different types of CI land-uses (e.g. manufacturing plants, service stations, etc.) as a result of the information made public about sites that are placed on a list. In addition, many contaminated properties may never get discovered by

[1] The EPA's list of NPL sites is a subset of all sites found on CERCLIS.

authorities, but they may be perceived as such. If perceptions matter, then properties with little or no contamination may be viewed as undesirable neighbors for nearby property owners in a way similar to properties listed on federal or state registries of contaminated sites. As such, the property value impacts could be even more substantial when taken as a whole as compared to only the impacts of known contaminated sites.

Contaminated sites may affect the economic potential of CI properties in close proximity as a result of investor concerns over contamination migration, possible increased employee health risks, or even negative sight externalities. If these concerns are significant, they would be manifested as reduced market values for nearby CI properties. As noted earlier, most of the previous research has focused on the effects of NPL sites on residential property values. Ihlanfeldt and Taylor (2004) is the only study known to investigate the impacts of less severely contaminated sites on CI property values, and they found significant property value losses for CI properties near hazardous waste sites in Atlanta, Georgia.

A similar argument can be made for properties that may be perceived as contaminated. The EPA defines "brownfield" as any abandoned, idled, or under-used industrial/commercial facility where the expansion or redevelopment is complicated by real or perceived contamination. However, perceived contaminated properties avoid the signaling effect from being placed on a list, but may be considered "undesirable" by the public due to suspected undiscovered releases or the threat of possible releases in the future. Therefore, CI properties in close proximity to sites that may be perceived as contaminated may also suffer reduced property values. There is currently no known evidence on this issue.

Regardless of whether one is analyzing residential or CI industrial property markets, reductions in property values subsequently leads to a reduction in the tax base for local governments, which can affect their ability to provide public services to the community. A greater understanding of the impacts of known contaminated sites and the role of perceived contamination provides valuable information regarding the potential benefits to local governments from site remediation. This research could also provide information to use for the prioritization of site remediation for sites located in Fulton County, Georgia. Policies could be implemented to target the remediation of sites which benefit minority and/or economically depressed areas to help spur economic development. These local areas could gain from an increase in the tax base, resulting in the collection of additional property tax revenues. Furthermore, the economic development could provide access to new employment opportunities for local residents.

This research addresses the role of perceptions by constructing a model that estimates the probability a CI property may be contaminated based on information about existing contaminated sites. The model incorporates factors that are likely to be key signals to investors in forming their perceptions that a site may be contaminated, regardless of whether any contamination has been previously documented by authorities. One primary factor will be the land-use of each CI property. This follows the assumption that investors in CI properties may form perceptions that specific types of land-uses (i.e., service stations, certain manufacturing facilities, strip malls with dry cleaners on site, etc.) are more likely to be contaminated than other land-uses. Ultimately, the probability of contamination model is utilized as a method for identifying those properties that may be perceived as contaminated.

To quantify the economic impacts of real and perceived environmentally contaminated properties, the analysis compares two sets of hedonic property value models estimated using a data set of CI property sales. The first set of hedonic models uses the EPA's CERCLIS and No Further Remedial Action Planned (NFRAP) reports and the Georgia Environmental Protection Division's (EPD) Hazardous Site Inventory (HSI) and Non-Hazardous Site Inventory (NonHSI) reports to identify sites with known contamination. For the second set of hedonic models, sites that may be perceived as contaminated identified by the empirical results of the probability of contamination model are incorporated. If the probability of contamination model is successful in identifying such properties, then it is expected that the sites identified as potentially contaminated may also negatively affect nearby CI property values.

In developing the hedonic property value models to measure the impacts of real and perceived contamination, several estimation issues are addressed. The first is proper identification of the relationship between price and proximity to a contaminated site. Because of the assumed nature of the externality effects of contaminated sites (real or perceived), the marginal effect of distance on price is expected to decrease as distance increases. Functional forms explored that satisfy this condition include a reciprocal relationship, semi-log and double-log models. The specification of the hedonic models are also carefully considered since there are over fifty variables available for estimation that describe each particular property. Examples include the property's land-use, building grade, property size, square footage of improvements on site, adequacy of parking on site, distance to the central business district, and proximity to transportation nodes, such as Hartsfield-Jackson International Airport, public transit stations, and highway exits.

Other estimation issues addressed result from the recognition that the impacts on CI property values may not only be a result of proximity to the nearest site, but also from the density of sites nearby. Additionally, the impacts may vary according to the characteristics of the sites, such as its size and land-use. Therefore, measures that control for the density of nearby sites, size of the nearest site, and land-use of the nearest sites are incorporated into the hedonic models estimated. Furthermore, it will be necessary to test and correct for spatial error correlation. Hedonic property value models are likely to have spatially correlated errors since properties in close proximity to each other will have similar unobservable characteristics. Although unbiased, parameter estimates are inefficient in the presence of spatially correlated errors, which may lead to incorrect inference. When appropriate, spatial hedonic models are estimated.

The theoretical basis of the hedonic property value model as applicable to CI property markets is reviewed in Chapter 2. In Rosen's (1974) early formulation of the underlying theory of the general hedonic model, markets for differentiated goods are modeled as the interactions between utility maximizing individuals (households) and profit maximizing firms. In the analysis conducted here, the agents on the demand side are not utility maximizing individuals, but rather profit maximizing firms. Palmquist (1989) adapted Rosen's model to agricultural land markets, under the conditions of profit maximizing demanders and suppliers of agricultural land. The framework set forth by

Palmquist and Rosen is extended to CI property markets in which conditions of profit maximization for both demanders and suppliers of the differentiated good are imposed. In addition to the underlying theory, Chapter 2 will discuss the measurement of externality effects with the hedonic model.

Chapter 3 describes the data utilized for the analysis. The area of analysis is Fulton County Georgia, which encompassed most of the City of Atlanta, and the two primary data needs are data on CI property sales and data on contaminated sites. The CI property data was purchased from a private vendor and is based on Fulton County tax records for which the private vendor annually updated individual property sales prices in addition to other changes in property characteristics. Contaminated sites were identified by two federal lists, the EPA's CERCLIS and NFRAP reports, and two state lists, the Georgia EPD's HSI and NonHSI reports.[2] Each site identified by these four lists were individually matched to their corresponding entry in the property data. Geographic information systems (GIS) are used extensively to develop measures to control for proximity to sites identified by the four lists, proximity to sites identified by the probability of contamination model and several other spatially-related property characteristics. In addition, Census data were appended to the CI property data to capture neighborhood characteristics.

Chapter 4 presents the empirical model used to estimate the likelihood a CI property may be perceived as contaminated. An ordered probit model that controls for

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[2]The Non Hazardous Site Inventory is not an official list published by the Georgia Environmental Protection Division. However, the Georgia Environmental Protection Division keeps records of these sites on file at their office.

potential sample selection is estimated to determine the likelihood a CI property has a "high" level of contamination, has a "low" level of contamination, and has no known contamination present. The probability of contamination model is then used as the means for identifying properties as having a high likelihood of being "highly" contaminated. These properties are then incorporated into hedonic property value models estimated in Chapter 6 to determine the extent to which they may emit negative externality effects on neighboring CI properties.

Chapters 5 and 6 present the empirical results of the hedonic property value models used to estimate the externality effects of environmentally contaminated properties. First, Chapter 5 describes the hedonic property value models estimated to determine the effects that properties with known contamination have on neighboring CI property values. A Base model is specified that is consistent with the assumed nature of the externality effects of contaminated sites. Next, other functional forms are explored and their results are compared to the Base model. A preferred model is determined and investigated further by incorporating controls for the density of sites nearby and characteristics of the nearest site. Lastly, the final set of preferred models are tested for spatial error correlation for which appropriately specified spatial models are then estimated. The set of preferred models developed in Chapter 5 are then replicated in Chapter 6 where additional "potentially contaminated" properties identified by the probability of contamination model estimated in Chapter 4 are incorporated into the analysis.

The final chapter, Chapter 7, utilizes the estimates reported in Chapters 5 and 6 to discuss the economic importance of the results from the estimated hedonic models. Comparisons are made between the hedonic models estimated in Chapters 5 and 6, marginal impacts are estimated, and total impacts on CI property values are computed. In addition, a discussion of future research is given.

CHAPTER 2

HEDONIC PROPERTY VALUE MODEL

Introduction

In this chapter, the hedonic property value model is reviewed as applicable to commercial and industrial (CI) property markets. Rosen (1974) provides one of the earliest references for the underlying theory of the general hedonic model. In this formulation, markets for differentiated goods are modeled as the interactions between utility maximizing individuals (households) and profit maximizing firms. In the analysis conducted here, the agents on the demand side are not utility maximizing individuals, but rather profit maximizing firms. Palmquist (1989) adapted Rosen's model to agricultural land markets, constructing a hedonic model of profit maximizing demanders and suppliers of agricultural land. The framework set forth by Palmquist and Rosen will be expressed in terms of CI property markets in which conditions of profit maximization for both demanders and suppliers of the differentiated good are imposed. In general, the theoretical model expressed here closely follows the model given by Palmquist, but similarities can also be drawn to Rosen's model. Additionally, the measurement of externality effects with the hedonic model will be discussed in this chapter.

Theoretical Background

Firms as Purchasers of Properties

The typical hedonic model expresses the purchaser of a property as a utility maximizing individual. In terms of CI property markets, the purchaser is a profit maximizing firm. As such, a CI property can be treated as a differentiated factor of production. It is assumed that individual firms are unable to affect the equilibrium prices for CI properties and therefore, take them as given. The equilibrium relationship between the price of a property and its characteristics can be represented by the hedonic price function:

$$P(Z) = P(z_i,...,z_n) \ . \tag{2.1}$$

where $P(Z)$ is the market price of a property and $Z = (z_i, ..., z_n)$ is a vector of characteristics that describes the property.

It is assumed that a firm purchases only one property that is used as an input, along with other inputs, in the production of a single output. The firm production function can be written as:

$$Q = Q(X,Z,\alpha) \ , \tag{2.2}$$

where Q is the output of the firm, X is a vector of non-property inputs, Z is the vector of property characteristics, and α is a vector of of firm specific characteristics. In addition, it is assumed that the production function given by (2.2) is a concave, twice differentiable, bounded, finite, non-negative real valued, and continuous function.

Following the model expressed by Palmquist (1989) for which land is treated as a differentiated factor of production in the production of agricultural crops, the variable profit function must be specified to determine a firm's willingness to pay for a particular property. Variable profits are defined as the value of output minus the value of non-property inputs. Generally, variable profits are defined as the value of output minus the value of variable inputs for a given set of fixed inputs. However, it is assumed that the property (described by the vector Z) purchased by a firm is considered as the only fixed input and so the definition is equivalent.

Firms maximize their variable profits subject to the production function constraint under the conditions of perfect competition in the output and inputs markets. The profit-maximization problem faced by a firm utilizing a particular property in the production process can be written as:

$$\begin{aligned} &\Pi^V = R \times Q - \sum_{j=1}^{m} c_j x_j \\ &s.t.\ Q = Q(X, Z, \alpha) \\ &\Pi^V \geq 0 \end{aligned} \tag{2.3}$$

where Π^V is variable profits, R is the market price for output Q, x_j are elements of the vector X of non-property inputs, c_j are elements of a vector, C, of prices for non-property inputs, and Z and α are defined as before. Variable profits are maximized when firms optimally choose non-property inputs that satisfy the following first-order conditions for inputs $j = 1, \ldots, m$:

$$\begin{aligned} &R \frac{\partial Q(X^*, Z, \alpha)}{\partial x_j} - c_j = 0 \quad \text{if} \ \ x_j^* > 0 \\ &R \frac{\partial Q(X^*, Z, \alpha)}{\partial x_j} - c_j \leq 0 \quad \text{if} \ \ x_j^* = 0\ . \end{aligned} \tag{2.4}$$

The conditions given by (2.4) state that a firm will be maximizing its variable profits while utilizing a particular property in the production process when the marginal revenue product from an additional unit of non-property input j used equals the marginal cost for non-property input j. From the maximization problem, input demand functions for non-property inputs can be obtained by solving for x_j:

$$x_j = x_j(R,Z,C,\alpha) \quad j = 1,\ldots,m. \tag{2.5}$$

The input demand functions can then be substituted back into equation (2.3) to result in the following variable profit function:

$$\Pi^{*V} \equiv \Pi^{*V}(R,Z,C,\alpha) = R \times Q(R,Z,C,\alpha) - \sum_{j=1}^{m} c_j x_j(R,Z,C,\alpha). \tag{2.6}$$

Subtracting the current period cost of purchasing a particular property from equation (2.6) will yield a firm's total profits[3] for the current period:

$$\Pi \equiv \Pi^{*V}(R,Z,C,\alpha) - P(Z) \times i = R \times Q(R,Z,C,\alpha) - \sum_{j=1}^{m} c_j x_j(R,Z,C,\alpha) - P(Z) \times i, \tag{2.7}$$

where $P(Z)$ is the hedonic price function that describes the price of a property with characteristics Z and i represents an interest rate. The interest rate i is the rate of return a firm would earn on an amount equal to the purchase price, $P(Z)$, if the firm did not choose to purchase the property. This corresponds to the opportunity cost faced by the firm for purchasing a property at a price $P(Z)$. A firm's total profits are now specified as a function of the price of the firm's output, the price of non-property inputs, the characteristics of the firm, and the characteristics of the particular property a firm chooses to utilize in their production process.

For the profit function given by equation (2.7), a firm's optimal choice of non-

[3]Without loss of generality, payments for other fixed factors could also be subtracted from variable profits to calculate total profits. However, here it is assumed that a firm does not make payments for other fixed factors.

property inputs have been made, which are a function of the price of its output, price of non-property inputs, the firm's characteristics, and property characteristics. The price of the firm's output and the prices of non-property inputs are determined in perfectly competitive markets and therefore are given for the firm. The decision now faced by a firm is to determine what property it should purchase to maximize its total profits. Differentiating equation (2.7) with respect to z_i, a firm's optimal choice for property characteristics can be determined. Firms maximize total profits by choosing property characteristics satisfying the following first order conditions for characteristics $i = 1, \ldots, n$:

$$\frac{\partial \Pi}{\partial z_i} = \frac{\partial \Pi^{*V}(\cdot)}{\partial z_i} - \frac{\partial P(Z)}{\partial z_i} \times i = R \times \frac{\partial Q(\cdot)}{\partial z_i} - \sum_{j=1}^{m} c_j \frac{\partial x_j(\cdot)}{\partial z_i} - \frac{\partial P(Z)}{\partial z_i} \times i = 0 \,. \tag{2.8}$$

Because the variable profit function is non-decreasing in property characteristics given the assumptions previously made about the production function, $\frac{\partial \Pi^{*V}}{\partial z_i}$ will be greater than or equal to zero.[4] Solving (2.8) for $\frac{\partial P(Z)}{\partial z_i}$ results in the following:

$$\frac{\partial P(Z)}{\partial z_i} = \frac{\partial \Pi^{*V}(\cdot)}{\partial z_i} \times \frac{1}{i} = [R \times \frac{\partial Q(\cdot)}{\partial z_i} - \sum_{j=1}^{m} c_j \frac{\partial x_j(\cdot)}{\partial z_i}] \times \frac{1}{i} \,, \tag{2.9}$$

which states that given the price of the firm's output and the costs for non-property inputs, a firm will be maximizing profits when the change in variable profits from an additional unit of z_i multiplied by the inverse of the interest rate i is equal to the marginal cost of an additional unit of z_i, or $\frac{\partial \Pi^{*V}}{\partial z_i} \times \frac{1}{i} = \frac{\partial P(Z)}{\partial z_i}$. The marginal cost of a characteristic is the marginal implicit price for the characteristic, $\frac{\partial P(Z)}{\partial z_i}$, and the price paid by a firm for an entire property with Z optimally chosen is then the market price, represented by the

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[4] This assumes the vector of property characteristics, Z, enters the production function in the same way as fixed factors for the standard definition of variable profits.

hedonic price function $P(Z^*)$.

The total profit function given by equation (2.7) can be restated in terms of a firm's bid, θ, for a particular property, where θ is defined as a firm's willingness to purchase a property with characteristics Z. Substituting θ into equation (2.7) results in:

$$\Pi = \Pi^{*V}(R,Z,C,\alpha) - \theta \times i = R \times Q(R,Z,C,\alpha) - \sum_{j=1}^{m} c_j x_j(R,Z,C,\alpha) - \theta \times i \,. \qquad (2.10)$$

Solving equation (2.10) for θ will lead to a firm's bid function which depends on, in addition to the characteristics of a property, the price of a firm's output, the price of non-property inputs, and the characteristics of a firm. The bid function can be defined as follows:

$$\theta \equiv \theta(Z,R,C,\Pi,\alpha) = (\Pi^{*V} - \Pi) \times \frac{1}{i} \qquad (2.11)$$

or alternatively stated:

$$\theta(Z,R,C,\Pi,\alpha) = [R \times Q(R,Z,C,\alpha) - \sum_{j=1}^{m} c_j x_j(R,Z,C,\alpha) - \Pi] \times \frac{1}{i} \,. \qquad (2.12)$$

A firm's bid for a property is therefore the difference between a firm's variable profits and its total profits multiplied by the inverse of the interest rate i. Differentiating the bid function with respect to a property characteristic leads to the following condition a firm satisfies when placing optimal bids for property characteristics:

$$\theta_{z_i} \equiv \frac{\partial \theta(\cdot)}{\partial z_i} = \frac{\partial \Pi^{*V}(\cdot)}{\partial z_i} \times \frac{1}{i} = [R \times \frac{\partial Q(\cdot)}{\partial z_i} - \sum_{j=1}^{m} c_j \frac{\partial x_j(\cdot)}{\partial z_i}] \times \frac{1}{i} \,, \qquad (2.13)$$

where θ_{z_i} will be greater than or equal to zero since the variable profit function is non-decreasing in property characteristics given the assumptions previously made about the production function.[5]

[5] Again, this follows the assumption that the vector of property characteristics, Z, enters the production function in the same way as fixed factors for the standard definition of variable profits

The bid function defines the amount a firm is willing to pay for a particular property for a given total profit level. The minimum price a firm must pay for a particular property is given by its market price, *P(Z)*. Further, a firm's marginal bid, θ_{z_i}, represents the additional amount a firm is willing to pay for higher levels of property characteristics, while $\frac{\partial P(Z)}{\partial z_i}$ represents the marginal implicit price in the market for additional levels of property characteristics. In equilibrium, the increase in a firm's bid for a marginal increase in one of the property characteristics must equal the increase in the market price for a marginal increase in the property characteristic. Comparing the results given by equation (2.9) and equation (2.13) leads to the following marginal conditions:

$$\theta_{z_i}(z_i^*;Z^*,\Pi^*,R,C,\alpha) = \frac{\partial P(z_i^*;Z^*)}{\partial z_i} \tag{2.14}$$

for property characteristics $i = 1, \ldots, n$, where Z^* represents the optimal levels of all property characteristics except z_i, Π^* is optimal total profits, and R, C, and α, are the same as previously defined. Additionally, a firm's total bid for a particular property must equal the market price for the property. This is given by the following total condition:

$$\theta(Z^*;\Pi^*,R,C,\alpha) = P(Z^*) \tag{2.15}$$

where Z^* represents optimal quantities of property characteristics and all other variables are as defined for equation (2.14). These conditions simply state that in equilibrium, a firm's marginal bid for an individual characteristic will be equal to the marginal implicit price of the characteristic in the market and a firm's maximum bid price for an entire property will equal the minimum price the firm must pay in the market. If this were not the case, a firm would be able to increase profits by purchasing a property with different characteristics.

Additional properties of the bid function are as follows. Differentiating (2.13) again with respect to z_i will yield the following:

$$\theta_{z_i z_i} \equiv \frac{\partial^2 \theta(\cdot)}{\partial z_i^2} = \frac{\partial^2 \Pi^{*V}(\cdot)}{\partial z_i^2} \times \frac{1}{i} = [R \times \frac{\partial^2 Q(\cdot)}{\partial z_i^2} - \sum_{j=1}^{m} c_j \frac{\partial^2 x_j(\cdot)}{\partial z_i^2}] \times \frac{1}{i}\,, \tag{2.16}$$

where $\theta_{z_i z_i} = \frac{\partial^2 \Pi^V(\cdot)}{\partial {z^2}_i} \leq 0$, since the variable profit function is concave in property characteristics given the assumptions previously made about the production function. Furthermore, differentiating θ with respect to a firm's total profits, Π, results in θ_Π = $-\frac{1}{i}$. This implies that for a firm to increase (decrease) total profits by X dollars, the firm must decrease (increase) its bid by $\frac{1}{i} \times X$ dollars, holding everything else constant.

The bid functions for two firms are depicted graphically in Figure 2.1, where buyer-firm one is shown purchasing a property with a larger quantity of z_i. Equilibrium can be described as the point where individual bid functions are tangent to the hedonic price function, with the point of tangency given by $\theta_{z_i^*} = \frac{\partial P(Z*)}{\partial z_i}$ for $i = 1, \ldots, n$. As can be seen, if a firm wanted to purchase a property with a higher level of z_i the firm must have a higher bid for the property or their bid would not be accepted in the market. Additionally, higher profits for a firm can be represented by a downward shift in the firm's bid function.

Firms as Producers of Properties

It is assumed that firms produce properties by building structures on parcels of land where an entire property can be described by a vector of characteristics, Z, and it is assumed that firms maximize profits by specializing in the production of properties of a particular type. This assumption can be generalized to multi-product types if we assume, as Rosen (1974) states, that a firm is considered "an arbitrary collection of atomistic production establishments, each one acting independently of the others" where there are no cost spillovers across the production plants of a firm. Following Palmquist (1989), the vector of property characteristics, *Z*, can be separated into two sub-vectors, Z' and Z'', where the attributes of $\square'$ are property characteristics within the firm's production control and the attributes of $\square''$ are property characteristics exogenous to the firm. Examples of $\square''$ may include the property's proximity to the central business district, nearest highway exit, or racial composition of its neighborhood.

Profits for the firm are given by:

$$\Pi = M \times P(Z',Z'') - C(Z',Z'',M,w;\boldsymbol{\beta}), \tag{2.17}$$

where *M* is the number of properties with characteristics Z' and $\square''$ the firm produces, $C(\cdot)$ is a cost function expressed as a function of $\square'$ and $\square''$, a vector of input prices, *w*, purchased in competitive markets, and a vector of firm specific characteristics, $\boldsymbol{\beta}$, and the hedonic function P(Z', Z'') describes the sales price of the property. It is assumed $C(\cdot)$ is convex where $C(Z',Z'',0,w;\boldsymbol{\beta}) = 0$ and C_Z and $C_M \geq 0$. Further, the marginal costs of producing more properties of a particular type are positive and increasing and the marginal costs of increasing each characteristic of a particular property are positive and non-decreasing. To maximize profits, a firm's optimal choice of property characteristics within their control, z_i', and their choice of how many units to produce, *M*, will satisfy the following first order conditions:

$$\frac{\partial P(Z'^{*},Z'')}{\partial z_i'} = \frac{\partial C(Z'^{*},\cdot)}{\partial z_i'}\frac{1}{M} \tag{2.18}$$

and

$$P(Z'^*,Z'') = \frac{\partial C(Z'^*,\cdot)}{\partial M} \,. \tag{2.19}$$

Equation (2.18) states that a firm's profits are maximized when the marginal price for characteristics within a firm's control, z_i', are equal to the marginal cost of producing an additional unit of z_i' per property. Equation (2.19) states that the marginal cost of producing an additional property with characteristics Z' and □ $''$ will equal the market price of a property with characteristics □ $'$ and □ $''$, holding everything else constant.

The production decision of a firm can be restated in terms of an offer function, Φ, defined as a firm's willingness to sell a property with particular characteristics while holding profit (and everything else) at a constant level. Substituting Φ into equation (2.17) yields the following:

$$\Pi = M \times \Phi - C(Z',Z'',M,w;\beta)\,, \tag{2.20}$$

The offer function is defined by solving (2.20) for Φ, resulting in:

$$\Phi \equiv \Phi(Z',Z'',M,\Pi,w;\beta) = \frac{1}{M}[\Pi + C(Z',Z'',M,w;\beta)]\,, \tag{2.21}$$

which indicates how a firm's offer is a function of property characteristics, number of properties of a particular type produced, profits, input prices, and firm characteristics.

To determine the firm's optimal offers, equation (2.21) is differentiated with respect to z_i' and M. First, a firm's optimal offer satisfies:

$$\Phi_{z_i'} \equiv \frac{\partial \Phi}{\partial z_i'} = \frac{\partial C(\cdot)}{\partial z_i'}\frac{1}{M}\,, \tag{2.22}$$

indicating a firm's marginal offer equals the marginal cost of producing z_i per property. Second, a firm's optimal offer will satisfy:

$$\Phi = \frac{\partial C(\cdot)}{\partial M}\,, \tag{2.23}$$

indicating that a firm's minimum offer price for a property with characteristics Z' and

□ $''$ will equal the marginal cost of producing a property with characteristics □ $'$ and Z''.

Since equation (2.22) represents a firm's minimum offer price for individual characteristics z'_i, while $\frac{\partial P(Z',Z'')}{\partial z'_i}$ represents the maximum price a firm will receive in the market, a firm's profits will be maximized when the following marginal conditions are satisfied:

$$\Phi_{z_i'^*} = \frac{\partial P(Z'^*,Z'')}{\partial z'_i} \tag{2.24}$$

for those property characteristics for which a firm has control over in producing. For the property characteristics exogenous to the firm, the characteristics' price and therefore a firm's offer price is completely demand-determined. As a result, a firm's offer price for these types of characteristics will be equal to the market price, since at a higher offer price a firm's offer would not be accepted in the market and a lower offer price would lead to lower profits for a firm. In turn, a firm's maximum offer price for a property with characteristics □ $'$ and □ $''$ optimally chosen will therefore equal the price the firm can receive in the market, given by the following total condition:

$$\Phi^* = P(Z'^*,Z'')\ . \tag{2.25}$$

If a firm were to submit a higher offer price than the market price for a particular property, a firm's offer would not be accepted. An offer price lower than the market price would result in lower profits for the firm.

Additional properties of the offer function are as follows. Marginal and total offers will be greater than or equal to zero since the marginal cost of a characteristic and marginal cost of a property are assumed to be non-decreasing functions in Z', □ $''$, and M. Differentiating equation (2.22) with respect to z'_i will yield the following:

$$\Phi_{z_i' z_i'} = \frac{\partial^2 C(\cdot)}{\partial z_i'^2} \frac{1}{M} . \tag{2.26}$$

However, convexity of the cost function does not guarantee equation (2.26) will be greater than zero due to nonlinearity of P(Z', Z''), which implies marginal implicit prices for property characteristics depend on quantity and therefore are not constant. To attain the desired second-order properties, it must be assumed that the hessian of the profit function given by (2.17) is symmetric and negative definite.

Differentiating the offer function with respect to Π implies $\Phi_{\Pi} = \frac{1}{M}$, which is greater than zero. Therefore, for a firm to increase (decrease) total profits by X dollars, the firm's offer must increase (decrease) by $(1/M) \times X$ dollars, holding everything else constant.

Offer functions for two sellers are given graphically in Figure 2.1, where seller-firm one is shown producing a property with a larger quantity of z_i. Equilibrium is depicted as the point where individual offer functions are tangent to the hedonic price function, with the point of tangency given by $\Phi_{z_i^*} = \frac{\partial P(Z*)}{\partial z_i}$ for $i = 1, \ldots, n$. For a firm that wanted to sell a property with a lower level of z_i, the firm must also lower their offer for the property or their offer would not be accepted in the market. In addition, higher profits for a firm can be represented by an upward shift in the firm's offer function.

The model given for firms as producers of properties can be simplified if all property characteristics are considered endogenous or within the control of the firm. This situation would be more descriptive of developers converting green-space with little or no zoning restrictions on building type or location. The vector explaining the full set of property characteristics, Z, are now all elements of the z' vector and the firm's profit maximizing decision making process encompasses a choice over all property characteristics.

In addition to expressing the model for producers of properties in which all property characteristics are considered endogenous to the firm, the model can also be expressed where all property characteristics are considered exogenous to the firm or not within a firm's control of production. This is descriptive of the situation in which all CI properties are in the resale market. Here, new structures are not built on land, but rather existing structures with particular characteristics are supplied to the market by current property owners. Because the property has already been constructed, it can be assumed that the firm does not have the ability to vary the level of property characteristics that are supplied in the market. As a result, the supply of all property characteristics is fixed. The vector explaining the full set of property characteristics, *Z*, are now all expressed as elements of the □ $''$ vector, such that the firm does not make a production decision for any property characteristic. Therefore, the equilibrium market price for individual property characteristics, as well as an entire property, will be completely demand determined.

Market Equilibrium

The hedonic price function, $P(Z) = P(z_i, \ldots, z_n)$, describes the market equilibrium price of a property as a function of its characteristics. Market equilibrium is achieved through the interaction of multiple buyers and sellers when an individual firm's optimal bid (buyer) is perfectly matched with an individual firm's optimal offer (seller), where the price at which a buyer and seller are matched is given by $P(Z)$. The hedonic price function represents a joint envelop function of multiple bid and offer functions. Graphically, equilibrium can be depicted as the point where individual bid and offer functions are tangent to each other, both sharing in common a point on the hedonic function. The point in common is given by $\Phi_{z_i^*} = \frac{\partial P(Z^*)}{\partial z_i} = \theta_{z_i^*}$ for $i = 1, \ldots, n$. Therefore, the point of tangency is where a seller's marginal offer is equivalent to a buyer's marginal bid which is equal to marginal price in the market for a typical property characteristic, z_i. Figure 2-1 demonstrates this for two buyers and two sellers where buyer-firm 1 is shown purchasing a property with a larger quantity of z_i and seller-firm 1 is shown producing a property with a larger quantity of z_i.

The hedonic price function is assumed to be increasing for all elements of Z and by expressing the hedonic price function as a joint envelope function of bid and offer functions, no *a priori* expectations can made about its shape. However, under certain conditions or assumptions it may be possible to do so.[6] The nonlinearity of $P(Z)$ implies the marginal implicit prices will depend on the quantity of the characteristic. If $P(Z)$ was linear in the characteristics, the marginal implicit prices would be constant. Individual characteristics are assumed to be indivisible leading to the assumption that arbitrage is not possible. Therefore, once bundled, a property cannot be unbundled into individual property characteristics and sold in pieces. Furthermore, it is assumed that with the large number of buyers and sellers in the market, the addition or subtraction of individual buyers or sellers does not affect the market. As a result, both take the market price,

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[6]For example, Freeman (1993, pp 373-374) uses clean air as an example how one might assume the hedonic price function to be concave from below.

represented by *P(Z)*, as given.

An important issue to note is that the hedonic price function itself does not reveal information about individual bid or offer functions other than at the optimal choice of property characteristics. Although, in an extreme case where purchasers differ and all producers are identical, all offer functions would be identical. One offer function would depict the offer functions for all firms in the market. The unique offer function would therefore be equivalent to the hedonic price function, *P(Z)*. Similarly, if producers differ and all buyers are identical, one bid function would characterize all bid functions. The unique bid function would then represent the hedonic price function, *P(Z)*. However, it is reasonable to assume that firms on the demand and supply side are not identical and have characteristics that separate themselves from other firms, and so equilibrium is characterized as given in Figure 2.1.

Typically, it is assumed that supply restrictions or constraints do not exist when discussing the hedonic property value model. Something that may affect the quantity of property characteristics supplied in the market are local government zoning laws. Zoning laws can be a way for local governments to control how land is apportioned across multiple land-use categories, such as commercial, industrial, and residential. Zoning regulations can be in the form of restrictions on building height or style for particular geographic locations. Often these types of zoning laws are instituted as a method to minimize potential externality effects between nonconforming land-use types, such as industrial or commercial and residential. The result is that the supply of land available for commercial or industrial property development is restricted.

In general, zoning regulations can limit the number of properties with certain characteristics supplied in the market which may result in a discontinuous range of property characteristics available. These characteristics can be thought of as being exogenous to firms on the supply side since firms do not have control over the amounts in which they are supplied in the market. In the theoretical model they are expressed as elements of the z^{H} vector of property characteristics. The equilibrium market price for property characteristics considered exogenous to the firm are completely demand determined. However, it is assumed that a sufficient amount of variation in property characteristics exists in the market (as given by the description of the data in Chapter 3) and any supply constraints, that would lead to discontinuities in levels of property characteristics available, are not binding.

Measuring the Benefits of Hazardous Waste Site Cleanup with the Hedonic Model

The ability to accurately measure the externality effects of property contamination is important for quantifying the potential damages associated with contamination, and therefore important for determining the benefits that may arise from appropriately designed clean-up policies. This assumes that the remediation of contaminated sites removes any externality effects contaminated sites may have on nearby properties, such that there are no stigma effects associated with a site after in has been remediated. In addition to this assumption, if contaminated sites are viewed as a localized externality and depending on how the equilibrium hedonic price function is affected from the clean-up of contaminated sites, benefit estimates can then be approximated directly with the hedonic price function.

A localized externality, such as a contaminated site, only affects properties in close proximity to it. Therefore, a policy that requires the clean-up of a small number of contaminated sites (ie. the most severely contaminated) may provide benefits to only a small percentage of the total number of CI properties within Fulton County. It may be assumed that the equilibrium hedonic price function would not be affected in this case. Benefit estimates can then be derived through direct estimation of a hedonic price function.

For this analysis a large number of contaminated sites are used to determine the externality effects for CI properties located in close proximity. As such, the overall percentage of properties affected when considering all contaminated sites may be quite large even though an individual site may only affect a small percentage of the total number of properties within Fulton County. Consequently, the equilibrium hedonic price function may be affected if all contaminated sites were remediated. How the hedonic price function would be affected cannot be predicted with ex-ante information only. However, Bartik (1988) shows that if other property characteristics are not changed in response to the implementation of a policy and costs of changing other property characteristics are unaffected by a policy, the hedonic price function may be used to provide an upper-bound for the potential benefits that may arise and the need to derive the underlying demand or bid functions is not necessary. As a result, benefit estimates from the remediation of all contaminated sites may be approximated through the direct estimation of a hedonic price function.

In general, the estimated benefits received by a CI property owner affected can be stated as the difference in property value after the clean-up of the contaminated site and prior to clean-up. In the simplest case, this can be written as,

$$tb_j = P(z_0^1, z_1^0 \ldots, z_n^0) - P(z_0^0, z_1^0 \ldots, z_n^0), \tag{2.27}$$

where z_0^0 and z_0^1 represent the property characteristic controlling for the externality effects of contaminated sites on property value before and after clean-up and $z_1^0, \ldots, z_n^0$ are all other property characteristics, which are assumed to not change. If the externality effects of contaminated sites are measured as the linear distance to the nearest site, z_0^0 would be represented by this distance. The level of z_0^1 would be represented as the distance from contaminated sites at which zero externality effects are present, a result of only having ex-ante information. Therefore, equation (2.27) simply measures the difference in a property's value that is affected by a contaminated site and the value of the identical property at the distance from a contaminated site where zero externality effects exist.

Total benefits from the clean-up of the contaminated site is then the sum of benefits received by the individual CI property owners:

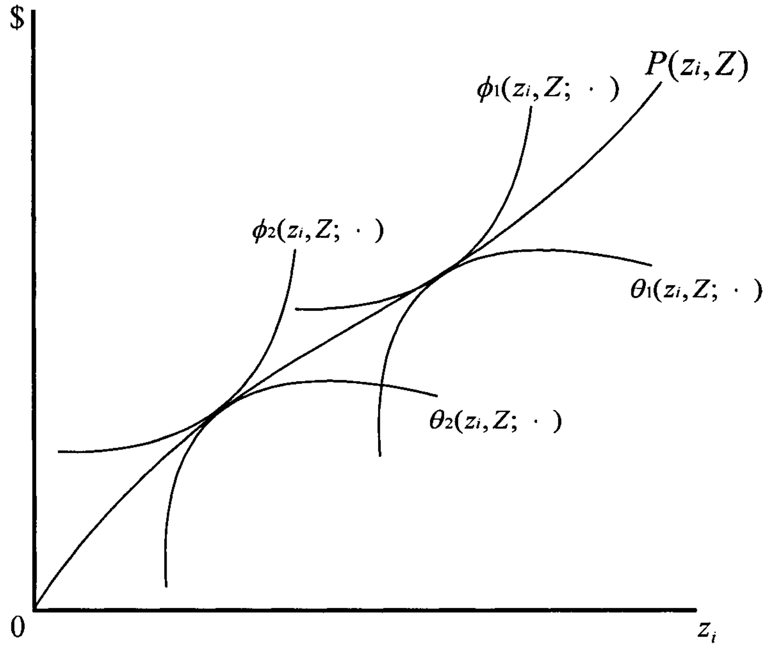
$$TB = \sum_{j=1}^{m} tb_j, \tag{2.28}$$

where $j = 1, \ldots, m$ are the m CI property owners affected. Equation (2.27) and (2.28) are applicable regardless of whether or not the equilibrium hedonic price function is affected. Although, as stated earlier, if the equilibrium hedonic price function is affected then the estimates given by these equations are only an upper-bound.

Conclusion

This chapter reviewed the hedonic property value model as applicable to CI property markets for which agents on the demand and supply side are profit-maximizing firms. Estimation of the hedonic price function can be used to determine increases in property values for individual CI property owners that may result from the clean-up of contaminated sites. Summing the gains in property values over all that are affected would result in an approximation of the total benefits that may be achieved from the clean-up of contaminated sites. The estimation of benefits in this manner assumes no stigma effects exists once a site has been remediated. The issues related to proper specification and estimation of the hedonic price function to derive benefit estimates are examined in Chapter 5.

Figure 2.1. Market Equilibrium



CHAPTER 3

COMMERCIAL/INDUSTRIAL PROPERTY DATA AND CONTAMINATED SITE DATA

Introduction

This chapter describes the data used to estimate the empirical models. The study area is Fulton County Georgia, which encompassed most of the City of Atlanta. For the analysis, there are two main data needs. The first is a database of commercial and industrial (CI) property sales. The CI property data was purchased from a private vendor and is based on Fulton County tax records for which the private vendor annually updated individual property sales prices in addition to other changes in property characteristics. The second main data need is the identification of contaminated sites. Two federal lists, the Unites States Environmental Protection Agency's Comprehensive Environmental Response, Compensation, and Liability Information System (CERCLIS) and No Further Response Action Planned (NFRAP) reports, and two state lists, the Georgia Environmental Protection Division's Hazardous Site Inventory (HSI) and Non Hazardous Site Inventory (NonHSI) reports, were used to address this need.[7] Each site identified by these four lists were individually matched to their corresponding entry in the property

[7]The Non Hazardous Site Inventory is not an official list published by the Georgia Environmental Protection Division. However, the Georgia Environmental Protection Division keeps records of these sites on file at their office.

data.

To more fully describe CI properties, several spatially-related variables were created using ArcView Geographic Information Systems (GIS). Also, Census data were appended to each CI property to capture neighborhood characteristics. Each of these data sets is described in turn below. Next, the data used to identify contaminated properties is discussed and finally the variables used to describe the spatial relationship between CI properties and contaminated properties are covered.

Commercial and Industrial Property Sales Data

The CI property sales data purchased from the private vendor is based on the property records kept by the Fulton County Tax Assessors office. This database contains information on the most recent recorded sales price and date in addition to property-specific characteristics for each CI property located in Fulton County. Of central importance to the analysis is to accurately determine each property's spatial location, a process known as geocoding. This process allows spatially-related variables to be created, census data to be appended, and the spatial relationship between CI properties and contaminated sites to be determined. CI properties were geocoded utilizing Fulton County's digitized tax parcel base- map by matching individual property records in the sales data to its corresponding record in tax parcel map through unique parcel identification numbers. The recorded latitude and longitude coordinates for individual parcels are based on the property's centroid computed by ArcView GIS. The physical characteristics and sales price information will be discussed first followed by the spatially-related variables and neighborhood characteristics.

Commercial and Industrial Property Characteristics

The CI property data contains several variables that describe the physical characteristics of each property, in addition to having a record of most recent sales price and date. The data contains information on variables which broadly describe each property's primary land use, land area, structure size and structure characteristics, number of improvements on each parcel, and parking.

The land-use code assigned by the tax assessor is one of the primary variables in the property data describing individuals properties. A total of 139 different land-uses are represented, which were subsequently group into seven major land-use categories. The categories include retail, office, industrial, apartment/hotel/motel, auto-related, and vacant land.[8] Each of these categories were created to represent separate property markets, since it may be reasonable to assume that potential property owners in the retail category would not necessarily consider for purchase properties in the apartment/hotel/motel or office categories and vice versa.[9] The apartment/hotel/motel category was the largest, consisting of 2,458 observations and the office category was the smallest with 706 observations.

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[8]There is also a miscellaneous category including land uses that could not be placed into one of the other six, such as public or exempt properties. A total of 428 observations are in this category. However, they will not be described in greater detail.

[9] It should be noted that this may not always be the case since an investor may demolish an existing facility/building on a property and construct a new facility/building associated with a different major land-use category.

Tables 3.1 to 3.6 describe in more detail the types of land-uses that comprise each of the six major sub-categories. For retail properties, the most common land-uses include retail, single occupancy at 35.4 percent; retail, multi occupancy at 16.3 percent; and downtown, row type at 13.2 percent. Most office properties are categorized as office building, low rise (59.6 percent) followed by office building, high rise at 15.6 percent. In the industrial category, forty-three different land-uses are represented, with warehouse (or prefab warehouse) being the majority at 73.9 percent. Three land-uses represent slightly over 85.0 percent of the properties in the apartment/hotel/motel category: apartment, garden three story and under (51.4 percent), residential, commercial land (27.3 percent), and residential, apartment land (9.7 percent). Auto-related is primarily comprised of parking miscellaneous at 51.6 percent and auto service garage at 29.8 percent. In reference to vacant land, 89.9 percent is classified as commercial and the remaining 10.1 percent is apartment or industrial.

The variables for each property characteristic used in the analysis are defined in Table 3.7 and Table 3.8 gives the descriptive statistics of these variables for all land-uses combined and for the six major land-use categories.

Overall, the average sales price for CI properties is $1,537,687 and sales prices varied from one dollar to $188 million. Of the six major land-use categories, office had the highest average sales price ($4,701,096) and retail had the lowest ($933,122). When estimating the empirical models, only observations representing "arms length transactions" will be used. For example, it may be assumed that sales prices lower than $10 thousand do not represent arms length transactions and that including these observations in the estimated models may affect the results.

Average property size in terms of land area is 2.1 acres and for individual land-uses, vacant land is the largest at 4.8 acres. However, among the land-use categories with structural improvements on them, industrial was the largest (3.1 acres). In addition, the average amount of commercial floor space for properties with structural improvements on them is 10,500 square feet. Not surprisingly, industrial (30,300 square feet) and office (22,700 square feet) were the two highest among the individual categories. Interestingly, apartment/hotel/motel are the oldest in terms of age of primary structure (42.5 years), which is almost seven years greater than the overall average of 35.8 years.

Other variables that broadly describe the primary structure for non-vacant properties include exterior wall type, interior wall condition, and building grade. Each variable is assigned by the tax assessor. The most common exterior wall type is brick at 43.2 percent while glass is the least common at 1.9 percent. This similarly observed among individual land-uses, except for auto-related where the most common exterior wall type is concrete (46.4 percent). Little variation is observed for interior wall condition where over 94.0 percent exhibit normal interior wall conditions according to either individual land-uses or for all land-uses combined. The building grades assigned by the tax assessor indicate the general quality of the structure and can be a value between A and E. The highest building grade a CI property can be assigned is A, which means the structure is in excellent condition, and E is the lowest meaning the structure is in poor condition. Generally, the structures on properties with structural improvements are in average condition, represented by a building grade of C. Only 3.4 percent of all properties with structural improvements have structures that are in excellent condition.

The CI property data also contains variables assigned by the tax assessor that describe the parking conditions for individual properties. Little variation is found in the availability of parking and proximity of parking as 87.3 percent of CI properties have adequate parking and 85.8 percent have parking located on the premises. This is also observed for individual land-use categories, but even more so for office, industrial, and auto-related. In terms of the type of parking available for CI properties, 66.1 percent have off street parking and 20.8 percent have a combination of both on and off street parking. Roughly the same proportions are noticed for five of the six land-use categories. Not surprisingly, vacant land also has a high percentage of observations classified with no parking type available (23.2 percent).

In addition to the characteristics describing the structure, the property data contains information assigned by the tax assessor that describes a property's frontage type and general location. Properties can be assigned one of eight codes to describe its frontage and one of eight codes to describe its general location. Overall, the most frequent frontage type is secondary street (39.1 percent). A similar result is observed when the data is analyzed according to major land-use categories, except for apartment/hotel/motel where slightly over half have residential frontage type. Differences in the most frequently observed location type code exist among the major land-use categories. Major strip is most the common for retail (31.2 percent), office (22.0 percent), and auto-related (25.6 percent). As may be expected, commercial/industrial park and apartment/condominium complex are the highest for industrial (47.5 percent) and apartment/hotel/motel (54.0 percent). Neighborhood or spot is most frequently observed for vacant land (36.8 percent) and when all land-uses are combined (23.0 percent).

Spatially-Related Property Characteristics

Several spatially related variables were created using ArcView GIS to capture the characteristics of each property's location. Descriptions of the variables created are given in Table 3.7. They include proximity of each property to the central business district (CBD), nearest highway exit, Hartsfield Atlanta Airport, nearest public transit station, and the tax jurisdiction in which each property is located. Table 3.8 provides the summary statistics for these variables for all CI properties and by major land-use category.[10]

To create distance to the CBD, Five Points MARTA transit station was used as the CBD reference point and distance to this point was calculated. Ihlanfeldt (1998) provides evidence for differences in price gradients for office rental space for north or south Fulton County. As such, this may be an important spatial characteristic and therefore a variable indicating a property's location in north or south Fulton is created. North (south) Fulton is specified as north (south) of the CBD reference point.

Figure 3.1 displays Fulton County along with census tract boundaries, City of Atlanta boundary, major highways, MARTA station locations, Hartsfield Atlanta Airport

[10]Summary statistics reported for the spatially-related characteristics given in Table 3.8 are based on observations that were geocoded and that had a positive sales price.

and a north/south county divider. Average distance to the CBD is 6.47 miles for all CI properties. In addition, a significant portion of CI properties are located within the City of Atlanta (69.4 percent). Interestingly, the office category (9.71 miles) is found to be the least clustered around the CBD and auto-related (4.78) the most clustered in terms of average distance to the CBD. Office and auto-related also represent the lowest and highest for proportion of properties located in the City of Atlanta among the major land-use categories. Generally, the percentage of properties in the northern part of Fulton County by individual land-use category is consistent with the overall percentage (59.3 percent). However, a significant portion of office properties (83.4 percent) are located in north Fulton while vacant land is evenly distributed between the north and south.

Another important characteristic is a property's proximity to public transit stations (MARTA). Properties in close proximity to a station may benefit from easier means of access for employees, thereby leading to increase property values. Proximity to MARTA was computed as the linear distance to the nearest open station at the time of sale for each CI property. The average distance to a MARTA station for CI properties is 2.83 miles and 43.2 percent were within one mile of a station at the time of sale. Auto-related properties are found to be the most clustered around MARTA stations both in terms of average distance (2.01 miles) and percentage within one mile (53.1).

To further characterize a CI property's relative accessibility, the linear distance to the nearest highway exit was calculated. Highway exits is defined to include major highway interchanges. Similar to proximity to a MARTA station, properties located in close proximity to either highway exits may benefit from easier means of access for their employees and customers. In addition, benefits can stem from easier means of accessibility for receiving inputs and/or delivering outputs. As a whole and by major land-use category, average distance to nearest highway exit is around one mile for CI properties. The highest proportion of properties within one mile of a highway exit is found among auto-related (65.6 percent) and office (65.0 percent) properties, nearly ten percent greater than what is observed for all CI properties (55.4 percent).

It is reasonable to assume that proximity to Hartsfield Atlanta International Airport, which is slightly over eight miles to the southwest of the CBD, can have an effect on commercial and industrial property values and it can be argued that the effect may be positive or negative. Properties in close proximity to the airport may benefit from lower transportation costs, therefore resulting in higher property values. However, airport noise and airplane exhaust may be viewed as nuisances, thereby negatively affecting property values. The average distance between CI properties and Hartsfield Atlanta Airport is 10.88 miles. Due to Hartsfield's geographic location of being over eight miles southwest of the CBD, only a small percentage of CI properties are located within five miles (15.8 percent). Similar results are observed among individual land-use categories, except for office properties which are furthest on average from Hartsfield (15.87 miles) and have the lowest percentage of properties within five miles (10.8 percent). This is a result of over eighty-three percent of office properties being located in the northern part of Fulton County.

The exact nature of the relationship between sales prices and proximity to Hartsfield, the CBD, MARTA stations, and highway exits, may vary by major land-use and will be something that is explored empirically.

Neighborhood Characteristics of Commercial and Industrial Properties

In addition to creating spatially related variables with ArcView, the software was used to determine the 1990 census tract location for each property. Census tracts were assigned to each property based on its location within Fulton County according to the centroid coordinates computed by ArcView. The census variables used were obtained from the Atlanta Regional Commission (ARC) and Donnelly, Inc. These variables vary by year (from 1980 to 1997) and are based on 1980 and 1990 census tract information, but summarized according to 1980 census tract geography. As a result, the 1990 census tract locations of CI properties were converted to 1980 tract numbers. The ARC and Donnelly, Inc. interpolate each variable for the years between 1980 and 1997. The census data was appended to the property data according to its 1980 census tract location and by matching the census data year to the year of sale for each property.[11]

Table 3.7 defines the census variables used to broadly describe neighborhood characteristics and Table 3.8 provides the summary statistics for these variables according to major land-use category and for all CI properties. The types of neighborhood characteristics that affect CI property values are different from those that affect residential property values, with some exceptions. Variables believed to be important include population totals, population density, racial composition, median household income,

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[11]All properties with a sale date prior to 1980 were given 1980 census data and all properties with a sale date after 1996 were given 1996 data as a result of incomplete data for 1997.

employment totals, and employment densities.

Population related variables may describe the potential employee base available for firms nearby. Racial composition and median income levels may provide insight into the type and/or quality of the surrounding area. Variables related to employment levels by major industry sector may be used to control for agglomeration economies and/or other spillover effects of being located near other firms in related industries. The population and employment variables are from the Atlanta Regional Commission (ARC) and income levels are from Donnelly, Inc.

Total census tract populations varied from as low as 270 persons per tract to as high as 54,762 persons per tract. Properties in the apartment/hotel/motel and auto-related categories were generally located in the more densely populated areas, with average population densities of 6.7 and 6.3 persons per acre, when compared to the overall average of 5.6 person per acre. Most properties were primarily located in minority neighborhoods as only office (27.4 percent) and apartment/hotel/motel (47.3) have average percent nonwhite populations under fifty percent. Collectively, average percent nonwhite population is 50.0 percent. A broad range of income levels were observed as real median household income varied from \$773 to \$97,120. Only office (\$29,289) has a higher average real median household income than the overall average (\$20,442). Properties in the auto-related category were generally located in the poorest neighborhoods.

Other important neighborhood characteristics for CI properties may include overall employment levels as well as the employment levels for different industry sectors in census tracts depending on the industry with which a CI property is associated. Minor industry sectors were combined to compute employment totals for four major industry groups as follows: total retail (sum of retail trade and wholesale trade), total services (sum of finance, insurance, and real estate and services), total industrial (sum of construction, manufacturing, and transportation, communications, and utility), and total government (sum of federal, state, and local government).

Total employment for all industry groups varied from 94 to 44,467 jobs per census tract with an average employment density of 11.6 jobs per acre. Comparing the four major employment industry sectors, total services employment was the dominant employment sector both in terms of average total employment (3,126 jobs per tract) and by average employment density (5.0 jobs per acre). As may be expected, average total employment was greatest for the office land-use category (13,376 jobs). Surprisingly, properties in auto-related had the highest average employment density (24.9 jobs per acre). Similar to what is observed for all CI properties, the most densely employed sector among individual land-use categories was the service sector varying from 1.8 jobs per acre (industrial) to 11.5 (auto-related).

Contaminated Sites

Two lists maintained by the EPA and two lists maintained by the EPD are used to determine the presence of contamination on tested sites in Fulton County, Georgia. The EPA's CERCLIS and NFRAP lists are described first followed by the EPD's HSI and NonHSI lists. The overlap of sites across the four lists is discussed next and the spatial distribution of contaminated sites within Fulton County is covered last.

CERCLIS Sites

The Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA) enacted by congress in 1980 provided a means for the Environmental Protection Agency (EPA) to manage releases of hazardous substances that may endanger human health or the environment. Revenues from a tax on chemical and petroleum industries, initiated by the act, are placed in a trust fund to help finance the clean up of those hazardous waste sites that were abandoned or where responsible parties could not be found or were unable to pay for clean up efforts. CERCLA was amended in 1986 by the Superfund Amendments and Reauthorization Act (SARA) to address some issues raised during the first six years of the act.

When the EPA is notified of a release or suspected release of hazardous substances at a site, it is entered into the Comprehensive Environmental Response, Compensation, and Liability Information System (CERCLIS), the EPA's publically accessible database of sites with hazardous substance releases.[12] The EPA can be notified of a hazardous substance release by the local population and state agencies or the EPA can make the discovery themselves. For the sites listed in CERCLIS, such information as the site's name, address, discovery date, and types of actions taken by the EPA with associated dates can be obtained. Once discovered, the EPA evaluates each site following a series of steps to determine the severity of the release and to address what remedial

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[12]Sites listed on CERCLIS can be viewed online at: www.epa.gov/superfund/sites/cursites/

actions to take.

The mechanism the EPA uses in ascertaining the severity of contamination present at a site is to utilize information collected during the preliminary assessment and site inspection phase to calculate a Hazardous Ranking System (HRS) score.[13] Four separate pathways are scored under the HRS, which are related to either ground water migration, surface water migration, soil exposure, and air migration, and are combined to calculate an overall score for the site.[14] Sites with a HRS score above 28.50 are eligible for placement on the National Priorities List (NPL), a classification the EPA assigns to the most severely contaminated properties. For Georgia in 2000, 360 sites are listed in CERCLIS and 14 are classified as NPL.

In Fulton County, Georgia twenty-two sites were listed in CERCLIS through 1999 and zero were designated as NPL sites. As indicated in Table 3.9, the majority of these CERCLIS sites were identified and listed in 1980, with no more than three sites added in any other year. Table 3.10 indicates the land-use codes for those properties listed on CERCLIS. As can be expected, CERCLIS sites are primarily properties with commercial and industrial land-use code designations[15], with one site classified as residential. Three land-use types account for slightly over fifty percent of the total number of sites

[13]The HRS addresses factors that look at the likelihood a site had a release or has the potential to release a contaminant into the environment, characteristics of the contaminant, and the location of people and sensitive environments.

[14]The overall site score is calculated by combining one or more pathway scores using a root-mean-square equation.

[15]Properties on CERCLIS were matched to their corresponding entry in the property value database where twenty-one out of the twenty-two total CERCLIS sites could be matched. The remaining one could not be accurately matched to an entry in the property data due to the information provided in the CERCLIS reports.

(warehouse, vacant land, and other manufacturing NEC). Overall, twelve different land-uses are represented by the sites listed. The average size of these sites in terms of land area is 26.5 acres, and the largest site covers 125.8 acres.

NFRAP Sites

NFRAP sites are contaminated or potentially contaminated properties that were initially entered into CERCLIS, but are no longer in need of further investigation or cleanup of contamination by the EPA and for which no additional steps will be taken to list the site on the NPL. It addition, sites where contamination is not serious enough to warrant further federal action may be referred to state agencies. The EPA also terms these sites as candidates for archive or archived CERCLIS.[16] The archival of sites was started to try to eliminate the perceived risk of being associated as a CERCLIS site since the level of contamination present may not have been severe and any major threat to human health and the environment may not exist. Therefore, the NFRAP designation does not necessarily mean contamination is not present, but rather that the EPA will not conduct any further investigation of a site unless additional information is provided to the EPA for which they use to determine if further investigation is deemed necessary.

A site can be classified as a NFRAP site during any step of the EPA site evaluation process. Through 1999, 100 properties in Fulton County have been designated as NFRAP sites. The majority of NFRAP sites were initially identified as CERCLIS sites around 1980, as indicated in Table 3.9, and the "official" NFRAP classification for most

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[16]NFRAP sites can be viewed online at: www.epa.gov/superfund/sites/arcsites/

of these sites occurred primarily during 1985, 1989, and 1990. On average, a site received NFRAP designation within 5.6 years of initial identification and investigation by the EPA. Table 3.10 presents the land-use codes of NFRAP sites.[17] Warehouse represents the most frequent land-use code, accounting for 19.2 percent of the sites listed as NFRAP. Overall, NFRAP sites can be categorized by twenty-one different land-use codes. The average size of NFRAP sites is 9.3 acres, with one site covering 90.7 acres of land.

Georgia's Hazardous Site Inventory

The Hazardous Site Response Act (HSRA) enacted in 1992 authorized the Georgia Environmental Protection Division (EPD) to clean up contaminated sites throughout the state that threaten human health or the environment. If those responsible for contamination were unable to finance cleanup efforts, the act also enabled the EPD to utilize the Hazardous Waste Trust Fund to cover costs associated with the cleanup of individual sites.[18]

Since July 1, 1994, the EPD publishes annually the Hazardous Site Inventory

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[17]Eighty-four out of the 100 total NFRAP sites could be matched to an observation in the property data. The remaining sixteen could not be accurately matched to an entry in the property data due to the information provided in the NFRAP reports.

[18]The Hazardous Waste Trust Fund is financed by fees collected by the EPD from industries and government agencies that generate, manage, or dispose of hazardous wastes, hazardous substances, and solid wastes. Revenue is also generated from fines levied on violators of Georgia's environmental laws.

(HSI), a publicly accessible list of Georgia's worst known contaminated sites.[19] For each listed site, the EPD keeps a file that records such information as the site's name and location, tax parcel ID number, ownership, type of contaminants released, date placed on HSI, and the current cleanup priority and status. The Rules for Hazardous Site Response (RHSR), issued under the HSRA, provide the guidelines for how it is to be determined if a site is placed on the HSI. According to the RHSR, a property owner must determine if the EPD is to be notified when a the release of a regulated substance is discovered in soil or groundwater. Upon notification, the EPD decides if the release is above a threshold level for a separate groundwater pathway (GW) and onsite pathway (OS) score, which are calculated according to the Reportable Quantities Screening Method (RQSM).[20] If the calculated GW score is above ten and/or the OS score is above twenty, then the site is placed on the HSI. For the initial publishing in 1994, 279 sites throughout the state had been identified and listed on the HSI, and this total has grown to 426 through 1999. Of the 426, 44 were located within Fulton County.

Once placed on the HSI, a site can be categorized into one of four classes. Each of these classes describes the EPD cleanup standards that have been or still need to be met for all sites listed on the HSI. The EPD denotes a site as CLASS I if known human exposure to a regulated substance has occurred, releases are still occurring, or serious

[19]Sites listed on the HSI can be viewed online at: www.ganet.org/dnr/environ/

[20]The RQSM assigns numerical values to the following factors describing the released substance: toxicity, quantity, and physical state, closeness to nearby residents and drinking wells, degree to which the release is contained, accessability 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 the numerical values to calculate a single soil and/or groundwater score that falls between zero and one hundred.

environmental damage has been caused. CLASS I sites are of highest priority to the EPD. CLASS II sites are sites that require further evaluation by the EPD to determine whether corrective action is needed. For CLASS II sites, the property owner is allowed to voluntarily cleanup the site and have the results submitted to the EPD. Those sites with a CLASS III status are sites that do not meet the EPD's residential cleanup standards, but meet other EPD cleanup standards. CLASS III sites are designated as still being in need of corrective action. Sites the EPD designates as CLASS IV are sites where corrective action is currently underway or has already been completed and they meet the EPD's minimal cleanup standards. Sites in any of the four classes can be reclassified or removed from the HSI if EPD cleanup standards are met or if the EPD determines after further investigation that a release of a regulated substance above the threshold levels has not occurred.

Since the first publishing of the HSI in 1994, a minimum of two additional sites have been placed on the list each year through 1999, as indicated in Table 3.9. At the end of 1999, the EPD had identified and listed a total of forty-four sites on the HSI. Of these forty-four sites, 15.9 percent are CLASS I, 65.9 percent are CLASS II, 2.3 percent are CLASS III, and 15.9 percent are CLASS IV.

Most HSI sites are commercial or industrial properties, according to the county land-use codes, with one site designated with a residential land-use code.[21] Table 3.10 gives the distribution of land-use codes for sites on the HSI. Properties classified as warehouse account for 22.7 percent of the total sites listed, commercial vacant lots

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[21]The HSI site with a residential land-use code is also a CERCLIS site.

account for 13.6 percent and manufacturing/processing account for 6.8 percent of the listed sites. In all, twenty-one different land-uses codes are represented. The average size, in land area, of HSI sites is 15.9 acres, with one site extended over 226 acres.

Georgia's Non Hazardous Site Inventory

Sites for which both the calculated GW score and OS score were found to be lower than the threshold level required to place the site on the HSI are classified as "NonHSI". The EPD does not officially publish a list of sites that are screened, but are not placed on the HSI, however records for each site the EPD tests are kept on file at their office. The NonHSI list was manually recorded for Fulton County by entering the information contained is these records into a database. Through 1999, the EPD had evaluated 290 sites in Fulton County which subsequently scored below the GW and OS threshold and were therefore classified as NonHSI.[22] The number of sites added yearly since 1994 is indicated in Table 3.9. A minimum of twenty-two sites were added annually over this period of time.

The frequency of land-use codes for sites listed on the NonHSI is reported in Table 3.10. Warehouse again accounts for the highest percentage of sites (20.9 percent).[23] Strip shopping and single occupancy retail are the next highest at 6.7 percent. In all, fifty-six different land-uses are represented by sites on the NonHSI. The average

[22]Since the NonHSI list was only manually generated for Fulton County, the total number of NonHSI sites in Georgia is unknown.

[23]Two hundred thirty-two out of the 290 total NonHSI sites could be matched to an observation in the property data. The remaining fifty-eight could not be accurately matched to an entry in the property data due to the information provided in the NonHSI reports.

size of these properties is 6.3 acres, and the largest sites was 90.7 acres.

List Overlaps

As a result of the federal and state agencies using different mechanisms to determine the severity and potential threat to nearby residents of contaminated properties, sites may be listed on CERCLIS, but not HSI and vice-versa. Sites may also appear on both lists simultaneously. Table 3.11 presents a cross-tabulation of the number of sites found concurrently on a federal list and state list. Ten CERCLIS sites, nineteen NFRAP sites, twenty-four HSI sites, and 217 NonHSI sites unique to their respective list. Seven CERCLIS sites can be found on the HSI and sixty-eight NFRAP sites on the NonHSI. Surprisingly, five CERCLIS sites are also found on the NonHSI and thirteen NFRAP sites are jointly listed on the HSI. Again, this is due to the differences between federal and state program goals and site evaluation processes.

For analysis purposes, sites listed on the NonHSI or NFRAP that are also listed on CERCLIS or HSI will be identified as CERCLIS or HSI sites only. Additionally, those sites found on both NFRAP and NonHSI will be identified as NFRAP sites only. As a result, fifty-nine total sites can be found on CERCLIS or the HSI, eighty-seven sites on NFRAP or NonHSI, and 217 sites on NonHSI only.

Spatial Distribution of Contaminated Sites

Figure 3.2 displays the spatial distribution CERCLIS and HSI sites identified within Fulton County, along with 1990 census tract boundaries, the City of Atlanta boundary, and major highways. For clarity in the map, CERCLIS and HSI sites are displayed with the same symbol. One CERCLIS site could not be geocoded given the information recorded for the site.[24] Thirty-three out of the 146 total census tracts within Fulton County contain at least one CERCLIS or HSI site. A significant portion of these sites, 32.1 percent, are located within three census tracts. Two of these tracts border each other and are located northwest of the CBD within the Atlanta city limits. The third tract is located west of the CBD and is only partially within the Atlanta city limits. In general, most of the sites are located in the central part of the county, where twenty-nine sites are located within the City of Atlanta and several additional sites just outside of the city limits. On average, CERCLIS/HSI sites are located 6.5 miles from the CBD center point.[25]

The relationship of CERCLIS/HSI sites to neighborhood characteristics are shown in Figures 3.3 and 3.4. These figures are similar to Figure 3.2, but they include the percent of the population in a census tract that is non-white and the median household income level by census tract. These figures indicate that CERCLIS/HSI sites are primarily located in the lower income, majority non-white neighborhoods. The average non-white population for census tracts with a CERCLIS/HSI site is 63.1 percent, slightly higher than the average non-white population of all census tracts in Fulton County (59 percent). Thirty sites are located in census tracts with non-white populations greater than fifty percent, and twenty-seven of these sites are in census tracts with non-white

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[24] All location and neighborhood statistics reported for the combined list of CERCLIS and HSI sites are based only on the fifty-eight sites that could be geocoded.

[25] Five Points MARTA transit station was used as the cbd reference point.

populations greater than seventy-five percent. Twelve sites are found in a census tract with non-white population less than twenty-five percent.

Figure 3.4 highlights the relationship of median household income and CERCLIS/HSI sites. Twenty-eight sites are located in census tracts with a median household income of less than $25 thousand and only two sites can be found in a census tract with a median income level greater than $50 thousand.

The spatial distribution of NFRAP and NonHSI sites within Fulton County is displayed in Figure 3.5, along with 1990 census tract boundaries, the City of Atlanta and major highways for the area. For clarity in the map, NFRAP and NonHSI sites are displayed with the same symbol, but descriptive statistics will be reported separately for each list. A total of 304 sites were either found on NFRAP (19 sites), on the NonHSI (217 sites), or jointly on both (68 sites). As stated earlier, sites listed on both NFRAP and NonHSI are identified as NFRAP sites only for analysis purposes. Seventy-one of the eighty-seven NFRAP sites and 172 of the 217 NonHSI sites were able to be geocoded as a result of information available for these sites.[26]

NFRAP and NonHSI sites are primarily found in the central portion Fulton County where 63.2 percent of NFRAP sites and 76.2 percent of NonHSI sites are located within the City of Atlanta. The average distance between NFRAP and NonHSI sites and the CBD is 5.1 and 5.5 miles respectively. Interestingly, NonHSI sites are generally located in north Fulton (74.4 percent) whereas more NFRAP sites are found in south

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[26]All location and neighborhood statistics reported for NFRAP and NonHSI sites are based only on those that could be geocoded.

Fulton (57.4 percent).

The relationship of NFRAP and NonHSI sites to neighborhood characteristics are shown in Figures 3.6 and 3.7. NFRAP sites are mainly located in minority neighborhoods. The average non-white population for census tracts with a NFRAP site is 68.1 percent, which is higher than the average for all census tracts in Fulton County (59.0 percent). Nearly fifty-five percent of NFRAP sites (39 sites) are located in neighborhoods with minority populations of over seventy-five percent. Different from NFRAP, NonHSI sites are located in neighborhoods with minority populations significantly lower than average for all census tracts, where average non-white population for census tracts with a NonHSI site is 45.2 percent. Almost sixty-three percent of NonHSI sites (108 sites) are located in neighborhoods with non-white populations under fifty percent and nearly forty-nine percent (84 sites) in neighborhoods with non-white populations under twenty-five percent.

Figure 3.7 displays the relationship between NFRAP and NonHSI and median household income levels. NFRAP sites are more likely than NonHSI sites to found in lower income neighborhoods, where 67.6 percent of NFRAP sites and 44.2 percent of NonHSI sites are located in census tracts with median income levels lower than $25 thousand. Overall, average median income levels for neighborhoods with a NFRAP site ($21,817) is approximately $5,800 lower than what is observed for neighborhoods with a NonHSI site ($27,664).

Spatial Relationship Between CI Property Sales and Contaminated Sites

Figures 3.8 to 3.19 display the geographic distribution of CI property sales relative to contaminated sites for the following major land-use categories: retail, office, industrial, apartment/hotel/motel, auto-related, and vacant. These figures also identify the City of Atlanta and major highways. The spatial relationship between CI property sales and CERCLIS/HSI sites is discussed first followed by the relationship between CI sales and NFRAP and NonHSI sites.

CI Property Sales and Proximity to CERCLIS/HSI Sites

A higher percentage of CI property sales occurred within the northern section of Fulton County (59.3 percent). Additionally, a significant portion of all CI property sales occurred within the City of Atlanta (69.4 percent). In terms of the six major land-use categories given previously, sales generally followed a similar pattern to all CI property sales and those sales that occurred in the northern or southern parts of Fulton County mainly followed the path of a major highway. The spatial distribution of retail, office, industrial, apartment/hotel/motel, auto-related, and vacant property sales respectively relative to CERCLIS/HSI sites within Fulton County are displayed in figures 3.8 to 3.13 along with the City of Atlanta and major highways.

Figures 3.8 to 3.13 show that a large number of sales for each of the six major land-use categories have occurred in close proximity to CERCLIS/HSI sites. Overall, 82.6 percent of CI property sales occurred within two miles of one CERCLIS/HSI sites. As may be expected , industrial (89.5 percent) was highest among individual land-use categories due to the large number of properties with industrial land-uses found on

CERCLIS and HSI. For the remaining five major land-use categories, 89.0 percent of auto-related, 84.3 percent of apartment/hotel/motel, 82.0 percent of retail, 80.6 percent of vacant land, and 62.9 percent of office property sales occurred within two miles of at least one CERCLIS/HSI site.

The distance between CI sales and the nearest CERCLIS/HSI site ranged from zero feet to 13.0 miles with an overall average of 1.4 miles. Among major land-use categories, industrial (0.9 miles) properties are nearest, on average, to CERCLIS/HSI sites followed by auto-related (1.0 mile), apartment/hotel/motel (1.3 miles), and retail (1.3 miles). Both vacant land (1.6 miles) and office (2.4) are greater than the overall average.

It may be reasonable to assume that any negative effect proximity to contaminated sites has on CI property values will decrease as distance increases, up to a distance at which no effects are apparent. When the data is restricted to observations for which the nearest CERCLIS/HSI site is less than five miles[27], the average distance becomes 1.0 mile for all CI property sales. In regards to individual land-use categories, industrial still has the lowest average (0.7 miles) and office the highest (1.5 miles). The order of the remaining four categories changes to auto-related (0.9 miles), vacant land (1.0 mile), apartment/hotel/motel (1.1 miles), and retail (1.1 miles).

In addition to distance to nearest CERCLIS/HSI site, the total number of sites within some minimum distance may be relevant to consider when estimating the negative effects of proximity to contaminated sites. As such, the number of sites within two and

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[27]While the exact minimum distance to be considered is an empirical question, five miles is used for illustrative purposes only.

five miles was calculated.[28] On average, CI properties have 15.9 CERCLIS/HSI sites within a five mile radius and 4.1 sites within a two mile radius. In terms of individual land-use categories, industrial (16.7) is highest followed by auto-related (18.3), vacant land (15.4), apartment/hotel/motel (16.5), retail (15.9), and office (11.0) for average number sites within five miles. The same order is observed among land-use categories when considering only the number of sites within two miles (5.3, 5.1, 4.1, 3.7, 3.8, and 2.6 respectively).

CI Property Sales and Proximity to NFRAP and NonHSI Sites

NFRAP and NonHSI sites follow the same general spatial patterns as CERCLIS/HSI sites with the exception that there are more NFRAP and NonHSI sites and a higher number of them in close proximity to CI properties. The spatial distribution of retail, office, industrial, apartment/hotel/motel, auto-related, and vacant property sales respectively relative to NFRAP and NonHSI sites within Fulton County are displayed in figures 3.14 to 3.19 along with the City of Atlanta and major highways. For clarity in the maps, NFRAP and NonHSI sites are displayed with the same symbol. Surprisingly, a slightly lower percentage of CI property sales occurred within two miles of a NFRAP site (80.4 percent) compared to what is observed for CERCLIS/HSI sites. However, the opposite is noticed for NonHSI sites where a significantly higher proportion of CI sales occurred within two miles of a single NonHSI site (91.8 percent). This is primarily a

[28]While the exact minimum distance to be considered is an empirical question, five miles and two miles are used to illustrative purposes.

result of there being a greater number of NonHSI sites than both CERCLIS/HSI and NFRAP. Among individual land-use categories, only office (63.5 percent) and industrial (91.0 percent) have a higher proportion of sales occurring within two miles of a NFRAP site than a CERCLIS/HSI site. For NonHSI sites, all major land-use categories have a least eighty-five percent of sales occurring within two miles of a single site.

CI properties are slightly further away from NFRAP sites (1.4 miles) and significantly closer to NonHSI sites (0.6 miles) in terms of average distance to nearest site when compared to CERCLIS/HSI sites. However, CI properties are more densely surrounded by both NFRAP and NonHSI sites within two and five mile radiuses. Overall, CI properties average 6.1 (23.9) NFRAP sites and 19.4 (64.1) NonHSI sites within two (five) miles. Similar patterns are observed among major land-use categories. Again, this is mainly a result of there being a greater number of NFRAP and NonHSI sites than CERCLIS/HSI sites.

Table 3.1. Land-Use Code Frequencies for Retail

Land-Use	Description	Frequency	Percent
321	Restaurant	150	9.02
323	Food stand	7	0.42
325	Fast food	103	6.19
327	Bar / lounge	46	2.77
328	Night club / dinner theater	11	0.66
340	Super regional shopping	1	0.06
341	Regional shopping mall	2	0.12
344	Strip Shopping	88	5.29
347	Supermarket	13	0.78
348	Convenience food market	114	6.86
361	Funeral Home	11	0.66
362	Veterinary Clinic	13	0.78
363	Legitimate theater	1	0.06
364	Motion picture theater	2	0.12
365	Cinema / theater	1	0.06
366	Tv / radio / film studio	4	0.24
367	Social / fraternal hall	13	0.78
370	Greenhouse / florist	5	0.30
371	Downtown row type	219	13.17
373	Retail, single occupancy	588	35.36
374	Retail, multi occupancy	271	16.30
Total		1663	100

Table 3.2. Land-Use Code Frequencies for Office Category

Land-Use	Description	Frequency	Percent
349	Medical office building	61	8.64
351	Bank	29	4.11
352	Savings institution	2	0.28
353	Office building, low rise	421	59.63
354	Office building, high rise	110	15.58
355	Office condo	83	11.76
Total		706	100

Table 3.3. Land-Use Code Frequencies for Industrial Category

Land-Use	Description	Frequency	Percent
391	Cold storage facility	8	0.71
392	Lumber storage	9	0.80
393	Auxiliary improvement	3	0.27
395	Truck terminal	18	1.60
396	Mini warehouse	24	2.14
397	Office / warehouse	17	1.51
398	Warehouse	766	68.15
399	Warehouse, prefab	65	5.78
401	Manufacturing / processing	60	5.34
405	Research and development	3	0.27
413	Asphalt plant	3	0.27
415	Bakery	3	0.27
421	Aluminum and foil manufacturing	12	1.07
429	Electric components manufacturing	4	0.36
433	Food processing	8	0.71
443	Metal manufacturing	19	1.69
452	Paper finishing / converting	5	0.44
455	Plastics products manufacturing	5	0.44
457	Print shop	13	1.16
461	Rubber manufacturing tire recapping	3	0.27
469	Woodworking shop	6	0.53
471	Jewelry / toys / musical instruments	3	0.27
499	Other manufacturing NEC	28	2.49
711	Telephone utility NEC	10	0.89
720	Radio / TV transmitter building	3	0.27
misc	Miscellaneous	26	2.31
Total		1,124	100

Note: For miscellaneous, eighteen land-uses with either one or two observations were combined.

Table 3.4. Land-Use Code Frequencies for Apartment/Hotel/Motel Category

Land-Use	Description	Frequency	Percent
105	Mixed residential / commercial	4	0.16
201	Residential, apartment land	238	9.68
209	Apartment loft / retail	24	0.98
210	Mid-rise apartment	7	0.28
211	Apartment, garden three story and under	1,263	51.38
212	Apartment, high rise	8	0.33
250	Super luxury hotel	6	0.24
251	Luxury hotel	5	0.20
252	First class hotel	6	0.24
253	NM-rise hotel	14	0.57
254	Luxury budget motel	21	0.85
255	Economy motel	14	0.57
256	Micro-budget motel	15	0.61
301	Residential / commercial land	671	27.30
314	Hotel / motel, high rise with restaurant	2	0.08
315	Hotel / motel, low rise with restaurant	1	0.04
316	Nursing home	35	1.42
318	Boarding / rooming house	29	1.18
319	Mixed residential / commercial	39	1.59
369	Day care center	56	2.28
Total		2,458	100

Table 3.5. Land-Use Code Frequencies for Auto-Related Category

Land-Use	Description	Frequency	Percent
331	Auto dealer, full service	34	4.09
332	Auto service garage	248	29.84
333	Service station, with bays	49	5.90
334	Service station, without	29	3.49
336	Car wash, manual	11	1.32
337	Car wash, automatic	5	0.60
338	Parking garage / deck	26	3.13
339	Parking miscellaneous	429	51.62
Total		831	100

Table 3.6. Land-Use Code Frequencies for Vacant Land Category

Land-Use	Description	Frequency	Percent
200	Apartment, vacant land	81	6.34
300	Commercial, vacant	1,155	89.87
400	Vacant industrial	49	3.79
Total		1,285	100

Table 3.7. Description of Property, Spatially-Related and Neighborhood Characteristics

Variable Name	Variable Description
Property Characteristics	
saleprice	Sales Price
acre	Total land area
sqft	Square feet of commercial floor space
age	Age of primary structure
yrbuilt	Year primary structure was built
numimp	Total number of Improvements
extframe	Dummy = 1 if exterior wall type is frame
extbrick	Dummy = 1 if exterior wall type is brick
extstone	Dummy = 1 if exterior wall type is stone
extglass	Dummy = 1 if exterior wall type is glass
extconc	Dummy = 1 if exterior wall type is concrete
extmisc	Dummy = 1 if exterior wall type is other
intbnorm	Dummy = 1 if interior wall condition is below normal
intnorm	Dummy = 1 if interior wall condition is normal
intanorm	Dummy = 1 if interior wall condition is above normal
intmisc	Dummy = 1 if interior wall condition is miscellaneous
bgradea	Dummy = 1 if building grade equals A
bgradeb	Dummy = 1 if building grade equals B
bgradec	Dummy = 1 if building grade equals C
bgraded	Dummy = 1 if building grade equals D
bgradee	Dummy = 1 if building grade equals E
ptnone	Dummy = 1 if parking type is none
ptoffst	Dummy = 1 if parking type is off street
ptonst	Dummy = 1 if parking type is on street
ptboth	Dummy = 1 if parking type is on and off street
ptdeck	Dummy = 1 if parking type is deck
ppfar	Dummy = 1 if parking proximity is far
ppnear	Dummy = 1 if parking proximity is near
ppadj	Dummy = 1 if parking proximity is adjacent
pponsite	Dummy = 1 if parking proximity is on site
pqnone	Dummy = 1 if parking quantity is none
pqmin	Dummy = 1 if parking quantity is minimal
pqadeq	Dummy = 1 if parking quantity is adequate
pqabund	Dummy = 1 if parking quantity is abundant
loc2	Dummy = 1 if location code is cbd

Table 3.7. continued

Variable Name	Variable Description
loc3	Dummy = 1 if location code is business cluster
loc4	Dummy = 1 if location code is major strip
loc5	Dummy = 1 if location code is secondary strip
loc6	Dummy = 1 if location code is neighborhood or spot
loc7	Dummy = 1 if location code is commercial/industrial park
loc8	Dummy = 1 if location code is industrial site
loc9	Dummy = 1 if location code is apartment/condominium complex
front1	Dummy = 1 if frontage code is cbd street
front2	Dummy = 1 if frontage code is major strip
front3	Dummy = 1 if frontage code is secondary artery
front4	Dummy = 1 if frontage code is secondary street
front5	Dummy = 1 if frontage code is frontage road
front6	Dummy = 1 if frontage code is private road
front7	Dummy = 1 if frontage code is waterfront
front9	Dummy = 1 if frontage code is residential
Spatially-Related Characteristics	
cbd	Distance to central business district
marta	Distance to nearest MARTA transit station
marta1m	Dummy variable = 1 if CI property is located within 1 mile of MARTA transit station
exit	Distance to nearest highway exit
exit1m	Dummy variable = 1 if CI property is located within 1 mile of highway exit
harts	Distance to Hartsfield Atlanta Airport
harts5m	Dummy variable = 1 if CI property is located within 5 miles of Hartsfield Atlanta Airport
north	Dummy variable = 1 if CI property is located north Fulton County
juris1	Dummy variable = 1 if CI property is located in Alpharetta
juris2	Dummy variable = 1 if CI property is located in Atlanta
juris3	Dummy variable = 1 if CI property is located in College Park
juris4	Dummy variable = 1 if CI property is located in East Point
juris5	Dummy variable = 1 if CI property is located in Fairburn
juris6	Dummy variable = 1 if CI property is located in Fulton
juris7	Dummy variable = 1 if CI property is located in Hapeville
juris8	Dummy variable = 1 if CI property is located in Palmetto
juris9	Dummy variable = 1 if CI property is located in Roswell

Table 3.7. continued

Variable Name	Variable Description
Neighborhood Characteristics	
totpop	Total population of census tract
white	White population of census tract
nonwhite	Non-white population of census tract
minority	Percent non-white population of census tract
popdens	Population density of census tract
rmedinc	Real median household income of census tract
con	Construction employment
ret	Retail trade employment
whol	Wholesale trade employment
mfg	Manufacturing employment
tcu	Trans, communications, and utility employment
fire	Finance, insurance, and real estate employment
svcs	Services employment
fed	Federal government employment
state	State government employment
local	Local government employment
indemp	Total industrial employment (sum of con, mfg, tcu)
retemp	Total retail trade employment (sum of whol, ret)
servemp	Total services employment (sum of fire, svcs)
priv	Total private employment
gov	Total government employment
employ	Total employment
empdens	Total Employment density
privdens	Total private employment density
govdens	Total government employment density
inddens	Total industrial employment density
retdens	Total retail trade employment density
servdens	Total services employment density

Table 3.8. Summary Statistics for Property Data

	All Land-uses				Retail		Office		Industrial		Apartment / Hotel / Motel		Auto-Related		Vacant Land	
Variable Name	N	Mean	Min	Max	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean
Property Characteristics																
saleprice	8,067	1,537,687	1	188,000,000	1,663	933,122	706	4,701,096	1,124	1,050,097	2,458	1,139,218	831	1,553,309	1,285	1,760,672
acre	8,065	2.1	0.001	256.6	1,663	0.9	706	2.0	1,123	3.1	2,458	1.7	831	0.9	1,284	4.8
sqft	8,067	10.5	0	1,334.2	1,663	7.3	706	22.7	1,124	30.8	2,458	7.4	831	4.3	1,285	0.0
age	6,265	35.8	0	199	1,653	37.1	702	22.0	1,095	30.2	2,423	42.5	392	29.6	-	-
yrbuilt	6,265	1957	1800	1999	1,653	1955	702	1972	1,095	1963	2,423	1950	392	1963	-	-
numimp	8,067	1.5	1	39	1,663	1.3	706	1.4	1,124	1.8	2,458	2.0	831	1.2	1,285	1.0
extframe	6,265	0.1138	0	1	1,653	0.0829	702	0.0527	1,095	0.0128	2,423	0.2121	392	0.0281	-	-
extbrick	6,265	0.4318	0	1	1,653	0.4253	702	0.4573	1,095	0.5507	2,423	0.4024	392	0.2628	-	-
extglass	6,265	0.0190	0	1	1,653	0.0133	702	0.1125	1,095	0.0082	2,423	0.0012	392	0.0153	-	-
extconc	6,265	0.1775	0	1	1,653	0.2819	702	0.1225	1,095	0.2091	2,423	0.0615	392	0.4643	-	-
extmisc	6,265	0.2579	0	1	1,653	0.1966	702	0.2550	1,095	0.2192	2,423	0.3227	392	0.2296	-	-
intbnorm	6,265	0.0065	0	1	1,653	0.0067	702	0.0057	1,095	0.0128	2,423	0.0041	392	0.0051	-	-
intnorm	6,265	0.9577	0	1	1,653	0.9558	702	0.9815	1,095	0.9425	2,423	0.9554	392	0.9796	-	-
intanorm	6,265	0.0164	0	1	1,653	0.0284	702	0.0071	1,095	0.0365	2,423	0.0041	392	0.0026	-	-
intmisc	6,265	0.0193	0	1	1,653	0.0091	702	0.0057	1,095	0.0082	2,423	0.0363	392	0.0128	-	-
bgradea	6,264	0.0335	0	1	1,653	0.0417	701	0.1127	1,095	0.0018	2,423	0.0244	392	0.0026	-	-
bgradeb	6,264	0.1023	0	1	1,653	0.1131	701	0.2397	1,095	0.0192	2,423	0.0941	392	0.0944	-	-
bgradec	6,264	0.7110	0	1	1,653	0.6721	701	0.6020	1,095	0.8858	2,423	0.6942	392	0.6862	-	-
bgraded	6,264	0.1478	0	1	1,653	0.1633	701	0.0456	1,095	0.0895	2,423	0.1849	392	0.1990	-	-
bgradee	6,264	0.0037	0	1	1,653	0.0091	701	0.0000	1,095	0.0037	2,423	0.0004	392	0.0077	-	-
ptnone	8,067	0.0493	0	1	1,663	0.0355	706	0.0057	1,124	0.0098	2,458	0.0045	831	0.0181	1,285	0.2319

Table 3.8. Continued

	All Land-uses				Retail		Office		Industrial		Apartment / Hotel / Motel		Auto-Related		Vacant Land	
ptoffst	8,067	0.6606	0	1	1,663	0.7529	706	0.8286	1,124	0.8149	2,458	0.5395	831	0.8363	1,285	0.4319
ptonst	8,067	0.0751	0	1	1,663	0.0806	706	0.0227	1,124	0.0231	2,458	0.0862	831	0.0108	1,285	0.1626
ptboth	8,067	0.2084	0	1	1,663	0.1287	706	0.0977	1,124	0.1521	2,458	0.3653	831	0.1276	1,285	0.1735
ptdeck	8,067	0.0066	0	1	1,663	0.0024	706	0.0453	1,124	0.0000	2,458	0.0045	831	0.0072	1,285	0.0000
ppfar	8,067	0.0454	0	1	1,663	0.0289	706	0.0042	1,124	0.0098	2,458	0.0037	831	0.0156	1,285	0.2195
ppnear	8,067	0.0295	0	1	1,663	0.0445	706	0.0312	1,124	0.0062	2,458	0.0264	831	0.0060	1,285	0.0506
ppadj	8,067	0.0669	0	1	1,663	0.0704	706	0.0283	1,124	0.0231	2,458	0.0740	831	0.0181	1,285	0.1401
pponsite	8,067	0.8582	0	1	1,663	0.8563	706	0.9363	1,124	0.9609	2,458	0.8959	831	0.9603	1,285	0.5899
pqnone	8,067	0.0477	0	1	1,663	0.0295	706	0.0028	1,124	0.0098	2,458	0.0045	831	0.0168	1,285	0.2319
pqmin	8,067	0.0743	0	1	1,663	0.0956	706	0.0326	1,124	0.0320	2,458	0.0952	831	0.0241	1,285	0.0988
pqadeq	8,067	0.8732	0	1	1,663	0.8701	706	0.9547	1,124	0.9546	2,458	0.8971	831	0.9483	1,285	0.6669
pqabund	8,067	0.0048	0	1	1,663	0.0048	706	0.0099	1,124	0.0036	2,458	0.0033	831	0.0108	1,285	0.0023
loc2	8,067	0.0584	0	1	1,663	0.0710	706	0.1303	1,124	0.0178	2,458	0.0203	831	0.1901	1,285	0.0257
loc3	8,067	0.0461	0	1	1,663	0.1022	706	0.0694	1,124	0.0027	2,458	0.0378	831	0.0289	1,285	0.0257
loc4	8,067	0.1633	0	1	1,663	0.3121	706	0.2195	1,124	0.0472	2,458	0.0797	831	0.2563	1,285	0.1409
loc5	8,067	0.1785	0	1	1,663	0.3037	706	0.2195	1,124	0.0996	2,458	0.0964	831	0.2130	1,285	0.1977
loc6	8,067	0.2301	0	1	1,663	0.1816	706	0.1586	1,124	0.2091	2,458	0.2160	831	0.2443	1,285	0.3681
loc7	8,067	0.1045	0	1	1,663	0.0247	706	0.0822	1,124	0.4751	2,458	0.0090	831	0.0469	1,285	0.1160
loc8	8,067	0.0285	0	1	1,663	0.0024	706	0.0057	1,124	0.1486	2,458	0.0008	831	0.0144	1,285	0.0319
loc9	8,067	0.1907	0	1	1,663	0.0024	706	0.1147	1,124	0.0000	2,458	0.5399	831	0.0060	1,285	0.0942
front1	8,067	0.0342	0	1	1,663	0.0463	706	0.0850	1,124	0.0027	2,458	0.0163	831	0.0963	1,285	0.0125
front2	8,067	0.1217	0	1	1,663	0.2285	706	0.1700	1,124	0.0516	2,458	0.0574	831	0.2010	1,285	0.0903
front3	8,067	0.1946	0	1	1,663	0.2874	706	0.2181	1,124	0.1593	2,458	0.1237	831	0.2467	1,285	0.1946

Table 3.8. Continued

	All Land-uses				Retail		Office		Industrial		Apartment / Hotel / Motel		Auto-Related		Vacant Land	
Spatially-Related Characteristics																
front4	8,067	0.3906	0	1	1,663	0.3397	706	0.4674	1,124	0.6842	2,458	0.2754	831	0.3514	1,285	0.4031
front5	8,067	0.0040	0	1	1,663	0.0018	706	0.0014	1,124	0.0053	2,458	0.0020	831	0.0036	1,285	0.0109
front6	8,067	0.0087	0	1	1,663	0.0000	706	0.0142	1,124	0.0098	2,458	0.0065	831	0.0012	1,285	0.0249
front7	8,067	0.0001	0	1	1,663	0.0006	706	0.0000	1,124	0.0000	2,458	0.0000	831	0.0000	1,285	0.0000
front9	8,067	0.2461	0	1	1,663	0.0956	706	0.0439	1,124	0.0872	2,458	0.5187	831	0.0999	1,285	0.2638
cbd	8,067	6.47	0.06	28.36	1,663	6.47	706	9.71	1,124	6.13	2,458	5.87	831	4.78	1,285	7.21
marta	8,067	2.83	0	23.04	1,663	2.81	706	3.93	1,124	3.02	2,458	2.44	831	2.01	1,285	3.38
marta1m	8,067	0.4316	0	1	1,663	0.4167	706	0.4193	1,124	0.3034	2,458	0.4890	831	0.5307	1,285	0.3961
exit	8,067	1.08	0.01	10.08	1,663	1.06	706	1.09	1,124	1.19	2,458	1.06	831	0.88	1,285	1.17
exit1m	8,067	0.5544	0	1	1,663	0.5532	706	0.6501	1,124	0.4173	2,458	0.5496	831	0.6558	1,285	0.5665
harts	8,067	10.88	0.94	36.33	1,663	10.53	706	15.87	1,124	9.99	2,458	10.54	831	9.57	1,285	10.86
harts5m	8,067	0.1582	0	1	1,663	0.1756	706	0.1076	1,124	0.1272	2,458	0.1859	831	0.1516	1,285	0.1416
north	8,067	0.5930	0	1	1,663	0.5466	706	0.8329	1,124	0.5454	2,458	0.6188	831	0.6005	1,285	0.5089
juris1	8,067	0.0369	0	1	1,663	0.0349	706	0.0807	1,124	0.0285	2,458	0.0260	831	0.0132	1,285	0.0591
juris2	8,067	0.6941	0	1	1,663	0.6873	706	0.5042	1,124	0.7571	2,458	0.7107	831	0.7786	1,285	0.6654
juris3	8,067	0.0254	0	1	1,663	0.0277	706	0.0227	1,124	0.0080	2,458	0.0391	831	0.0193	1,285	0.0171
juris4	8,067	0.0512	0	1	1,663	0.0523	706	0.0482	1,124	0.0561	2,458	0.0525	831	0.0529	1,285	0.0436
juris5	8,067	0.0200	0	1	1,663	0.0247	706	0.0042	1,124	0.0294	2,458	0.0118	831	0.0132	1,285	0.0342
juris6	8,067	0.0876	0	1	1,663	0.0734	706	0.1615	1,124	0.0836	2,458	0.0765	831	0.0566	1,285	0.1105
juris7	8,067	0.0175	0	1	1,663	0.0271	706	0.0113	1,124	0.0089	2,458	0.0207	831	0.0168	1,285	0.0101
juris8	8,067	0.0077	0	1	1,663	0.0114	706	0.0042	1,124	0.0053	2,458	0.0057	831	0.0024	1,285	0.0140
juris9	8,067	0.0519	0	1	1,663	0.0595	706	0.1048	1,124	0.0222	2,458	0.0557	831	0.0457	1,285	0.0358

Table 3.8. Continued

	All Land-uses				Retail		Office		Industrial		Apartment / Hotel / Motel		Auto-Related		Vacant Land	
Neighborhood Characteristics																
totpop	8,067	8,509.28	270	54,762	1,663	8,361.25	706	13,524.47	1,124	8,097.80	2,458	7,627.19	831	6,521.40	1,285	9,278.22
white	8,067	5,789.12	0	50,025	1,663	5,597.69	706	11,429.66	1,124	4,704.73	2,458	5,225.40	831	4,075.39	1,285	6,072.95
nonwhite	8,067	2,720.16	26	12,961	1,663	2,763.56	706	2,094.81	1,124	3,393.07	2,458	2,401.78	831	2,446.01	1,285	3,205.27
minority	8,067	0.500	0.004	1	1,663	0.517	706	0.274	1,124	0.535	2,458	0.473	831	0.555	1,285	0.586
popdens	8,067	5.60	0.09	27.67	1,663	5.46	706	4.31	1,124	4.14	2,458	6.70	831	6.26	1,285	5.22
rmedinc	8,067	20,442.30	773.73	97,119.88	1,663	19,960.06	706	29,289.46	1,124	19,446.21	2,458	20,172.18	831	17,230.02	1,285	19,670.98
con	8,067	320.10	0	1,826	1,663	283.05	706	474.59	1,124	486.86	2,458	242.95	831	280.95	1,285	310.16
ret	8,067	1,459.53	0	10,306	1,663	1,433.99	706	2,570.29	1,124	1,110.21	2,458	1,443.80	831	1,265.37	1,285	1,343.48
whol	8,067	851.61	0	6,613	1,663	654.50	706	1,133.79	1,124	1,769.54	2,458	531.93	831	645.59	1,285	893.50
mfg	8,067	853.03	0	6,938	1,663	665.68	706	831.02	1,124	1,889.26	2,458	499.93	831	897.67	1,285	847.72
tcu	8,067	817.37	0	15,567	1,663	771.80	706	1,086.71	1,124	906.47	2,458	791.83	831	900.59	1,285	645.49
fire	8,067	719.63	0	7,848	1,663	675.19	706	1,552.78	1,124	331.64	2,458	711.16	831	911.91	1,285	550.59
svcs	8,067	2,406.17	0	17,353	1,663	2,194.20	706	4,462.99	1,124	1,758.24	2,458	2,271.56	831	2,861.79	1,285	2,080.00
fed	8,067	230.99	0	4,767	1,663	276.96	706	298.42	1,124	158.53	2,458	204.43	831	367.32	1,285	160.46
state	8,067	350.81	0	10,074	1,663	508.95	706	444.84	1,124	324.41	2,458	127.31	831	741.70	1,285	292.29
local	8,067	455.70	0	5,699	1,663	542.23	706	520.97	1,124	458.82	2,458	365.84	831	480.27	1,285	461.11
indemp	8,067	1,990.50	0	17,781	1,663	1,720.53	706	2,392.32	1,124	3,282.59	2,458	1,534.71	831	2,079.21	1,285	1,803.38
retemp	8,067	2,311.14	0	15,309	1,663	2,088.50	706	3,704.08	1,124	2,879.75	2,458	1,975.73	831	1,910.96	1,285	2,236.98
servemp	8,067	3,125.79	0	21,079	1,663	2,869.40	706	6,015.78	1,124	2,089.88	2,458	2,982.73	831	3,773.70	1,285	2,630.59
priv	8,067	7,466.75	22	34,129	1,663	6,714.12	706	12,191.95	1,124	8,291.98	2,458	6,525.49	831	7,789.18	1,285	6,714.82
gov	8,067	1,037.49	0	17,598	1,663	1,328.14	706	1,264.23	1,124	941.76	2,458	697.58	831	1,589.29	1,285	913.86
employ	8,067	8,464.92	94	44,467	1,663	8,006.56	706	13,376.41	1,124	9,193.98	2,458	7,190.74	831	9,353.17	1,285	7,584.80

Table 3.8. Continued

	All Land-uses				Retail		Office		Industrial		Apartment / Hotel / Motel		Auto-Related		Vacant Land	
empdens	8,067	11.64	0.01	233.67	1,663	11.92	706	17.23	1,124	6.21	2,458	9.96	831	24.90	1,285	7.62
privdens	8,067	9.25	0.01	176.64	1,663	8.74	706	14.12	1,124	4.76	2,458	8.40	831	19.89	1,285	5.91
govdens	8,067	2.39	0	58.69	1,663	3.18	706	3.11	1,124	1.45	2,458	1.56	831	5.01	1,285	1.71
inddens	8,067	2.45	0	54.41	1,663	2.06	706	3.11	1,124	1.73	2,458	2.34	831	5.27	1,285	1.60
retdens	8,067	1.83	0	31.86	1,663	1.82	706	2.42	1,124	1.24	2,458	1.84	831	3.10	1,285	1.19
servdens	8,067	4.97	0	110.77	1,663	4.86	706	8.60	1,124	1.80	2,458	4.21	831	11.53	1,285	3.13

Table 3.9. Number of Contaminated Sites Listed by Year

Year	CERCLIS	NFRAP (Date listed)	NFRAP (Date archived)	HSI	NonHSI
1979	0	12	0	-	-
1980	9	36	1	-	-
1981	3	13	0	-	-
1982	0	0	4	-	-
1983	0	3	0	-	-
1984	0	9	2	-	-
1985	0	4	21	-	-
1986	0	0	5	-	-
1987	0	1	1	-	-
1988	0	1	2	-	-
1989	0	2	27	-	-
1990	0	4	13	-	-
1991	1	2	3	-	-
1992	2	5	3	-	-
1993	1	2	1	-	-
1994	1	3	5	23	108
1995	0	0	8	3	48
1996	1	2	1	2	22
1997	1	1	1	2	38
1998	2	0	1	4	30
1999	1	0	1	10	41
Total	22	100	100	44	287

Note: One NFRAP site was discovered in 1976 and added to 1979 total. The list date for three NonHSI sites could not be determined.

Table 3.10. Land-Use Code Frequencies for Contaminated Sites

Land-Use Code	Description	CERCLIS	NFRAP	HSI	NonHSI
209	Apartment loft/retail	0	0	0	2
211	Garden apartment, three story and under	0	1	0	10
250 / 251	Super luxury hotel / Luxury hotel	0	0	0	4
254	Luxury budget motel	0	0	0	1
301	Residential, commercial land	1	0	0	1
310	Unsound commercial structure	1	0	1	0
320	Commercial auxiliary improvement	1	2	2	1
321 / 327	Restaurant / Bar / Lounge	0	0	0	8
332	Auto service garage	1	3	0	3
334	Service station, without bays	0	0	0	1
335 / 395	Truck stop / truck terminal	1	2	1	3
337	Car wash, automatic	0	0	0	1
338 / 339	Parking garage, deck / parking miscellaneous	0	0	0	3
342 / 343	Community shopping / Neighborhood shop	0	1	1	4
344	Strip shopping	0	2	1	16
347	Supermarket	0	0	0	2
353 / 354	Office Building, low rise / high rise	0	0	1	10
365	Cinema / theater	0	1	0	0
371	Downtown row type	0	0	1	0
373	Retail, single occupancy	0	0	1	16
374	Retail, multi occupancy	0	0	0	4
392	Lumber storage	0	1	1	1
398	Warehouse	4	16	10	50
396 / 397 / 399	Warehouse mini / office / prefab	0	1	1	3
401	Manufacturing / processing	0	6	3	7
421	Aluminum and foil manufacturing	1	9	1	9
443	Metal manufacturing	0	5	2	10
451	Paint manufacturing	1	2	0	2
452	Paper finishing / converting	0	1	0	3
499	Other manufacturing NEC	3	7	2	6
699	Improved government exempt	0	2	1	7
710	Telephone equipment building	0	0	1	0
misc-vac	Miscellaneous, vacant land	6	12	6	17
misc-res	Miscellaneous, residential	1	3	1	7
misc-manu	Miscellaneous manufacturing / processing	0	5	5	8
misc-exem	Miscellaneous, government / exempt	1	1	1	6

Table 3.11. Cross Tabulation of Contaminated Sites

	CERCLIS	HSI	NFRAP	NonHSI	Total
CERCLIS	10	7	0	5	22
HSI	7	24	13	0	44
NFRAP	0	13	19	68	100
NonHSI	5	0	68	217	290

Figure 3.1. Fulton County, Georgia

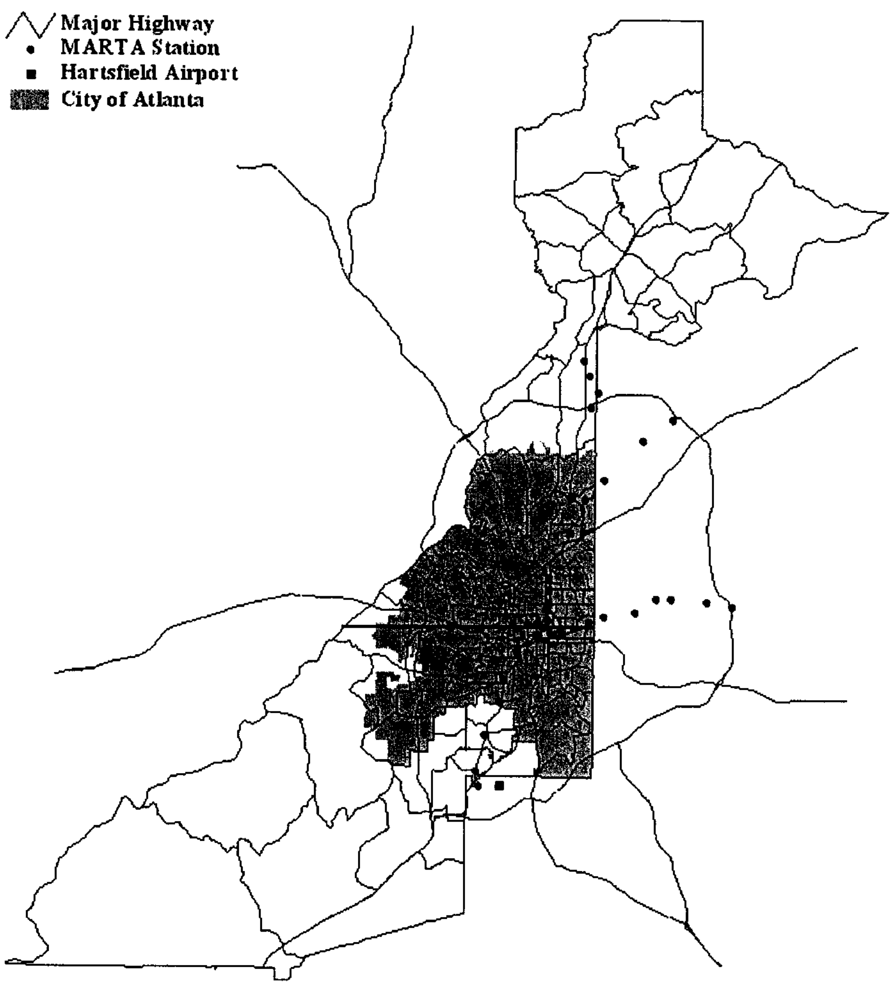


Figure 3.2. Distribution of CERCLIS / HSI Sites

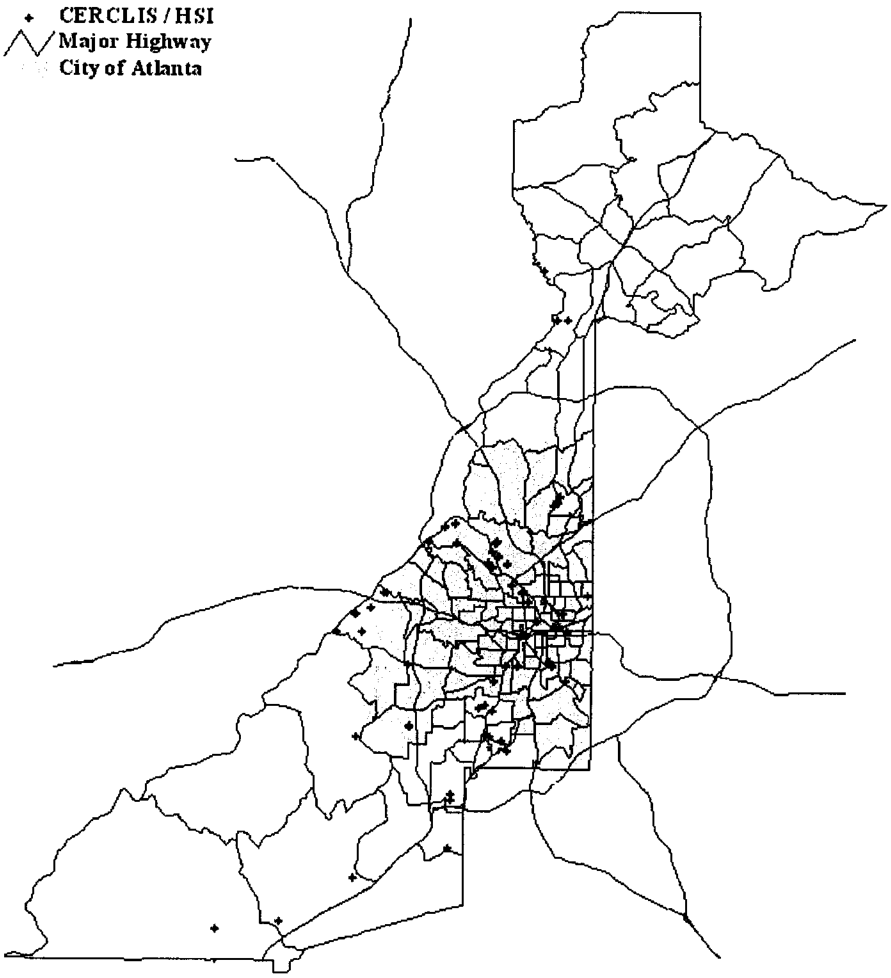


Figure 3.3. Distribution of CERCLIS / HSI Sites and Census Tract Racial Composition

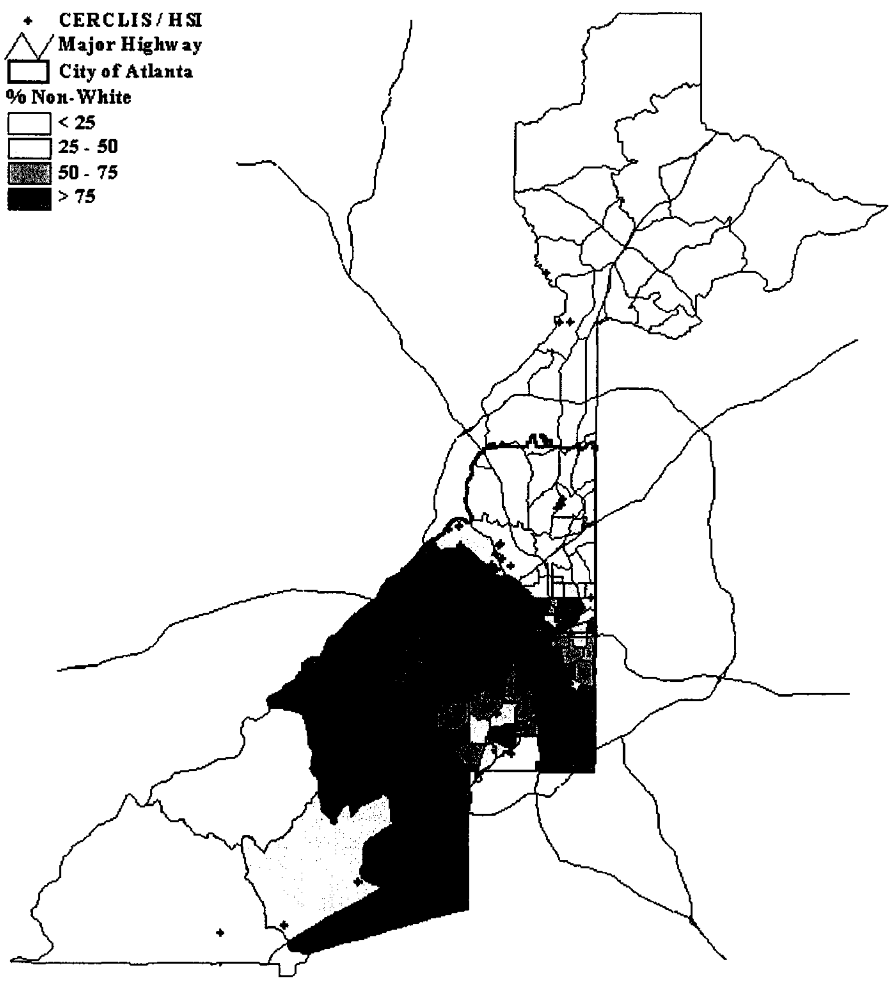


Figure 3.4. Distribution of CERCLIS / HSI Sites and Census Tract Median Income

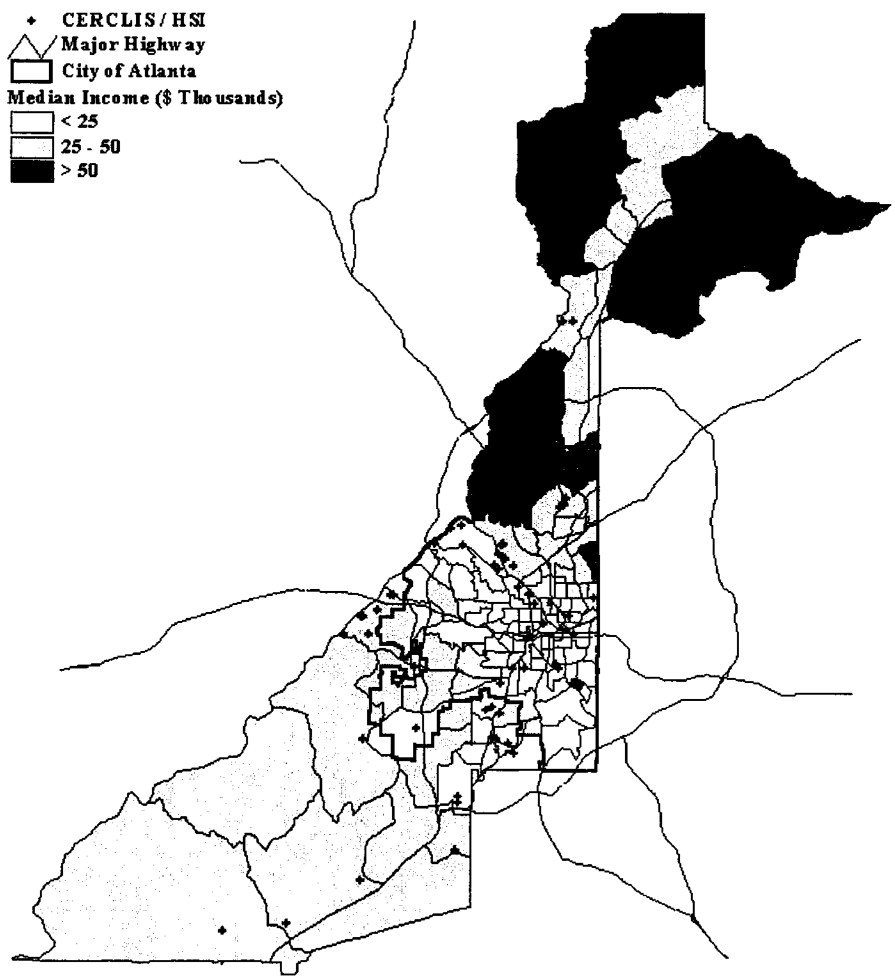


Figure 3.5. Distribution of NFRAP / NonHSI Sites

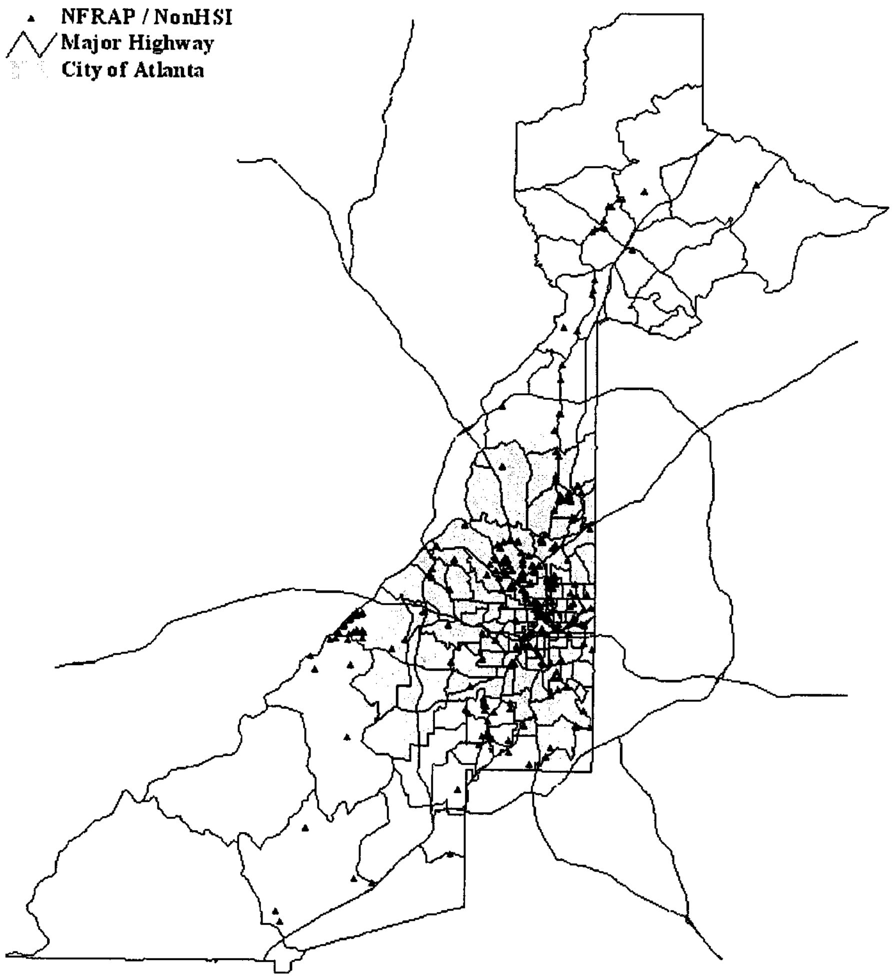


Figure 3.6. Distribution of NFRAP / NonHSI Sites and Census Tract Racial Composition

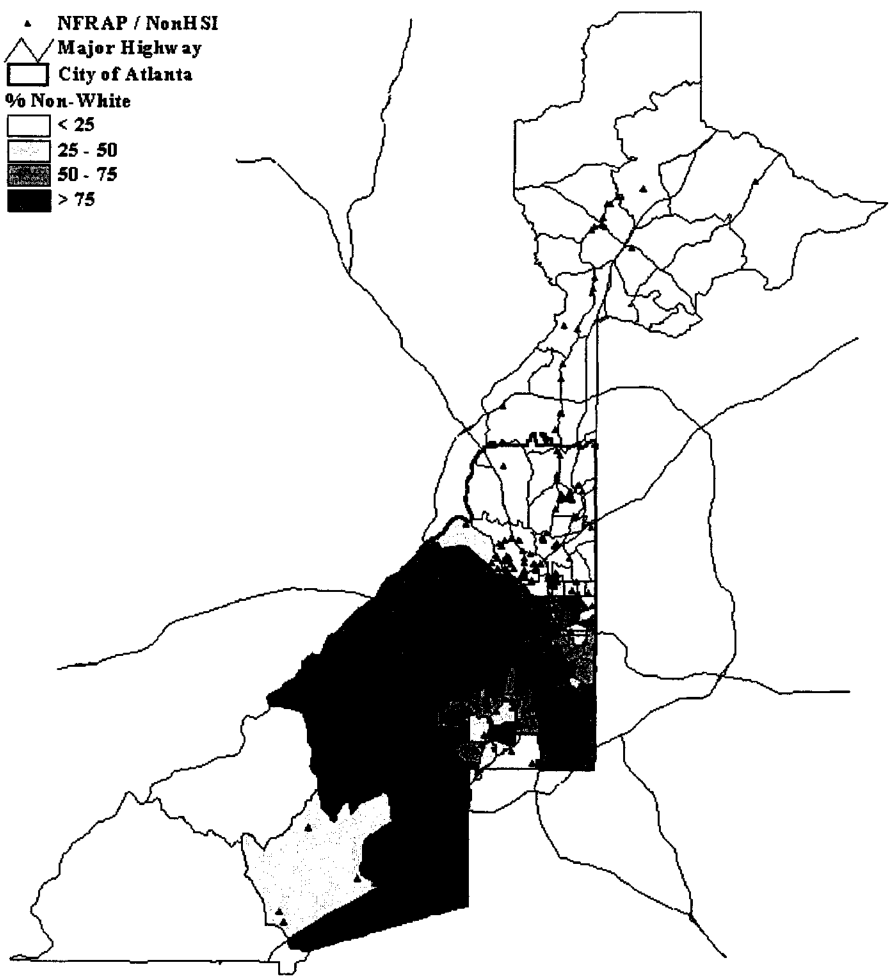


Figure 3.7. Distribution of NFRAP / NonHSI Sites and Census Tract Median Income

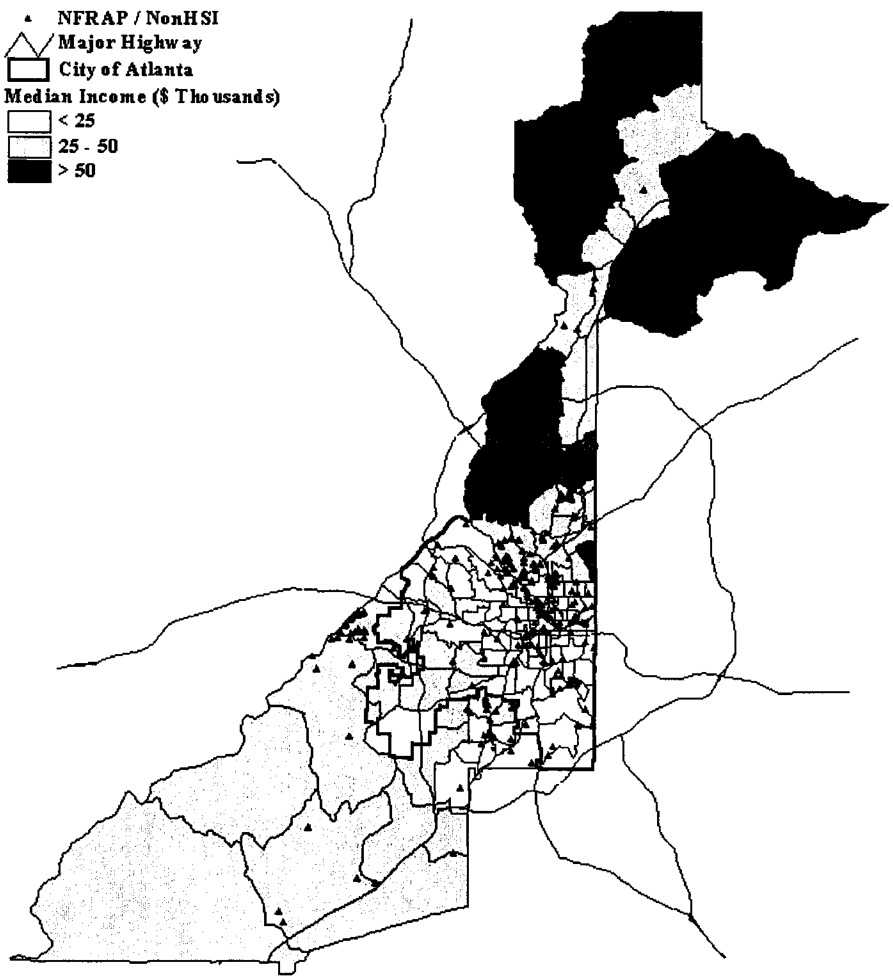


Figure 3.8. Distribution of Retail Sales and CERCLIS / HSI Sites

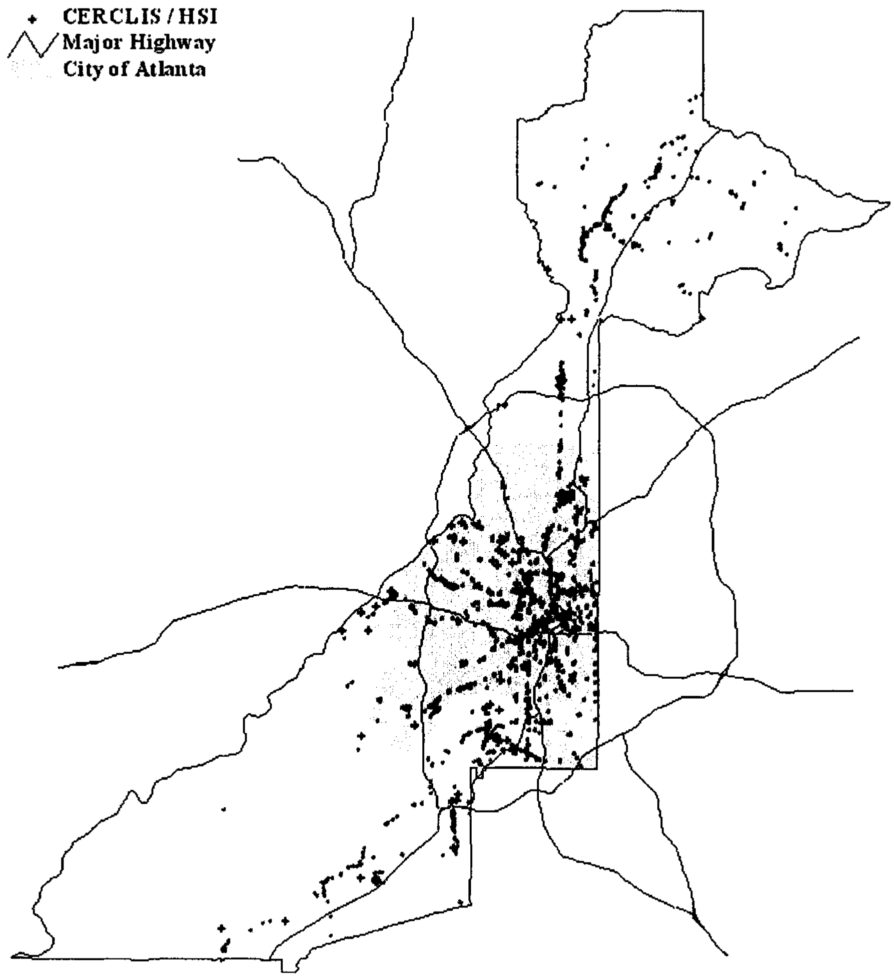


Figure 3.9. Distribution of Office Sales and CERCLIS / HSI Sites

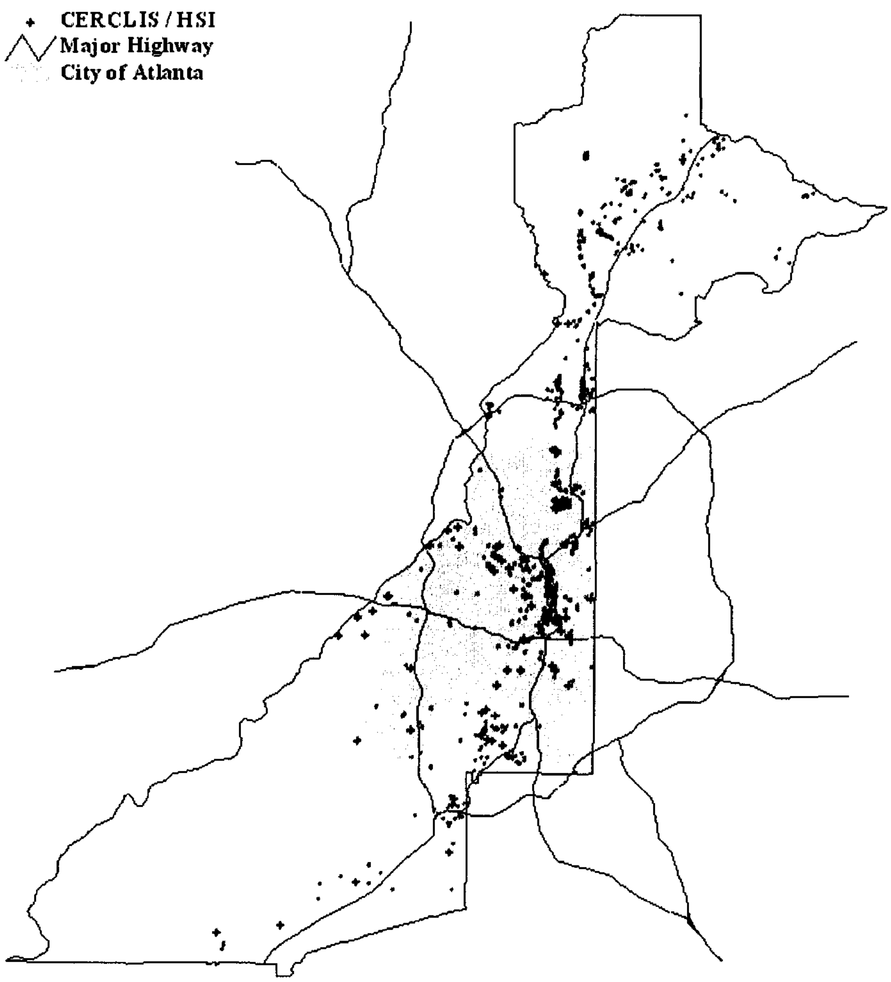


Figure 3.10. Distribution of Industrial Sales and CERCLIS / HSI Sites

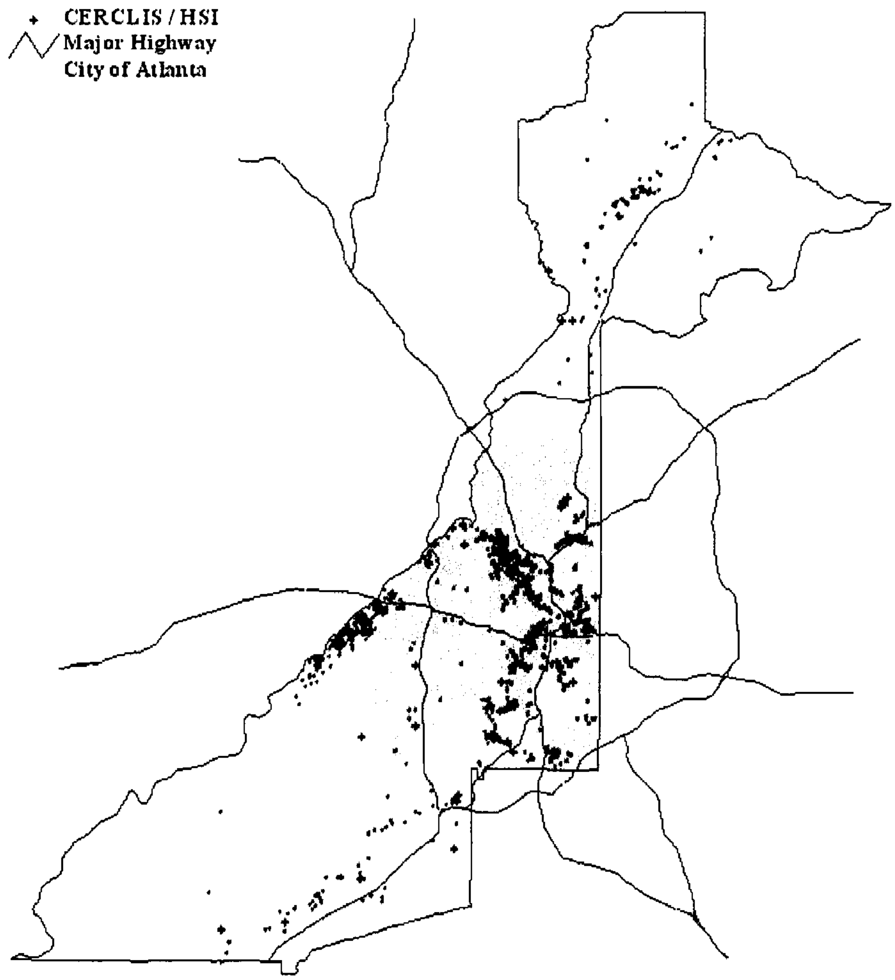


Figure 3.11. Distribution of Apartment/Hotel/Motel Sales and CERCLIS / HSI Sites

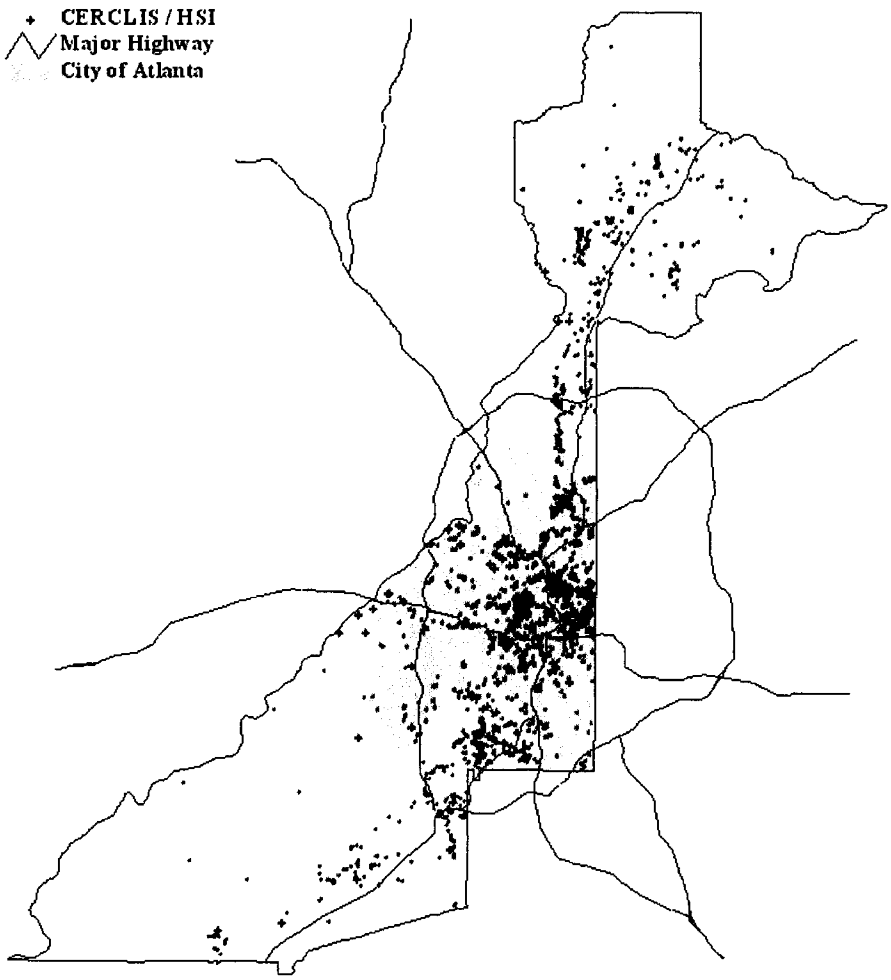


Figure 3.12. Distribution of Auto Related Sales and CERCLIS / HSI Sites

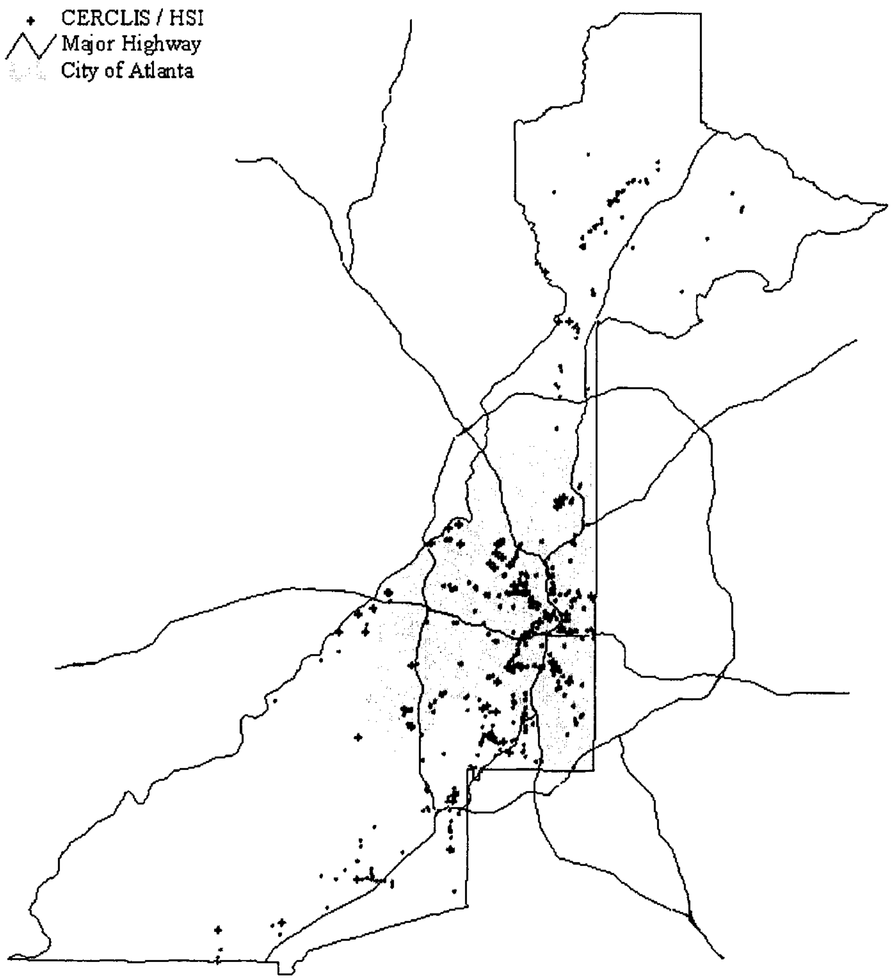


Figure 3.13. Distribution of Vacant Property Sales and CERCLIS / HSI Sites

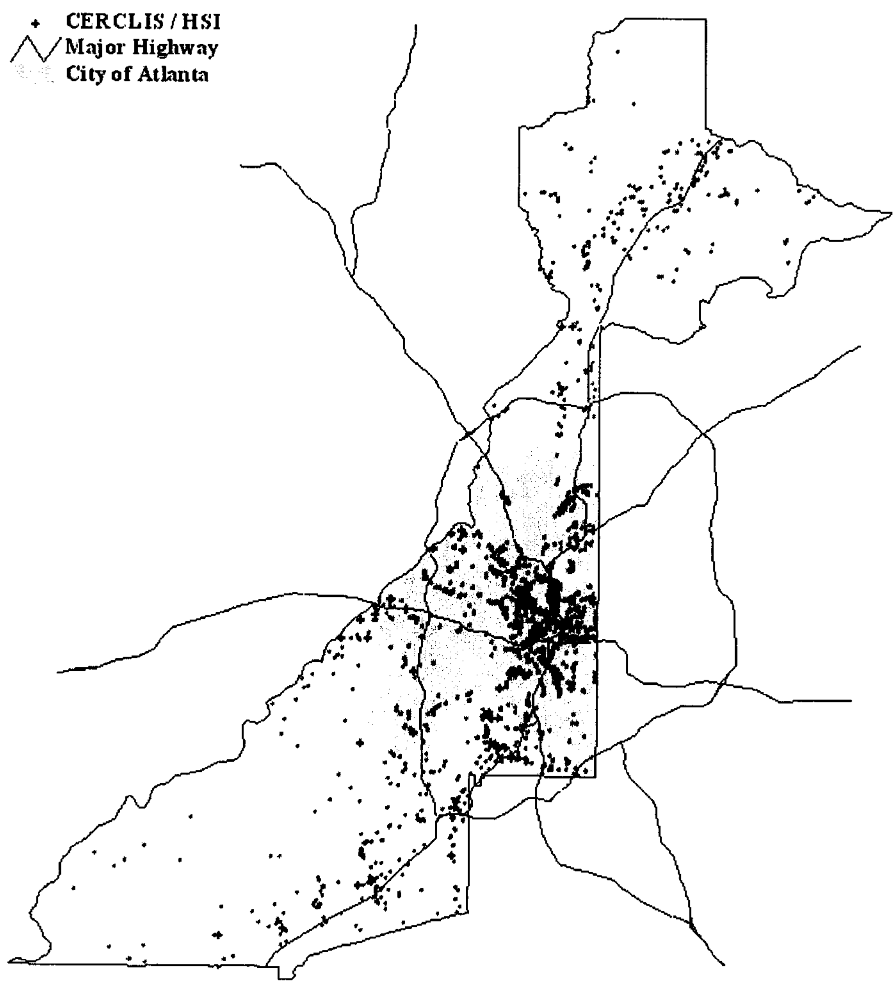


Figure 3.14. Distribution of Retail Sales and NFRAP / NonHSI Sites

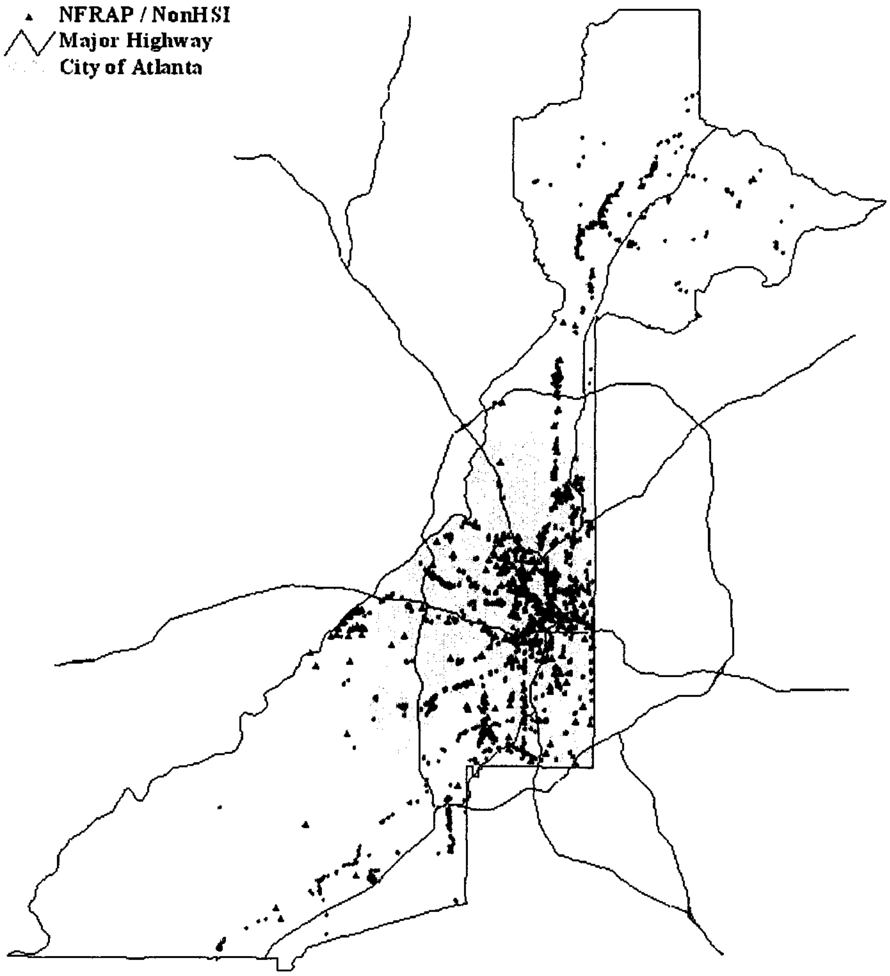


Figure 3.15. Distribution of Office Sales and NFRAP / NonHSI Sites

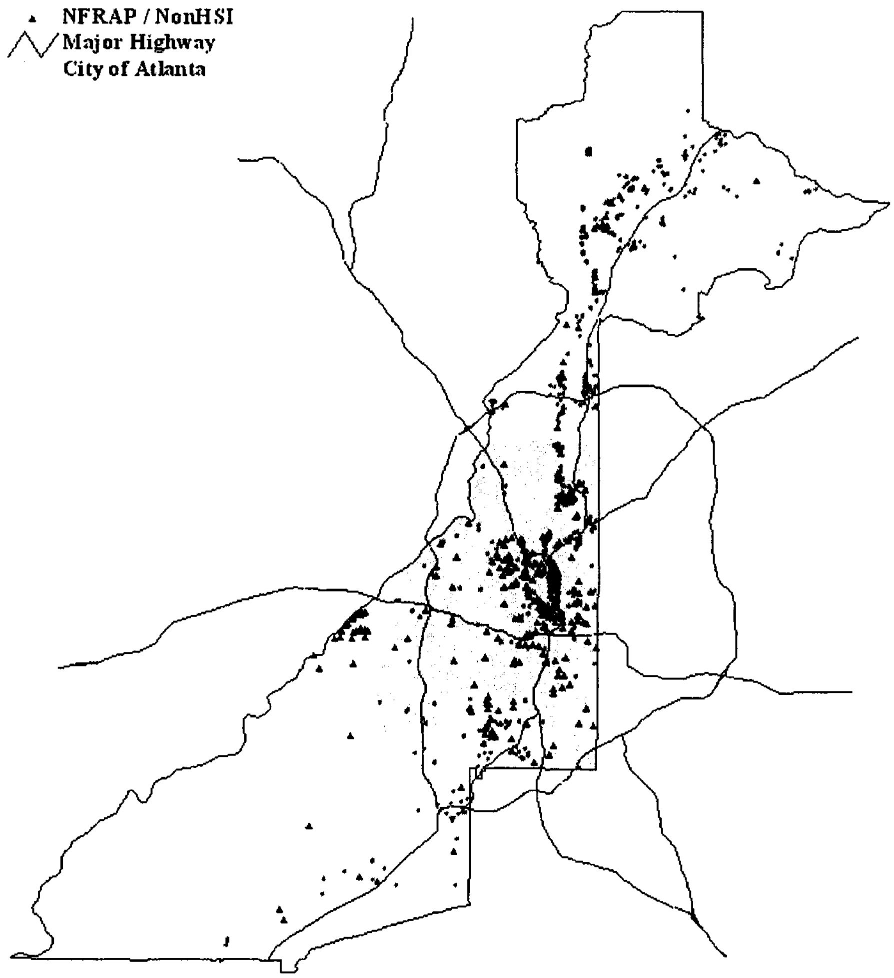


Figure 3.16. Distribution of Industrial Sales and NFRAP / NonHSI Sites

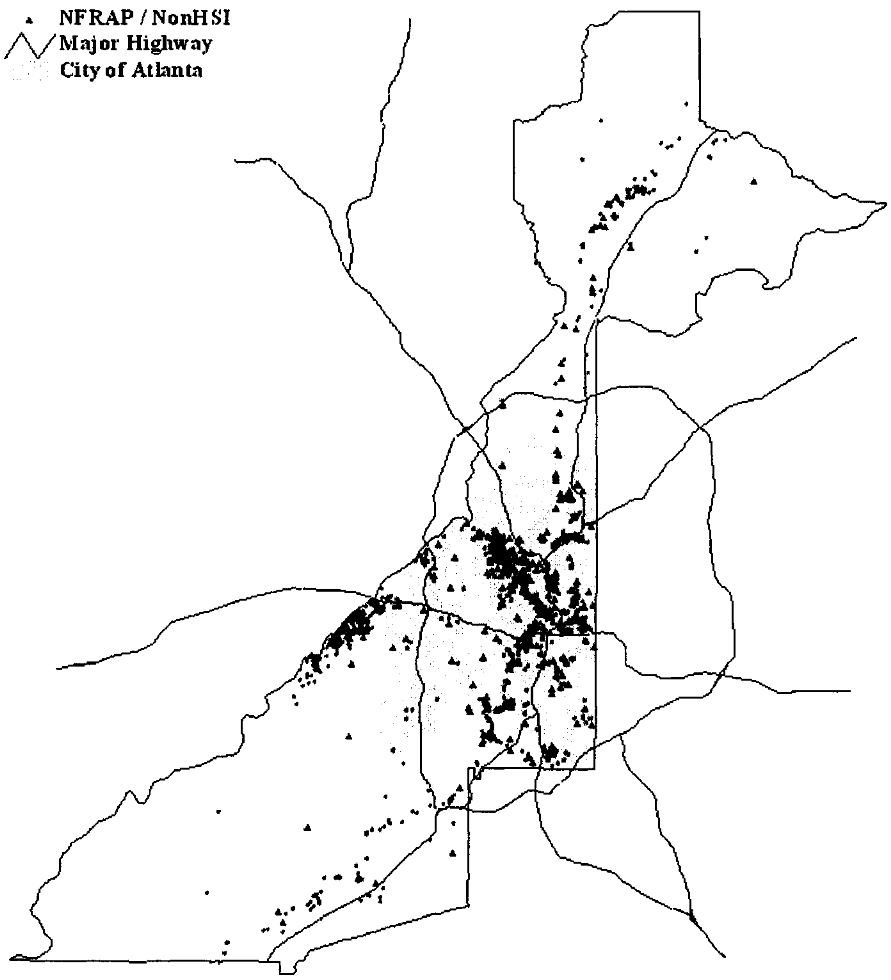


Figure 3.17. Distribution of Apartment/Hotel/Motel Sales and NFRAP / NonHSI Sites

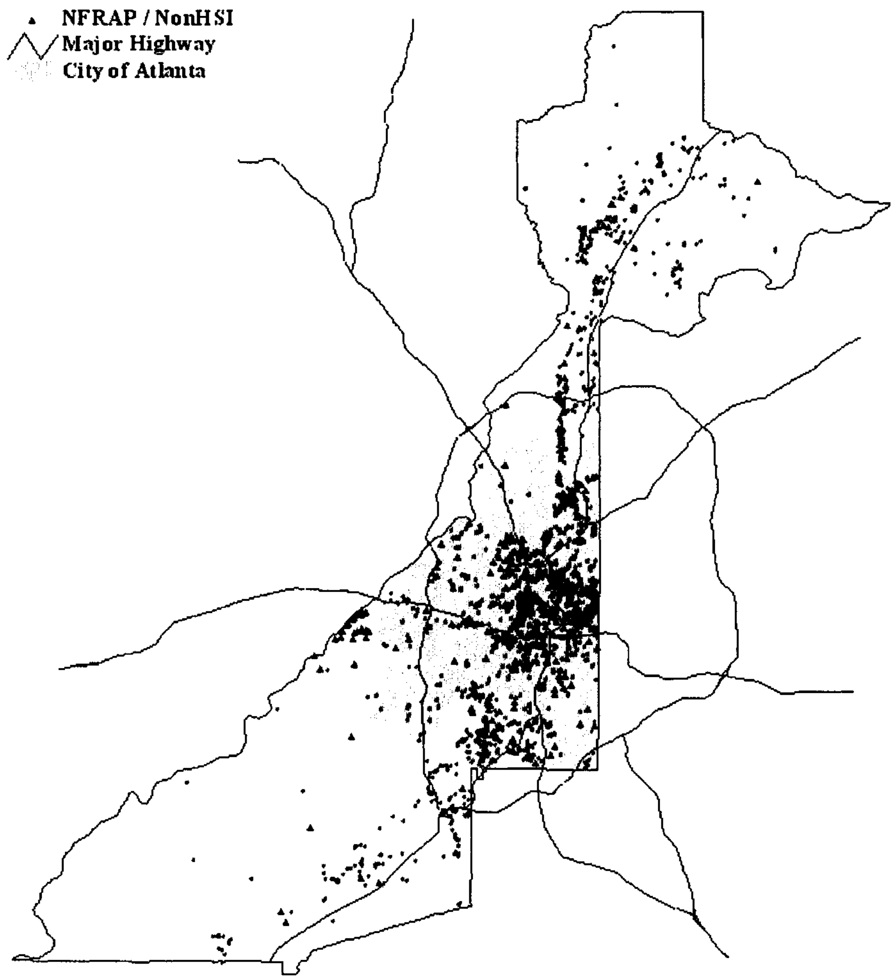


Figure 3.18. Distribution of Auto Related Sales and NFRAP / NonHSI Sites

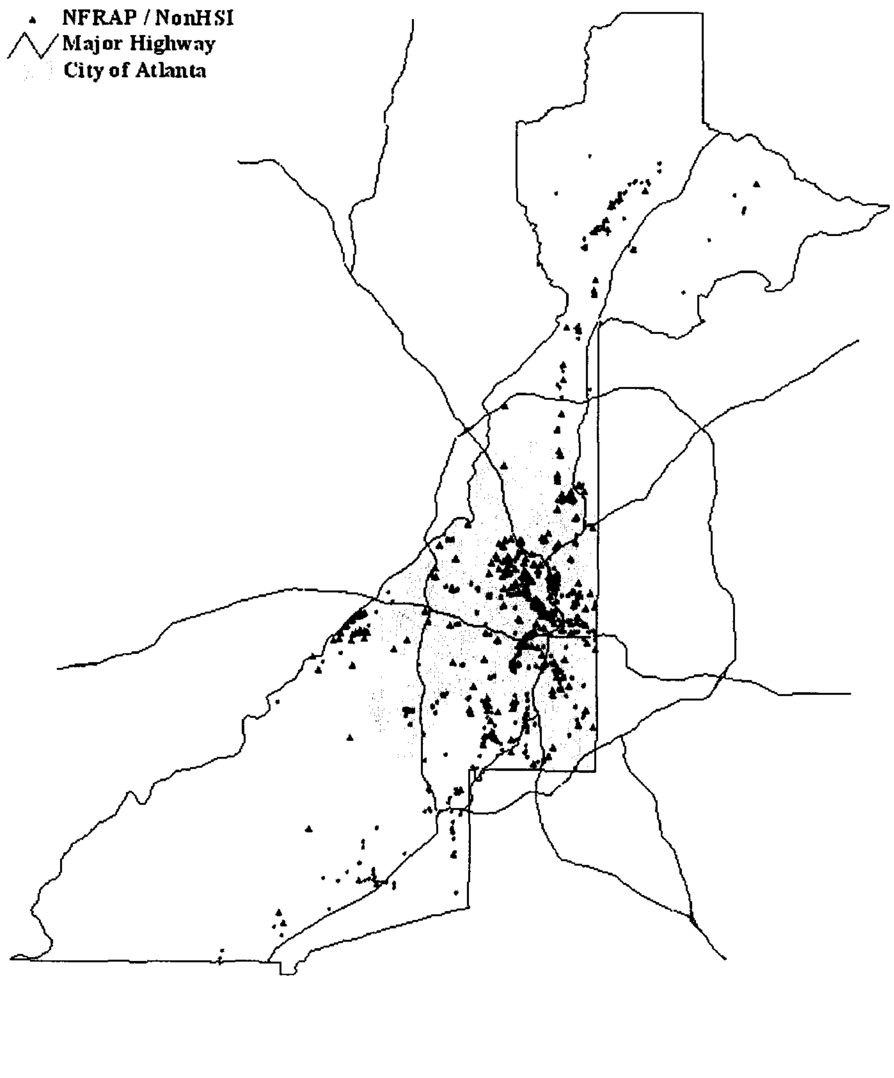
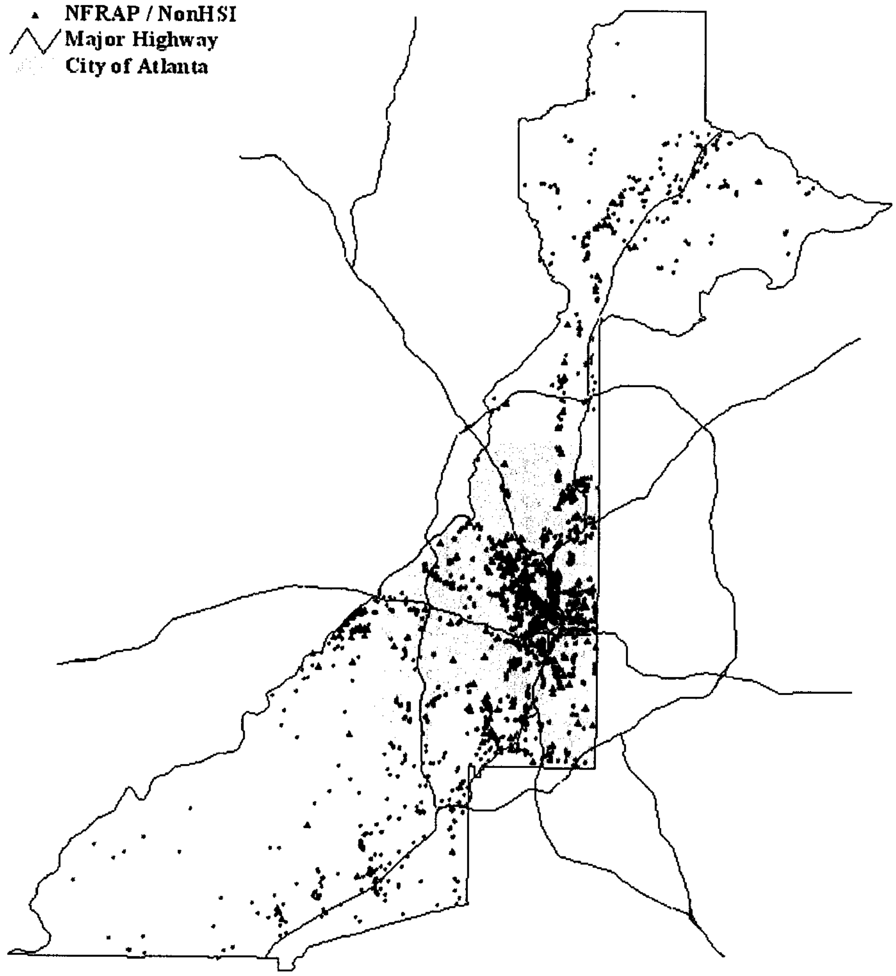


Figure 3.19. Distribution of Vacant Land Sales and NFRAP / NonHSI Sites



Chapter 4

Estimating the Probability of Contamination for Commercial and Industrial Properties

Introduction

The Environmental Protection Agency (EPA) defines a "brownfield" as any abandoned, idled, or under-used industrial/commercial facility where expansion or redevelopment is complicated by real or *perceived* contamination. Federal and state agencies commonly compile publicly accessible lists of properties with known contamination for various geographic areas. The placement of contaminated properties on lists, after a discovery has been made, is a way of signaling to the local community that these properties may now represent potential dangers hindering their redevelopment. These complications can spill over to other nearby properties. If *perceptions* matter, then properties with little or no contamination may also be viewed as undesirable neighbors for nearby property owners in a way similar to properties with a documented record of contamination. These properties avoid the signaling effect from being placed on a list, but may still be considered "undesirable" by the public due to suspected current releases or the threat of possible releases in the future.

This chapter addresses the issue of perceptions by estimating a model that calculates the probability each CI property in the study area is contaminated. The probability model incorporates factors that are likely to be key signals to investors in forming their perceptions that a site might be contaminated, regardless of whether any contamination has been previously documented by authorities. One important factor will be the land-use of each property. This follows the assumption that investors in CI properties may form perceptions that specific types of land-uses (i.e., service stations, certain manufacturing facilities, strip malls with dry cleaners on site, etc.) are more likely to be contaminated than other land-uses.

The probability of contamination model will be used as a means of identifying properties as having a high likelihood of being contaminated. These properties will then be incorporated into hedonic property value models to determine the extent to which they emit negative externality effects on neighboring CI properties. If such evidence is found, then this would suggest that properties perceived as contaminated may be viewed by nearby property owners in a way similar to properties with a documented record of contamination. The estimation of the hedonic property value models will be discussed in Chapter 6.

Probability of Contamination

Methodology

The probability of contamination model uses the information about contaminated sites contained in two federal lists (CERCLIS and NFRAP) maintained by the EPA, two state lists (HSI and NonHSI) maintained by the Georgia Environmental Protection

Division (EPD),[29] and data on CI properties located in Fulton County, Georgia. The placement of a site on either of the four lists can be a result of contamination being discovered in one of several ways. Contaminants on CI properties may be detected at the time of sale since lenders require CI properties to undergo sites assessments when investors are in the process of obtaining financing for the purchase of a property. If the release of a regulated substance is discovered as a result of the site assessment at the time of sale, then, according to law, the EPA and/or EPD must be notified.[30] CI property owners are also obligated to inform the EPA and/or the EPD when the release of a regulated substance occurs regardless of whether or not the property is being sold. Additionally, suspected contaminant releases at a site can be reported by other nearby property owners.[31]

The contaminated site data is merged with the geocoded CI property data to spatially identify contaminated properties in Fulton County, Georgia. CI properties on either the CERCLIS or HSI are classified as having a "high level" of contamination, while CI properties on either the NFRAP or NonHSI are classified as having a "low level" of contamination. As a result, each CI property can be placed into one of three categories that describes the level of contamination on the property: no publically known contamination, low level of contamination, or high level of contamination. Due to the EPA and the EPD using different methods to determine the severity and potential threat

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[29] See Chapter 3 for a discussion on how a property is placed on either of the EPA or EPD lists.

[30] For example, according to the EPD's laws governing the Rules for Hazardous Sites Response (RHSR), any property where the release of a regulated substance occurred after February 20, 1994 (effective date of the RHSR) must either be on the HSI or NonHSI.

[31] It must be noted that it is possible that the release of a regulated substance goes entirely unreported to the EPA and EPD.

to nearby residents of properties with contaminant releases, sites on CERCLIS may also be listed on the NonHSI and sites on the HSI may simultaneously appear on NFRAP. For analysis purposes, CERCLIS or HSI sites also found on the NonHSI or NFRAP will be identified as CERCLIS or HSI sites only.[32] The reason is that investors are assumed to associate properties with the list that signifies the more severe level of contamination present.

For each CI property i, the level of contamination j present can be expressed by an indicator variable, $c_i = j$, defined as:

$$\begin{aligned} c_i &= 0 \ \ \textit{if property i has no known contamination} \\ c_i &= 1 \ \ \textit{if property i has a low level of contamination} \\ c_i &= 2 \ \ \textit{if property i has a high level of contamination .} \end{aligned} \tag{4.1}$$

The probability CI property i is found to have level of contamination j = 0, 1, or 2, $Pr(c_i = j)$, can be given as:

$$Pr(c_i = j) = Pr(T_i)Pr(c_i = j \mid T_i = 1), \tag{4.2}$$

where T_i is an indicator variable that equals one if property i has been tested for contamination and equal to zero otherwise. Equation (4.2) states that the probability CI property i is found to have no contamination, a low level of contamination, or a high level of contamination, $Pr(c_i = j)$, is equal to the probability CI property i is tested for contamination, $Pr(T_i)$, multiplied by the probability CI property i is found to have no contamination, a low level of contamination, or a high level of contamination present

[32] Table 3.11 in Chapter 3 provides a cross-tabulation of the number of sites found concurrently on a federal and state list.

given that CI property i has been tested for contamination, $Pr(c_i = j \mid T_i = 1)$.

With the probability of contamination model expressed according to equation (4.2), one must be able to determine the likelihood a property is tested for contamination, $Pr(T_i)$, separate from the probability a property is contaminated given it has been tested, $Pr(c_i = j \mid T_i = 1)$. This would require information on how the EPA and EPD determine the need to test specific properties with a suspected contaminant release, which is not available. However, one can assume that $Pr(T_i) = 1$ for properties which appear on one of the four lists and for properties with positive sales prices. The latter assumption is believed to be reasonable since lenders require sites assessments when investors are in the process of obtaining financing for the purchase of the property. As such, properties which have sold in "arms length transactions" can be considered to have been tested. Equation (4.2) thus simplifies to the following for properties which are on a list or which have sold:

$$Pr(c_i = j) = Pr(c_i = j \mid T_i = 1) . \tag{4.3}$$

The empirical model used to estimate equation (4.3) can be built around a latent regression model:

$$c_i^* = x_i^{\prime}\beta + \varepsilon_i , \quad i = 1,2,\ldots,n , \tag{4.4}$$

where c_i^* is an unobserved continuous variable measuring the true level of contamination at property i, x_i is a vector of explanatory variables, β is a vector of parameters to be estimated, and ε_i is unobserved error. What is observed for each CI property is an indicator variable, defined by equation (4.1), that specifies the one of three ordinal categories in which each CI property is classified. The observed outcome for c_i is determined according the following:

$$c_i = j \quad if \quad \alpha_j < c_i^* < \alpha_{j+1}, \quad j = 0,1,2 \tag{4.5}$$

where $c_i = 0$ represents no contamination, $c_i = 1$ low level of contamination, $c_i = 2$ high level of contamination and α_0, α_1, α_2 and α_3 are unknown ancillary parameters. The ancillary parameters represent thresholds that determine how a given value of c_i^* maps into c_i and are defined such that $\alpha_0 = -\infty$, $\alpha_3 = \infty$, and $\alpha_1 < \alpha_2$, where α_1 and α_2 are estimated empirically.

It follows from equation (4.5) that when expressing the observed outcomes in terms of probabilities, one obtains:

$$\begin{aligned} Pr(c_i = j) &= Pr(\alpha_j < c_i^* < \alpha_{j+1}) \\ &= Pr(\alpha_j < x_i'\beta + \varepsilon_i < \alpha_{j+1}) \\ &= Pr(\alpha_j - x_i'\beta < \varepsilon_i < \alpha_{j+1} - x_i'\beta) \\ &= F(\alpha_{j+1} - x_i'\beta) - F(\alpha_j - x_i'\beta), \end{aligned} \tag{4.6}$$

where F is the cumulative distribution function of ε_i and x, β, α_j and α_{j+1} are defined as before. Stated explicitly for the three categories, the probability that $c_i = 0$ (no contamination), $c_i = 1$ (low level of contamination), and $c_i = 2$ (high level of contamination) is:

$$
\begin{aligned}
Pr(c_i = 0) &= F(\alpha_1 - x_i'\beta) \\
Pr(c_i = 1) &= F(\alpha_2 - x_i'\beta) - F(\alpha_1 - x_i'\beta) \\
Pr(c_i = 2) &= 1 - F(\alpha_2 - x_i'\beta).
\end{aligned} \tag{4.7}
$$

The probability of contamination model given in equation (4.7) is estimated for all CI properties in non-vacant land-use categories where the errors are assumed to be normally distributed, such that $\varepsilon_i \sim N(\mu, \sigma_2)$. Vacant land-use categories, defined as properties without structural improvements on them, were not used since it was assumed that CI property investors do not form perceptions that vacant parcels of land with different zoning are more likely to be contaminated than other vacant parcels of land. As such, including these observations would not provide additional information in the empirical models. Under the assumption of normality, the general probability of contamination model corresponds to an ordered probit model. The three probabilities expressed in equation (4.7) can now be rewritten as:

$$
\begin{aligned}
Pr(c_i = 0) &= \Phi(\alpha_1 - x_i'\beta) \\
Pr(c_i = 1) &= \Phi(\alpha_2 - x_i'\beta) - \Phi(\alpha_1 - x_i'\beta) \\
Pr(c_i = 2) &= 1 - \Phi(\alpha_2 - x_i'\beta),
\end{aligned} \tag{4.8}
$$

where Φ is the cumulative distribution function for the standard normal. Parameters estimates for β, α_1 and α_2 can be obtained through maximum likelihood estimation. The likelihood function associated with the ordered probit model is given by:

$$
L = \prod_{i=1}^{n} \prod_{j=0}^{2} [\Phi(\alpha_{j+1} - x_i'\beta) - \Phi(\alpha_j - x_i'\beta)]^{m_{ij}}, \tag{4.9}
$$

where $m_{ij} = 1$ if property i falls into the j[th] category of contamination (j = 0, 1, 2) and is equal to zero otherwise. Taking the log of equation (4.9) leads to:

$$\ln(L) = \sum_{i=1}^{n} \sum_{j=0}^{2} m_{ij} \log[\Phi(\alpha_{j+1} - x_i^{\prime}\beta) - \Phi(\alpha_j - x_i^{\prime}\beta)], \tag{4.10}$$

and when maximized will yield the vector of parameter estimates, $\hat{\beta}$, and estimates for the ancillary parameters, $\hat{\alpha}_1$ and $\hat{\alpha}_2$.[33]

After obtaining parameter estimates, the probability CI property i falls into category j can be computed. The probability that property i has level of contamination j is denoted by $\hat{P}_i^j$, again where j = 0 represents no contamination, j = 1 is low level of contamination, and j = 2 is high level of contamination. Following (4.8), probability estimates for the ordered probit model are computed as:

$$\begin{aligned} \hat{P}_i^0 &= \Phi(\hat{\alpha}_1 - x_i^{\prime}\hat{\beta}) \\ \hat{P}_i^1 &= \Phi(\hat{\alpha}_2 - x_i^{\prime}\hat{\beta}) - \Phi(\hat{\alpha}_1 - x_i^{\prime}\hat{\beta}) \\ \hat{P}_i^2 &= 1 - \Phi(\hat{\alpha}_2 - x_i^{\prime}\hat{\beta}), \end{aligned} \tag{4.11}$$

where these three probability estimates will sum to one.

Using the probability estimates just computed, CI properties can then be classified into one of three categories that characterizes the level of contamination present at a property, given by $\hat{c}_i = j$ (j = 0, 1, 2). To accomplish this, the researcher needs to choose how to interpret the predicted probability that a CI property falls into each category. For instance, the following is a decision rule that may be selected that classifies properties into one of the three categories of contamination:

$$\begin{aligned} \hat{c}_i = 0 \quad &\mathit{if} \quad \hat{P}_i^0 > \hat{P}_i^1 \quad \mathit{and} \quad \hat{P}_i^0 > \hat{P}_i^2 \\ \hat{c}_i = 1 \quad &\mathit{if} \quad \hat{P}_i^1 > \hat{P}_i^2 \quad \mathit{and} \quad \hat{P}_i^1 > \hat{P}_i^0 \\ \hat{c}_i = 2 \quad &\mathit{if} \quad \hat{P}_i^2 > \hat{P}_i^1 \quad \mathit{and} \quad \hat{P}_i^2 > \hat{P}_i^0. \end{aligned} \tag{4.12}$$

---

[33] Note, $\Phi(\alpha_0 = -\infty) = 0$ and $\Phi(\alpha_1 = \infty) = 1$.

According to this decision rule, the category with the highest predicted probability is the category assigned to the property. For example, if the three predicted probabilities for a CI property were $\hat{P}^1 = 0.30,\ \hat{P}^2 = 0.50,\ \hat{P}^3 = 0.20$, then the property would be classified as having a low level of contamination ($\hat{c} = 1$).

An alternate method for classifying CI properties into one of the three categories of contamination can be given as:

$$\begin{aligned} &\hat{c}_i = 0 \quad \textit{if} \quad \hat{P}_i^2 < k \ \textit{and} \ \hat{P}_i^1 < k \\ &\hat{c}_i = 1 \quad \textit{if} \quad \hat{P}_i^1 \geq k \ \textit{and} \ \hat{P}_i^2 < k \\ &\hat{c}_i = 2 \quad \textit{if} \quad \hat{P}_i^2 \geq k\,, \end{aligned} \tag{4.13}$$

where the value for k represents a specified cut-off point. For this decision rule, CI properties with an estimated probability of "high" contamination ($\hat{P}_i^2$) greater than or equal to k are classified as "highly" contaminated ($\hat{c}_i = 2$), CI properties with an estimated probability of "low" contamination ($\hat{P}_i^1$) greater than or equal to k and with a probability of "high" contamination less than k are classified as having a "low" level of contamination ($\hat{c}_i = 1$), and CI properties with estimated probabilities for both "high" and "low" contamination less than k are classified as "not contaminated" ($\hat{c}_i = 0$).

The decision rule expressed by equation (4.13) is more flexible than what is given by equation (4.12) since it allows the researcher to observe how the predicted outcomes vary under different restrictions (ie. for different values of k). The specific value actually chosen for k will be investigated once the model has been estimated. However, it may be reasonable to choose a value for k based on the frequency of contaminated sites observed in the sample of CI properties used to estimate the model. If CI properties are classified according the decision rule given by equation (4.12) (ie. into the category with the highest predicted probability), the researcher ignores how the number contaminated sites in the estimating sample may affect the predicted outcomes. Therefore, it may be more appropriate to choose equation (4.13) as the method for classifying CI properties into one of the three categories of contamination.

Sample Selection

As a result of the empirical model using only CI properties with positive sales prices and properties found on one of the four lists, the issue of sample-selection must be addressed. Proximity to contaminated sites may affect a current property owner's decision to put their property up for sale for fear of "public" discovery of contamination, a phenomenon known as "mothballing". In this instance, the decision to not sell can be a result of the current owner not wanting to be held liable for paying potentially high clean-up costs from a subsequent discovery of contamination. Therefore, whether or not a property has a recorded sales price may be correlated with the observed level of contamination. Not accounting for this correlation will lead to biased and inconsistent parameter estimates for $\hat{\beta}$, $\hat{\alpha}_1$ and $\hat{\alpha}_2$.

To correct for sample-selection bias, Heckman's (1979) two-step estimator will be employed in which sample-selection is treated as an omitted variable problem. The first step involves pooling data from properties that have sold and not sold to determine factors that affect the probability a property sells. Among the factors will be variables that control for proximity to contaminated sites with low levels and high levels of contamination. These are used to help capture possible effects of mothballing behavior.

The first stage is to estimate the sample-selection model via maximum likelihood estimation of a probit model, where the dependent variable, s_i, is a dummy variable equal to one if the property sold and equal to zero otherwise. The associated likelihood function is given as:

$$L = \prod_{i=1}^{n} [\Phi(z_i' \gamma)]^{s_i} [1 - \Phi(z_i' \gamma)]^{1-s_i}, \tag{4.14}$$

where z_i is a vector of explanatory variables that are believed to be determinants of property turnover and γ is a vector of parameters to be estimated.

After maximizing the log of the likelihood function, the parameters estimates for γ are used to generate the *inverse Mills ratio* (IMR), defined as:

$$\hat{\lambda}_i = \frac{\phi(z_i' \gamma)}{\Phi(z_i' \gamma)}, \tag{4.15}$$

where ϕ and Φ represent the probability density function and cumulative distribution function for the standard normal distribution, respectively. The IMR is then entered as a regressor in the ordered probit estimation of the probability of contamination model (equation 4.9), such that the IMR is treated as an omitted variable. The inclusion of the IMR in the ordered probit leads to consistent parameter estimates, where the specification error of an omitted variable would result if the IMR was not included. Although consistent, the parameter estimates are inefficient since the errors for estimated model in the second stage are heteroskedastic. Therefore, the second stage is estimated with a consistent asymptotic variance-covariance matrix for an assumed unknown form of heteroskedasticity.

In empirical work employing Heckman's two-step estimator, it is common for x, the vector of explanatory variables describing the probability a property is contaminated, and *z*, the vector of explanatory variables describing the probability a property sells, to have a large set of variables in common. In situations where no variables in *z* are excluded from *x*, it is then said that there are no exclusionary restrictions. The model is still identified, but only through the nonlinearity of the IMR. Puhani (2000) indicates that in these circumstances, "collinearity problems are likely to prevail as λ (the IMR) is an approximately linear function over a wide range of its argument." Therefore, it is suggested in practice that one determine variables to include in *z* which are important to the selection process (given by equation 4.14), but are not thought to be determinants of the second stage process (the probability of contamination model in this application). A description of the two sets of variables used in the first stage and second stage of the estimation process is given in the following section.

Explanatory Variables

Stage 2: Probability of Contamination Model

The primary issue in estimating the probability of contamination model is determining the factors that are likely to be key signals to investors in forming their perceptions that a site may be contaminated. In reference to the empirical model given by equation (4.9), the question is what are the explanatory variables that comprise the vector x_i. Variables that control for CI property land-use types, proximity to the central business district, and proximity to contaminated sites are among those that are thought to be important. Table 4.1 provides a complete list of the explanatory variables used in estimating equation (4.9). They can broadly be categorized into variables describing the physical characteristics of the property, the neighborhood and spatial characteristics of the property, and variables that capture the spatial relationship between CI properties and contaminated sites.

Of interest for the probability of contamination model are the variables controlling for the various CI land-uses, since it may be assumed that CI property investors may form perceptions that certain types of land-uses (i.e., service stations, some manufacturing facilities, strip malls with dry cleaners on site, etc.) are more likely to be contaminated than other land-uses. A total of 139 different land-use codes are represented in the property data. Similar land-uses were grouped together and used to identify thirty-nine aggregated land-use categories to be included in the models. An additional property characteristic used is the land area of the parcel (acre). Contaminated sites may be characterized by parcels with greater land area because CI property owners may be less inclined to undertake "safe" business operations if they are less visible to neighbors and if they believe they can keep any contaminant release contained on their own property.

Neighborhood characteristics are also thought to be important in estimating the probability of contamination model. The reason is that contaminated sites may be located in neighborhoods that are less affluent or more concentrated with minorities since CI property owners may believe there would be less organized opposition to polluting activities in these types of neighborhoods.[34] Variables included in the model are the percent nonwhite population of the census tract (nwhite) and the real median household

[34] Boer et al. (1997) report that in the Los Angeles area, those most affected by the siting of hazardous waste treatment, storage, and disposal facilities were low income minority communities.

income of the census tract (rminc).[35]

Figures 3.2 and 3.5 in Chapter 3 showed the spatial distribution of sites with high levels and low levels of contamination. These figures indicate that a CI property's location relative to the cbd may be an important factor in estimating the probability of contamination model. Further, these figures suggest that the probability a CI property is contaminated may vary according to a property's location in either the northwest, northeast, southwest, or southeast portion of Fulton County. To control for these factors, distance to the cbd (cbd)[36] and indicator variables that denote a property's location in one of the four quadrants of Fulton County were created (northeast, northwest, southeast, and southwest).[37] Interactions between distance to the cbd and the four indicator variables were used in the model to more fully characterize the spatial location of CI properties and its relation to the likelihood they are contaminated.

Figures 3.2 and 3.5 in Chapter 3 also indicate that the likelihood a property is contaminated may be correlated with the proximity of other contaminated sites, suggesting that contaminated sites may be clustered within small geographic areas. To control for proximity to contaminated sites, the inverse distance to the nearest site with a high level of contamination (invdhigh) and inverse distance to the nearest site with a low level of contamination (invdlow) was calculated. To control for the density of contaminated sites, the number of sites with a high level of contamination within one mile (highdens) and the number of sites with a low level of contamination within one

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[35] Variables are based on 1980 census tract geography.

[36] The Five Points MARTA transit station is used as the cbd reference point.

[37] These variables are defined relative to the cbd.

mile (lowdens) of each CI property was calculated.

The minor land-use categories listed in Table 4.1 were also aggregated to create seven "major" land-use categories, defined as retail (biguse1), office (biguse2), industrial (biguse3), apartment/hotel/motel (biguse4), auto-related (biguse5), vacant land (biguse6),[38] and public/exempt (biguse7).[39] These major land-use categories were used to create interaction terms for the variables discussed previously to control for differences across major land-use types that may exist in estimating the probability of contamination model.

Stage 1: Sample-Selection Model

As stated previously, it is typical for the sample selection model and the model estimated in the second stage (i.e. the probability of contamination model in this instance) to have variables in common. Although, the model is still identified if the same set are used, it is suggested that one determine variables that are important to the selection process and are not thought to be determinants of the second stage process. Variables used to estimate equation (4.9), the probability of contaminated model, were also used to estimate the sample-selection model, but careful consideration was taken to make sure that the set of variables was not identical.

The variables that indicate a property's major land-use category (i.e. biguse1,

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[38] The vacant land category was separated into vacant land-excluding paved parking lot (biguse6v) and vacant land-paved parking lot (biguse6p).

[39] Examples of properties in the Public/Exempt category include religious buildings, cemeteries, schools, and other types of public buildings. Public utilities are not included. Although properties in this major land-use may not be as likely to turn over as properties in other categories (e.g. Retail), positive sales prices were observed in the data for properties in this major land-use.

biguse2, biguse3, biguse4, biguse5, and biguse7) were used instead of the aggregated minor land-use dummies used to estimate equation (4.9). It was assumed that the likelihood a property sells only differs across major land-use categories, but does not differ within a major land-use category. Similar to the second stage model, the size of the property was also controlled for in the sample-selection model.

The following spatial variables were used in the selection model to control for the characteristics that describe each CI property's spatial location: distance to the central business district (cbd) and an indicator variable that describes a property's location in north or south Fulton County (north). This differs slightly from the probability of contamination model that uses distance to the cbd interacted with indicator variables that denote a property's location in one of the four quadrants of Fulton County (i.e. northeast, northwest, southeast, and southwest). This was done in the probability of contaminated model only because of the observed spatial pattern of contaminated sites. Ihlanfeldt (1998) provides evidence of differences in price gradients for office rental space for north or south Fulton County. As such, it was assumed that the likelihood a CI property sells is only be affected by its location relative to the cbd and its location in north or south Fulton County.

Neighborhood characteristics used in the selection model include percent change in nonwhite population of the census tract (pnwhite) and percentage change in real median household income of the census tract (princ) from 1980 to 1996. Relative changes in a neighborhood may affect the current CI property owner's ability to sell their property, such that the neighborhood has become a more or less desirable location.

The types of properties around a CI property may affect the likelihood it sells. To control for agglomeration effects, the density of CI properties for each major land-use category within one-half mile was calculated. In addition, changes in neighborhood economic conditions may also affect the likelihood a CI property sells. To proxy for economic factors, the change in total census tract employment (1996 - 1980) was calculated for four major industry sectors: retail, service, industrial, and government.[40] These variables are not included in the probability of contamination model since it was assumed that agglomeration effects or changes in neighborhood economics conditions are not important determinants of the likelihood a property is contaminated. It is reasonable to assume that CI property owners are not more/less likely to contaminate just because of their proximity to other properties with similar/dissimilar land-use types.

As discussed earlier, it is reasonable to assume that the likelihood a property sells may be affected by the proximity of contaminated sites. As such, the same variables used for the probability of contamination model are also used in the selection model: inverse distance to the nearest site with a high level of contamination (invdhigh), inverse distance to the nearest site with a low level of contamination (invdlow), the number of sites with a high level of contamination within one mile (highdens) and the number of sites with a low level of contamination within one mile (lowdens).

Lastly, the major land-use categories were also used to create interaction terms for variables in the selection model. Again, this was done to control for differences across major land-use types that may exist.

[40] Chapter 3 provides a complete description of the major industry sectors and how the employment totals are computed.

Sample-Selection Model Results

The first stage in determining the probability a CI property is contaminated involves estimating a probit model that determines the likelihood a property sells. The results of this model are then used to compute the IMR for inclusion as a regressor in the ordered probit estimation of the probability of contamination model. Parameter estimates for the sample-selection model were generated by maximizing the log of the following likelihood function:

$$L = \prod_{i=1}^{n} [\Phi(z_i^{\prime}\gamma)]^{s_i} [1 - \Phi(z_i^{\prime}\gamma)]^{1-s_i}, \tag{4.16a}$$

where the dependent variable, s_i, is equal to one if the property had a recorded sales price and date and equal to zero otherwise[41], and where:

$$\begin{aligned} z_i^{\prime}\gamma = {} & \sum_{x=1}^{7} \gamma_x^1 \times biguse_{xi} + \sum_{x=1}^{7} \gamma_x^2 \times acrebig_{xi} + \sum_{x=1}^{7} \gamma_x^3 \times acre2big_{xi} + \\ & \sum_{y=1}^{7}\sum_{x=1}^{7} \gamma_{xy}^4 \times big_y densbig_{xi} + \sum_{x=1}^{7} \gamma_x^5 \times northbig_{xi} + \sum_{x=1}^{7} \gamma_x^6 \times cbdbig_{xi} + \\ & \sum_{x=1}^{7} \gamma_x^7 \times cbd2big_{xi} + \sum_{x=1}^{7} \gamma_x^8 \times ncbdbig_{xi} + \sum_{x=1}^{7} \gamma_x^9 \times ncbd2big_{xi} + \\ & \sum_{x=1}^{7} \gamma_x^{10} \times pnwhitebig_{xi} + \sum_{x=1}^{7} \gamma_x^{11} \times princbig_{xi} + \sum_{x=1}^{7} \gamma_x^{12} \times cretempbig_{xi} + \\ & \sum_{x=1}^{7} \gamma_x^{13} \times cservempbig_{xi} + \sum_{x=1}^{7} \gamma_x^{14} \times cindempbig_{xi} + \sum_{x=1}^{7} \gamma_x^{15} \times invdhighbig_{xi} + \\ & \sum_{x=1}^{7} \gamma_x^{16} \times invdlowbig_{xi} + \sum_{x=1}^{7} \gamma_x^{17} \times highdensbig_{xi} + \sum_{x=1}^{7} \gamma_x^{18} \times lowdensbig_{xi}. \end{aligned} \tag{4.16b}$$

Detailed descriptions of these variables are given in Table 4.1. However, briefly they are:

$biguse_{xi}$ dummy variable indicating major land-use category of

[41] Sales dates for CI properties where the dependent variable was equal to one were identified over the years 1976 to 2000.

	property i,
$acrebig_{xi}$	interaction between size of property i in acres and major land-use dummy variables,
$acre2big_{xi}$	interaction between size of property i in acres squared and major-land use dummy variables,
$big_{y}densbig_{xi}$	interaction between density of properties by major land-use y within half mile and major land-use dummy variables,
$northbig_{xi}$	interaction between dummy variable indicating if property i is located north Fulton County and major land-use dummy variables,
$cbdbig_{xi}$	interaction between distance to cbd for property i and major land-use dummy variables,
$cbd2big_{xi}$	interaction between distance to cbd for property i squared and major land-use dummy variables,
$ncbdbig_{xi}$	interaction between $northbig_{xi}$ and distance to cbd for property i,
$ncbd2big_{xi}$	interaction between $northbig_{xi}$ and distance to cbd for property i squared,
$pnwhitebig_{xi}$	interaction between percentage change in nonwhite census tract population (1980-1996) property i is located and major land-use dummy variables,
$princbig_{xi}$	interaction between percentage change in real median census tract income (1980-1996) property i is located and major land-use dummy variables,
$cretempbig_{xi}$	interaction between change in census tract retail employment (1980-1996) property i is located and major land-use dummy variables,
$cservempbig_{xi}$	interaction between change in census tract service employment (1980-1996) property i is located and major land-use dummy variables,
$cindempbig_{xi}$	interaction between change in census tract industrial employment (1980-1996) property i is located and major land-use dummy variables,
$invdhighbig_{xi}$	interaction between <u>inverse distance</u> to nearest site with a high level of contamination for property i and major land-use dummy variables,
$invdlowbig_{xi}$	interaction between <u>inverse distance</u> to nearest site with a low level of contamination for property i and major land-use dummy variables,
$highdensbig_{xi}$	interaction between <u>density</u> of sites with a high level of contamination within one mile for property i and major land-use dummy variables,
$lowdensbig_{xi}$	interaction between <u>density</u> of sites with a low level of contamination within one mile for property i and major

land-use dummy variables.

The results of the sample-selection probit estimated using CI properties in non-vacant land-use categories are provided in Table 4.2. Excluding inverse distance to a site with either a high or low level of contamination, positive (negative) coefficients indicate an increase (decrease) in the probability a property sells, holding everything else constant. Joint tests of significance were also performed for each group of interaction variables given above. Using Wald tests, all sets of interaction variables in the model (excluding those that control for proximity to contaminated sites) are jointly significant at a minimum 0.10 level.[42] Individually, nearly half of the estimated coefficients were statistically significant (0.10 level). A brief discussion of the overall results of the selection model will be given before presenting the second stage probability of contamination model.

Coefficient estimates for the dummy variables controlling for major land-use category were negative and statistically significant (0.05 level) for retail ($biguse_1$), office ($biguse_2$), auto-related ($biguse_5$) and public/exempt ($biguse_7$). These results indicate that CI properties in apartment/hotel/motel ($biguse_4$), the reference category, and industrial ($biguse_3$) were the most likely to turn over. Additionally, land area has a significant (0.05 level) negative effect on the likelihood a property sells for CI properties in retail ($acrebig_1$), industrial ($acrebig_3$), apartment/ hotel/motel ($acrebig_4$), and public/exempt

[42] The following variables were interacted with the major land-use dummies and subsequently dropped after they were found to be jointly not significant: big_5dens, cgovemp, marta00hm, exit1m, and harts5m (see Table 4.1 for variable definitions). In addition, variables that controlled for square feet of floor space, age of primary structure, frontage type, and exterior wall type were also found to provide no additional explanatory power in the model.

($acrebig_7$). Larger properties may be more difficult to sell because they command higher prices in the market, holding everything else constant. Although they were also negative, the coefficients for office ($acrebig_2$) and auto-related ($acrebig_5$) were not significant.

The effects of a CI property's spatial location in Fulton County, relative to the central business district, varied by major land-use category. Properties located in north Fulton County were less likely to sell for the apartment/hotel/motel ($northbig_4$) category, but more likely to turn over for public/exempt ($northbig_7$). These two coefficients are significant at the 0.05 level, while the estimates for retail ($northbig_1$), office ($northbig_2$), industrial ($northbig_3$), and auto-related ($northbig_5$) are not significant. Distance to the CBD only has a significant (0.05 level) and negative effect on the likelihood a property sells for industrial ($cbdbig_3$). When distance to the CBD is interacted with the north/south indicator variable, the likelihood that a property located in north Fulton County sells increases as distance increases for retail ($ncbdbig_1$), industrial ($ncbdbig_3$), apartment/hotel/ motel ($ncbdbig_4$), and auto-related ($ncbdbig_5$), while the opposite is found for office ($ncbdbig_2$) and public/exempt ($ncbdbig_7$). However, only the coefficient for public/exempt ($ncbdbig_7$) is significant (0.05 level). In general, it appears that a property's location relative to the CBD is only an important factor in determining the likelihood a property sells for the industrial, apartment/hotel/motel, and public/exempt major land-use categories.

The variable $big_ydensbig_x$ was used to control of agglomeration effects where $big_ydensbig_x$ is defined as the interaction between the number of properties with major land-use y within one-half mile (big_ydens) and the major land-use dummies ($biguse_x$).

The estimated model includes interactions between each of the major land-use categories and density measures for retail (big_1dens), office (big_2dens), industrial (big_3dens), apartment/hotel/motel (big_4dens), vacant-excluding paved parking lot ($big_{6v}dens$), vacant-paved parking lot ($big_{6p}dens$), and public/exempt (big_7dens). The interaction variables for big_5dens and major land-use were dropped since they were found to be jointly not significant. A greater number of properties with the same major land-use in close proximity increases the likelihood of property turn-over the office, industrial, and apartment/hotel/motel properties. This is indicated by positive and significant (0.05 level) coefficients for office ($big_2densbig_2$), industrial ($big_3densbig_3$), and apartment/hotel/motel ($big_4densbig_4$). Although retail ($big_1densbig_1$) and public/exempt ($big_7densbig_7$) were negative, both were not significant. The results observed for the remaining interaction terms differed by major land-use.

The effects of the neighborhood characteristics on the likelihood a property sells varied according to major land-use. The variables $pnwhitebig_x$ and $princbig_x$ represent the interaction between the major land-use dummies and percentage change in nonwhite population of census tract and percentage change in real median income of census tract from 1980 to 1996, respectively. Increases in the percentage of a census tract's nonwhite population is only associated with a statistically significant (0.05 level) decrease in the likelihood of property turn-over for apartment/hotel/motel ($pnwhitebig_4$), while the opposite is observed for public/exempt ($pnwhitebig_7$). The percentage change in real median income has a positive and significant effect (0.05 level) on property turn-over for apartment /hotel/motel ($princbig_4$) only. Surprisingly, a negative and significant effect

(0.10 level) was observed for auto-related ($princbig_5$) and public/exempt ($princbig_7$). All remaining interaction terms between the major land-use categories and neighborhood characteristics were not significant.

The change in total census tract employment from 1980 to 1996 for three major industry sectors (retail, service, and industrial) were interacted with the major land-uses dummies to proxy for economic factors.[43] In general, the effects of the individual employment sectors varied by major land-use category. For example, increases in retail employment has a positive and significant (0.05 level) effect on the probability a property sells for public/exempt ($cretempbig_7$), but a negative and significant (0.05 level) effect for office ($cretempbig_2$) and industrial ($cretempbig_3$). Overall, several of the interaction terms were found to be statistically significant, regardless of their sign.

Interesting results are observed for the variables controlling for proximity to contaminated sites. Contrary to expectations, inverse distance to the nearest highly contaminated site was found to have a positive and significant (0.10 level) effect on the likelihood a property sells for the retail ($invdhighbig_4$) and public/exempt ($invdhighbig_7$) categories. This suggests that properties closer to highly contaminated sites are more likely to sell. Although consistent with expectations, the negative coefficients for office ($invdhighbig_2$) and industrial($invdhighbig_3$) were not significant. A Wald test indicates the coefficients for $invdhighbig_x$ are jointly not significant for the six major land-use categories. As such, the results suggest that proximity to a highly contaminated site does not have any adverse effect on the likelihood a property sells at least once.

[43] The interactions between major land-use categories and change in total census tract government employment were found to be jointly not significant and were subsequently dropped.

The results observed for distance to the nearest site with a low level of contamination ($invdlowbig_x$) were similar. Unlike $invdhighbig_x$, the coefficients estimates for $invdlowbig_x$ were jointly significant (0.05 level) for the six major land-use categories, and retail ($invdlowbig_1$) and public/exempt ($invdlowbig_7$) was individually significant (0.05 level) and positive. While not significant, only the estimate for industrial ($invdlowbig_3$) was negative. This further supports what was observed for the coefficient estimates for inverse distance to the nearest highly contaminated site, suggesting that the likelihood a CI property sells is not adversely affected by proximity to a single site with either a high or a low level of contamination.

As noted earlier, Figures 3.2 and 3.5 of Chapter 3 indicated that there are a large number of contaminated sites are found in Fulton County. Therefore, it may be the density of contaminated sites in close proximity that affect the probability a CI property sells rather than just the distance to the nearest site. CI properties with a higher number of contaminated sites may be expected to have a less likelihood of selling, holding everything else constant. The variables $highdensbig_x$ and $lowdensbig_x$ represent the interaction between the major land-use dummy variables and the density of contaminated sites within one mile. The coefficient estimates for the number of highly contaminated sites within one mile are statistically significant (0.05 level) and negative for industrial ($highdensbig_3$) and public/exempt ($highdensbig_7$). This is not surprising since CERCLIS/HSI sites are primarily CI properties in the industrial and public/exempt categories. Therefore, these properties are more likely to have a greater number of sites with a high level of contamination in close proximity. For the density of sites with a low level of contamination within one mile, only retail ($lowdensbig_1$) and public/exempt ($lowdensbig_7$) are statistically significant (0.05 level) and negative. Interestingly, this variable is positive and significant (0.05) for auto-related ($lowdensbig_5$). Although Wald tests reveal that both $highdensbig_x$ and $lowdensbig_x$ are jointly significant for the six major land-use categories, the results suggest the likelihood a property sells is only negatively affected by the density of sites with either a high or low level of contamination for properties in the retail, industrial, and public/exempt categories.

Estimating the Probability of Contamination

Ordered Probit Probability of Contamination Model Results

The results of the sample-selection probit were used to generate the inverse Mills ratio (IMR), which was then entered as an explanatory variable in the ordered probit estimation of the probability of contamination model. Parameter estimates for the probability of contamination model were generated by maximizing the log of the following likelihood function:

$$L = \prod_{i=1}^{n} \prod_{j=0}^{2} [\Phi(\alpha_{j+1} - x_i'\beta) - \Phi(\alpha_j - x_i'\beta)]^{m_{ij}}, \tag{4.17a}$$

where the dependent variable and m_{ij} are defined the same as for equation (4.9) and where:

$$
\begin{aligned}
x_i'\beta = {} & \sum_{y=1}^{39} \beta_j^1 \times lu_{yi} + \sum_{x=1}^{7} \beta_x^2 \times acrebig_{xi} + \sum_{x=1}^{7} \beta_x^3 \times acre2big_{xi} + \\
& \beta^4 \times cbdne_i + \beta^5 \times cbdnw_i + \beta^6 \times cbdse_i + \beta^7 \times cbdsw_i + \\
& \beta^8 \times cbd2ne_i + \beta^9 \times cbd2nw_i + \beta^{10} \times cbd2se_i + \beta^{11} \times cbd2sw_i + \\
& \sum_{x=1}^{7} \beta_x^{12} \times nwhitebig_{xi} + \sum_{x=1}^{7} \beta_x^{13} \times rmincbig_{xi} + \sum_{x=1}^{7} \beta_x^{14} \times pdensbig_{xi} + \\
& \sum_{x=1}^{7} \beta_x^{15} \times invdhighbig_{xi} + \sum_{x=1}^{7} \beta_x^{16} \times invdlowbig_{xi} + \sum_{x=1}^{7} \beta_x^{17} \times highdensbig_{xi} + \\
& \sum_{x=1}^{7} \beta_x^{18} \times lowdensbig_{xi} + \beta^{19} \times imr_i \ .
\end{aligned}
\tag{4.17b}
$$

A detailed description of these variables is provided in Table 4.1, but briefly they are:

lu_{yi}	dummy variable for aggregated minor land-use category,
$acrebig_{xi}$	interaction between size of property *i* in acres and major land-use dummy variables,
$acre2big_{xi}$	interaction between size of property *i* in acres squared and major land-use dummy variables,
$cbdne_i$	interaction between distance to cbd for property *i* and dummy variable indicating if property *i* is located in northeast Fulton County,
$cbdnw_i$	interaction between distance to cbd for property *i* and dummy variable indicating if property *i* is located in northwest Fulton County,
$cbdse_i$	interaction between distance to cbd for property *i* and dummy variable indicating if property *i* is located in southeast Fulton County,
$cbdsw_i$	interaction between distance to cbd for property *i* and dummy variable indicating if property *i* is located in southwest Fulton County,
$cbd2ne_i$	square of cbdne,
$cbd2nw_i$	square of cbdnw,
$cbd2se_i$	square of cbdse,
$cbd2sw_i$	square of cbdsw,
$nwhitebig_{xi}$	interaction between nonwhite population of census tract property *i* is located and major land-use dummy variables,
$rmincbig_{xi}$	interaction between real median income of census tract

	property *i* is located and major land-use dummy variables,
$pdensbig_{xi}$	interaction between population density of census tract property *i* is located and major land-use dummy variables,
$invdhighbig_{xi}$	interaction between inverse distance to nearest site with a high level of contamination for property *i* and major land-use dummy variables,
$invdlowbig_{xi}$	interaction between inverse distance to nearest site with a low level of contamination for property *i* and major land-use dummy variables,
$highdensbig_{xi}$	interaction between density of sites with a high level of contamination within one mile for property *i* and major land-use dummy variables,
$lowdensbig_{xi}$	interaction between density of sites with a low level of contamination within one mile for property *i* and major land-use dummy variables,
imr_i	inverse Mills ratio estimated for property *i*.

Equation (4.17a) was estimated using CI properties in non-vacant land-uses. Observations classified as "not contaminated" only include properties that have a recorded sales price above $10,000 and a sales date between the years 1980 and 2000.[44] The value for sales price was chosen such that prices greater than $10,000 are considered "arms length transactions". Additionally, properties with sales dates prior to 1980 were not used since this was the year CERCLA was enacted by congress. As such, these properties did not fall under CERCLA regulation. Therefore, it follows that all observations in the estimating sample are assumed to have been tested for contamination and that the level of contamination present (no, low, or high) is known.

The results of the ordered probit probability of contamination model are given in Table 4.3. Mixed residential/commercial (lu_6) is the reference category for the dummy

[44] Three percent of the CI properties in non-vacant land-uses had a recorded sales price below $10,000.

variables controlling for minor land-uses.[45] Relative to the reference category, CI properties with twenty-one different land-uses have a higher probability of being contaminated, while eight are less likely to be contaminated. Land-uses with large positive coefficient estimates tend to be properties in manufacturing and processing, while large negative coefficients are observed for nursing home/boarding home/day care (lu_{10}), office (lu_{18}), cold storage (lu_{21}), research and development (lu_{27}), and natural gas/mining (lu_{33}). These results are not surprising as one would expect CI properties with manufacturing/processing land-uses to have a higher likelihood of being contaminated when compared to other land-uses. Land area is also a significant factor in the model, indicating larger properties have a higher probability of being contaminated for all major land-use categories. This suggests that CI property owners may be less inclined to undertake "safe" business operations on properties with greater land area.

The spatial location of CI properties is an important determinant in the model. The variables cbdnw, cbdne, cbdsw, and cbdse represent the interaction between distance to the CBD and indicator variables that describe whether a property is located in the northwest, northeast, southwest, or southeast portion of Fulton County. The positive and significant coefficients (0.05 level) for these four interaction terms suggest that CI properties located a greater distance from the CBD have a higher probability of being contaminated, regardless of a property's location in northwest, northeast, southwest or southeast Fulton County. These results are consistent with expectations since the CBD is

[45] The following land-uses were not used to estimated equation (4.17) since they correspond to vacant properties: vacant apartment (lu_1), vacant commercial (lu_2), vacant industrial lu_3), vacant exempt (lu_4), vacant utility/other (lu_5), and parking-paved parking lot (lu_{39}).

commonly concentrated with a large number of office properties, which are usually not contaminated sites. Although the coefficients for cbdnw, cbdne, cbdsw, and cbdse are all positive, their magnitudes indicate the effects vary according to the direction from the CBD a property is located. For example, a CI property two miles from the CBD has the greatest likelihood of being contaminated if it is located in southeast Fulton County, holding everything else constant. Overall, the effect distance to the CBD has on the probability a property is contaminated is greatest if it is located in southeast Fulton County and lowest if it is located in southwest Fulton.

Census tracts with higher medium income levels were associated with a significant (0.05 level) negative effect on the likelihood a CI property is contaminated for office ($rmincbig_2$) only. Although the negative coefficients also observed for retail ($rmincbig_1$), apartment/hotel/motel ($rmincbig_4$), auto-related ($rmincbig_5$), and public/exempt ($rmincbig_7$) were not significant, the interaction terms were as a group jointly significant (0.10 level). This lends support to the hypothesis that CI properties are more likely to be contaminated in neighborhoods that are less affluent. Higher minority populations were found to have a significant (0.10 level) and negative effect on the probability a property is contaminated for retail ($nwhitebig_1$) and auto-related ($nwhitebig_5$), while negative and not significant for office ($nwhitebig_2$). Although positive coefficients are observed for Industrial ($nwhitebig_3$), apartment/hotel/motel ($nwhitebig_4$), and public/exempt ($nwhitebig_7$), they are not statistically significant. However, as a group, the interaction terms are jointly significant (0.10 level).

Interesting results are observed when analyzing the effects of the proximity to contaminated site variables used in the model. Only for industrial (invdhighbig$_3$) is an increase in distance to the nearest highly contaminated site associated with a lower probability of being contaminated. Surprisingly, inverse distance to the nearest highly contaminated site has a negative and statistically significant (0.05) effect for public/exempt (invdhighbig$_7$). In regards to the density sites within one mile, only for public/exempt (highdensbig$_7$) does an increase in the number of sites with a high level of contamination have positive and statistically significant (0.10 level) effect on the probability a CI property is contaminated. Regardless of the sign, the coefficients for all other major land-use categories were not significant. The estimates for invdhighbig$_3$ and highdensbig$_7$ are consistent with what was expected. Since a large percentage of the properties on CERCLIS/HSI are in the industrial and public/exempt categories, it is more likely that properties in these two categories are located near other CERCLIS/HSI sites, leading to these results. However, joint tests of significance reveal that both the density of highly contaminated sites within one mile and inverse distance to the nearest highly contaminated site are not significant, suggesting that these factors do not provide a signal for the likelihood a CI property is contaminated.

Unlike what is observed for highly contaminated sites, the proximity to sites with a low level of contamination is an important determinant in the model. Inverse distance to the nearest site with a low level of contamination is positive and statistically significant (0.10 level) for office (invdlowbig$_2$), industrial (invdlowbig$_3$), and apartment/hotel/motel (invdlowbig$_4$). Only for auto-related (invdlowbig$_5$) is a negative sign observed, but it is not significant. In addition, higher concentrations of sites with a low level of contamination within one mile are associated with a statistically significant (0.10 level) increase in the likelihood of being contaminated for the retail ($lowdensbig_1$), office ($lowdensbig_2$), industrial ($lowdensbig_3$), and apartment/hotel/motel ($lowdensbig_4$) categories. Both the density of sites and distance to the nearest site with a low level of contamination are also jointly significant (0.10 level) for the six major land-use categories combined. Contrary to what was observed for highly contaminated sites (i.e. CERCLIS/HSI sites), these results support the hypothesis that proximity to contaminated sites can signal the likelihood a CI property is itself contaminated.

Predicting Contamination Levels for CI Properties

The results of the ordered probit model were used to compute probability estimates for each of the three possible categories, defined previously by equation (4.11). The decision rule given by equation (4.13) was used to classify CI properties into one of three categories that characterizes the level of contamination present at the property. According to this decision rule, CI properties with an estimated probability of "high" contamination ($\hat{P}_i^2$) greater than or equal to k are classified as "highly" contaminated ($\hat{c}_i = 2$), CI properties with an estimated probability of "low" contamination ($\hat{P}_i^1$) greater than or equal to k and with a probability of "high" contamination less than k are classified as having a "low" level of contamination ($\hat{c}_i = 1$), and CI properties with estimated probabilities for both "high" and "low" contamination less than k are classified as "not contaminated" ($\hat{c}_i = 0$).

Table 4.4 provides predicted outcomes for observations in the sample used to estimate equation (4.17a). The first column in the table reports the observed number of properties in each category of contamination. Note that only 4.1 percent of the properties used in the sample to estimate the model were identified as having some known level of contamination. Thus, the values for k were chosen to be 0.05, 0.10, and 0.15 because of the low frequency of contaminated sites observed in the estimating sample.

Using a value for $k = 0.05$, nearly fifty percent of the CI properties that are on the CERCLIS/HSI lists were predicted to be highly contaminated. Overall, a total of 248 properties were predicted as having a high level of contamination with $k = 0.05$. This total falls to 127 and 69 for $k = 0.10$ and 0.15, respectively. For $k = 0.10$, 35.6 percent of the highly contaminated sites were correctly predicted and 27.1 percent were correctly predicted with $k = 0.15$. Note that regardless of the value for k used, nearly fifty percent of the properties on CERCLIS/HSI are predicted as being contaminated in some way.

Precision in the predicted outcomes is observed less frequently for CI properties on the NFRAP/NonHSI lists. Using a cut-off of $k = 0.05$, the maximum number of properties were predicted correctly (38.9 percent). Of note, 38.9 percent of the NFRAP/NonHSI properties were predicted to be highly contaminated when the cut-off is 0.05. Slightly over twenty-five percent and 13.8 percent of the properties on the NFRAP/NonHSI lists were predicted to be highly contaminated when $k = 0.10$ and 0.15, respectively. A total of 931 CI properties that have no known contamination present are predicted to have a low level of contamination if a cut-off of 0.05 is used. However, these totals drop to 279 and 146 as the cut-off value is increased to 0.10 and 0.15, respectively.

For the total number of CI properties among the three predicted categories, a significantly higher proportion of the sample are predicted to be in the high and low categories for $k = 0.05$ when compared to the other two cut-off values chosen. However, it is interesting to note that for $k = 0.15$, the model predicts a nearly identical proportion of contaminated sites to what is actually observed in the data. Sixty-nine properties are predicted to be highly contaminated and 216 are predicted as having a low level of contamination (see Table 4.4, $k = 0.15$). This is very similar to what is observed in the estimating sample where 59 properties are known to have a high level of contamination and 203 a low level.

The estimated ordered probit model is also used to compute the probability of contamination for CI properties not in the estimating sample (ie. non-vacant properties that did not have a recorded sales price above $10,000). Table 4.5 reports the predicted outcomes for both the 6,434 CI properties used in estimating the ordered probit model plus an additional 8,926 observations that did not have a recorded sales price above $10,000. This results in an increase in the total number of CI properties with no known contamination present from 6,172 to 15,098. Table 4.5 indicates that as many as 633 CI properties that are not contaminated may actually be perceived as highly contaminated. Even when a more strict cut-off value is chosen, 190 CI properties still fall into this scenario. The number of CI properties with no known contamination predicted to have a low level of contamination are 2,666, 968, and 548 for the cut-off values equal to 0.05, 0.10, and 0.15, respectively. It is interesting to note that the proportion of the sample of properties predicted as having a low level of contamination for $k = 0.15$ in Table 4.5 (4.0

percent) is similar to the proportion of the estimating sample observed to be on the NFRAP/NonHSI lists (3.2 percent, given in the first column of Table 4.4).

Additional Probability of Contamination Models Estimated

Probit Probability of Contamination Model Results

Due to the low proportion of CI properties identified as having low and high levels of contamination, the question arises as to whether or not the ordered probit model can identify an accurate distinction between these two categories. Thus, the ordered probit model was simplified to a probit model. In the probit model, the dependent variable for the model is a binary variable equal to one if the property is on either the CERCLIS, HSI, NFRAP, or NonHSI lists and equal to zero if there is no documented record of contamination on the property. This specification collapses the two categories of contamination (low and high) into one category.

The first step in estimating the probit model was identical to the first step in estimating the ordered probit, where the sample-selection model was used to generate the IMR to be included in the probit. The explanatory variables used for the probit model were identical to those used for the ordered probit for consistency across models. The results of the estimated model are given in Table 4.6.[46] In terms of coefficient signs and significance, the model's results are similar to what was observed for the ordered probit. Since the primary purpose of estimating this model was to compare the predicted

[46] A total of 124 observations in four land-uses were dropped since no contaminated sites are categorized as those land-uses. The land-uses were: nursing home/boarding home/day care (lu_{10}), cold storage (lu_{21}), research and development (lu_{27}), or natural gas/mining (lu_{33}).

outcomes to those of the ordered probit, a more detailed description of the empirical results will not be given.

Predicted outcomes for the probit model were computed in a similar way to that of the ordered probit. However, this model is only used to predict whether or not a CI property is contaminated and not the level of contamination. Therefore, to account for this difference, the decision rule given by equation (4.13) can be simplified to:

$$\begin{aligned} \hat{c}_i &= 0 \quad \text{if} \quad \hat{P}_i < k \\ \hat{c}_i &= 1 \quad \text{if} \quad \hat{P}_i \geq k, \end{aligned} \tag{4.18}$$

where $\hat{c}_i = 0$ represents the property is not contaminated, $\hat{c}_i = 1$ represents the property is contaminated, $\hat{P}_i$ is the estimated probability of contamination from the model, and k is a cut-off point used to classify CI properties as contaminated or not contaminated. Table 4.7 provides predicted outcomes for observations used in estimating the probit model. This table is similar to Table 4.4 except that a property can only be classified as contaminated or not contaminated. For ease of comparison, predicted outcomes are computed using the same values for k. Table 4.8 provides predictions for observation not used in estimating model.

The results reported in Table 4.7 are consistent with what is presented in Table 4.4. The proportion of properties with known contamination that are predicted to be contaminated at any level from the ordered probit model is nearly identical to what is observed from the probit model. For example, 211 properties with known contamination are predicted as high or low using the ordered probit model when $k = 0.05$ (80+25+78+28 in Table 4.4), while the probit model predicts 213 properties as contaminated (161+52 in Table 4.7). A similar pattern occurs for the other two cut-off values chosen. Additionally, the overall total number of CI properties that are predicted to be contaminated in both models differ very little. Although, the proportion of the total sample of properties predicted as contaminated is always greater for the probit model. This is due to the probit model predicting a higher number of CI properties with no known contamination as contaminated. These results are observed for predicted outcomes computed for properties in the estimating sample (see Table 4.4 and 4.7) and for the full sample (see Table 4.5 and 4.8).

Although the proportion of the sample of CI properties predicted to be contaminated in the ordered probit model and probit model are similar across the three cut-off values, the issue of whether the same properties are being identified as contaminated in both models can be raised. Table 4.9 provides a cross tabulation of the predicted outcomes for the ordered probit and probit probability of contamination models. The tabulations are expressed for properties that are found in the estimating samples of both models. For each cut-off value, all properties that are predicted to be highly contaminated by the ordered probit model are also predicted to be contaminated by the probit model. Fifty-two properties that are predicted to have a low level of contamination were subsequently predicted to be not contaminated by the probit model when the cut-off is equal to 0.05. This total falls when the cut-off increases to 0.10 (six properties) and 0.15 (zero properties). Surprisingly, the minimum number of properties that were predicted to be contaminated by the probit model, but were predicted to be not contaminated by the ordered probit, is observed when the cut-off is 0.05 (96 properties). However, regardless of the cut-off value chosen, approximately two percent of the properties predicted as not contaminated by the ordered probit model were subsequently predicted to be contaminated by the probit model.

In general, the results given in Table 4.9 suggest that the same properties are being predicted as contaminated, regardless of what model is used for prediction. However, it is important to note that a CI property with no known contamination is more likely to be predicted as contaminated by the probit model compared to the ordered probit model. Similar patterns are observed when comparisons between to the two models are made for predicted outcomes computed over the full sample of CI properties (see Table 4.10). To further examine the results generated by the ordered probit probability of contamination model, two additional models were estimated and are discussed in the next section.

Probability of Contamination Models and Sample Size

Additional investigation was done regarding the issue of the low proportion of properties identified as having a low or high level of contamination, and the ability of the ordered probit model to distinguish between the three levels of contamination. To address these issues further, the ordered probit and probit probability of contamination models were estimated using a random sample of CI properties with no known contamination and properties on the CERCLIS/HSI lists or NFRAP/NonHSI lists. The random sample was created from the 6,172 properties with no known contamination used to estimate equation (4.17a). Now, approximately seventy-eight percent of the estimating sample will consist of properties with no known contamination, compared to ninety-six percent of the sample used to estimate the ordered probit model. This allows the researcher to test if a higher proportion of properties in the estimating sample identified as having a low or high level of contamination has an effect on the ability to predict contamination levels at CI properties.

The initial step in estimating the models that use the random sample is identical to the initial step for the ordered probit model describe in the previous section (now referred to as OPFS model). First, a sample-selection model is estimated to generate the IMR. For consistency, the set of explanatory variables used is identical to the set used for the OPFS model. A discussion of the ordered probit model estimated using the random sample will be given first followed by a discussion of the probit model.

The results for the ordered probit probability of contamination model estimated using the random sample (now referred to as OPRS model) are provided in Table 4.11. The estimating sample consisted of 1,180 CI properties, of which 59 were on the CERCLIS/HSI lists and 203 were on the NFRAP/NonHSI lists. The sign and significance levels of the parameter estimates were similar to what was observed for the OPFS model. In cases where coefficient signs differed, the parameter estimates were generally found to be insignificant in both models. Overall, the results of the OPRS model appear to resemble the results of the OPFS model (given Table 4.3).

Analogous to the OPFS model, the three probability estimates computed by the OPRS model were used to classify CI properties into one of three categories that characterizes the level of contamination present at the property. The same decision rule as the OPFS model, (given by equation (4.13)), was used for the classification process. However, different values for k were selected for the decision rule because a higher proportion of the estimating sample are now observed to be properties with a documented record of contamination. Thus, to follow the proportion of the estimating sample observed to be properties with known contamination, the values for k were chosen to be 0.20, 0.25, and 0.30.

Table 4.12 provides predicted outcomes for CI properties in the estimating sample of the OPRS model. The first column of the table reports the observed number of properties in each category of contamination. Regardless of the cut-off value chosen, a minimum of 30.5 percent of the properties on the CERCLIS/HSI lists were predicted to be highly contaminated and at least 86.4 percent were predicted as being contaminated in some way. The number of properties on the CERCLIS/HSI lists correctly predicted by OPRS model for the three cut-off values chosen are nearly identical to the number correctly predicted by the OPFS model (see Table 4.4). However, unlike the OPFS model, the number of CERCLIS/HSI sites predicted to be contaminated in any way by the OPRS model remains constant as the cut-off value increases.

Some interesting results are observed for the predicted outcomes for CI properties on the NFRAP/NonHSI lists. The percentage correctly predicted remains relatively constant as the cut-off value is increased. However, the number of properties on the NFRAP/NonHSI lists predicted to be not contaminated increases for each increase in the cut-off value. Compared to the OPFS model, the OPRS model is more likely to correctly predict properties on the NFRAP/NonHSI lists. Although, it must be noted that the proportion of the estimating sample predicted to have a low level of contamination is considerably higher for the OPRS model when compared to the OPFS model (see Table 4.4). This appears to be a result of the OPRS model having a greater likelihood of predicting a property that has no known contamination to have a low level of contamination.

The lowest percentage of properties with no known contamination correctly predicted by OPRS model is 74.4 percent ($k = 0.20$). Overall, a maximum of 71.8 percent ($k = 0.30$) of the estimating sample is predicted to be not contaminated. This differs significantly from what is observed for the OPFS model where a minimum of 80.1 percent of the estimating sample is predicted to be not contaminated (see Table 4.4, $k = 0.05$). Again, this is mainly a result of the OPRS model having a greater likelihood of predicting properties with no known contamination to have a low level of contamination.

To further investigate the results of the OPRS model, the predicted outcomes generated by the OPRS model are compared to those generated by the OPFS model to determine if the same properties are being classified into identical categories. Table 4.13 provides a cross tabulation of the predicted outcomes for the OPFS and OPRS models. The tabulations are expressed for CI properties in the estimating sample of the OPFS model where the first column provides the number of properties the model classified into each category for the three cut-off values chosen. The comparisons are only made between the three cut-off values chosen for the OPFS model and the corresponding cut-off value chosen for the OPRS model. For example, the set of cross tabulations given in the upper left corner of Table 4.13 compares predicted outcomes when $k = 0.05$ in the

OPFS model and $k = 0.20$ in the OPRS model.

Table 4.13 indicates that CI properties predicted to be contaminated by the OPFS model are also being predicted to be contaminated by the OPRS model. The greatest overlap is observed for properties that are predicted to have a low level of contamination, where a minimum of 88.4 percent of the properties predicted to have a low level of contamination by the OPFS model have the same predicted outcome using the OPRS model. The degree of commonality between the two models is not necessarily as high for properties predicted to be highly contaminated by the base model. Still, a minimum of 58.1 percent of the properties predicted to have a high level of contamination by the OPFS model are classified in the same category by the OPRS model (when $k = 0.05$ for base model and $k = 0.20$ for OPRS model). Additionally, it must be noted that only two properties that are predicted to be highly contaminated by the OPFS model are predicted to be not contaminated by the OPRS model (when $k = 0.05$ for OPFS model and $k = 0.20$ for OPRS model). A similar observation is made for properties that are predicted to have a low level of contamination by the OPFS model. Furthermore, CI properties predicted to have no contamination by the OPFS model are generally predicted to have no contamination by the OPRS model. When the outcome of no contamination is not consistent across both models, CI properties are primarily predicted to have a low level of contamination by the OPRS model. The findings just discussed are also evident when the predicted outcomes for the full sample of CI properties are compared between the two models (see Table 4.14).

Overall, Tables 4.13 and 4.14 suggest that CI properties predicted to have a low or high level of contamination by the OPFS model are also being classified into the same category by the OPRS model. However, the total number of CI properties predicted to have a low level of contamination is significantly higher for the OPRS model. This is mainly a due to the OPRS model classifying properties that are predicted to have no contamination by the OPFS model as having a low level of contamination.

As mentioned earlier, a probit model was also estimated on the random sample of properties. In this model, the dependent variable does not make any distinction between high and low levels of contamination. The results of the probit model estimated using the random sample (now referred to as PRS model) are given in Table 4.15. The estimating sample consisted of 1,142 CI properties, where 54 were on the CERCLIS/HSI lists and 193 were on the NFRAP/NonHSI lists.[47] In terms of coefficient signs and significance, the parameters estimates were generally similar to what was observed for the OPFS model (given in Table 4.3).

Predicted outcomes for the PRS model were computed using the decision rule given by equation (4.18). To be consistent with the OPRS model, identical cut-off values were used. Table 4.16 provides predicted outcomes for the PRS model for observations in the estimating sample only. Regardless of the cut-off value chosen, a minimum of 81.5 percent of the properties on the CERCLIS/HSI and 73.6 percent of the properties on the NFRAP/NonHSI were correctly predicted as contaminated. The highest percentage of

[47] A total of 23 properties in two land-uses were dropped since no contaminated sites are categorized as those land-uses. The land-uses were: nursing home/boarding home/day care(lu_{10}) and natural gas/mining (lu_{33}). A total of 15 properties in 3 land-uses were also dropped because the only observations with these land-use were contaminated sites. The land-uses were: lumber storage (lu_{22}), clothing related manufacturing/processing (lu_{29}), and concrete/cement/asphalt etc plant (lu_{32}).

properties with no known contamination correctly predicted by PRS model is 85.6 percent (k = 0.30). However, the overall totals indicate a maximum of 72.4 percent (k = 0.30) of the estimating sample is predicted to be not contaminated. Compared to the predicted outcomes observed for the OPFS model, there is significant difference where a minimum of 80.1 percent of the estimating sample is predicted to be not contaminated (see Table 4.4, k = 0.05). This is mainly a result of a higher percentage of properties with no known contamination being predicted as contaminated by the PRS model, which is similar to what was observed for the OPRS model.

Similar to the comparisons made between the other models, a cross tabulation of the predicted outcomes of the PRS model and the OPFS model were computed to determine if the same properties are being predicted as contaminated. These results are provided in Table 4.17. Following the comparison made between the OPRS and OPFS models, the tabulations are expressed for CI properties in the estimating sample of the OPFS model only. The first column provides the number of properties the OPFS model classified into each category for the three cut-off values chosen. Again, comparisons are only made between the three cut-off values chosen for the OPFS model and the corresponding cut-off value chosen for the PRS model. For example, the upper left corner of Table 4.13 compares predicted outcomes from the OPFS model when k = 0.05 to those from the PRS model when k = 0.20.

Table 4.17 indicates that a large percentage of properties predicted as having either a low or high level of contamination by the OPFS model are also being classified as contaminated by the PRS model. A maximum of 52 properties classified as contaminated in any way by the OPFS model are predicted to be not contaminated by the PRS model (51+1, when $k = 0.20$ for PRS model and $k = 0.05$ for OPFS). This sum drops considerably to 5 and 1 when the cut-offs are 0.25 and 0.30 for the PRS model and 0.10 and 0.15 for the OPFS model, respectively. Additionally, the proportion of CI properties predicted to be contaminated is always greater for the PRS model, where the difference between the two models becomes rather substantial as the cut-off values are increased. As with the OPRS model, this is mainly a result of a higher percentage of properties with no known contamination being predicted as contaminated by the PRS model. The observations just discussed are also evident when the predicted outcomes for the OPFS and PRS models are compared over the full sample of CI properties (see Table 4.18).

Conclusion

Four probability of contamination models were estimated in this chapter: OPFS, PFS, OPRS, and PRS. The comparisons made between the four models indicate that the same CI properties are generally being classified as contaminated, regardless of the model chosen. Additionally, the ability of the ordered probit models to distinguish between a low and high level of contamination provides added flexibility over the probit models. Furthermore, the number of CI properties with no known contamination present that are predicted to be contaminated is significantly lower for the OPFS model. As such, the OPFS model appears to be a reasonable model to use to identify properties that may be perceived as contaminated by commercial and industrial real estate investors.

To further examine the reasonableness of the OPFS model, tabulations of the predicted outcomes across major and minor land-use categories were compared to the observed distribution of contaminated properties. First, the predicted outcomes across major land-use categories for CI properties in the estimating sample of the OPFS model are given in Table 4.19. As expected, the greatest difference between the number of properties predicted to have either a low or high level of contamination and what is observed for each land-use occurs when the cut-off is set at 0.05. This difference is most apparent for industrial, where an additional 471 properties (570-99 in Table 4.19) are classified as having a low level of contamination and 136 (176-40 in Table 4.19) as having a high level of contamination when k=0.05. However, as the cut-off value increases to 0.10 and 0.15, the differences are reduced substantially and the predicted outcomes more closely resemble the distribution of known contaminated properties within the specific major land-use categories.

Table 4.19 also demonstrates that most of the properties identified as having a high level of contamination are in the industrial category, regardless of the cut-off value. This is not surprising as 40 of the 59 total properties on CERCLIS/HSI are industrial properties. A similar observation can be made for properties classified as having a low level of contamination where the totals are primarily comprised of properties in industrial and retail. In this instance, 150 of the 203 total properties on the NFRAP/NonHSI are categorized as industrial or retail properties.

Tabulations of the predicted outcomes for the major land-uses were also generated for the full sample of CI properties, given in Table 4.20. The table indicates that an additional 681 properties may be perceived as having a high level of contamination (740-59 for k=0.05) and 2,567 as having a low level of contamination (2,770-203 for k=0.05). These values fall to 307 and 175 for high level of contamination and 842 and 415 for low level of contamination when the cut-off increases to 0.10 and 0.15, respectively. For each of the cut-off values, the majority of sites classified as highly contaminated are in the industrial or public/exempt land-use categories. Of the properties classified as having a low level of contamination, industrial, public/exempt, and retail are the dominant major land-uses.

Table 4.21 is similar to Table 4.19 except that the predicted outcomes are now expressed according to the aggregated minor land-use categories instead of the major land-uses. Regardless of the cut-off value chosen, only six land-uses (retail, multi-occ-non-food related (lu_{14}), general warehouse (lu_{23}), general manufacturing/processing (lu_{26}), glass/metal/plastic/etc products manufacturing/processing (lu_{31}), concrete/cement/asphalt etc plant (lu_{32}), and police/fire station/correctional facility/improved gov't owned (lu_{37})) predict more than five properties to be highly contaminated. Also, the number of properties predicted to have a low level of contamination for these six land-uses are generally higher than the totals for the other land-uses. This is to be expected since these six land-uses are also the land-uses that have the greatest number of properties identified on either the CERCLIS/HSI lists or NFRAP/NonHSI lists. Of note, four land-uses (nursing home/boarding home/day care (lu_{10}), cold storage (lu_{21}) research and development (lu_{27}), and natural gas/mining (lu_{33})) do not have any properties predicted to have a low or high level of contamination for any cut-off value. Again, this follows the actual pattern of contamination observed such that, there are no properties in these land-uses appearing on a state or federal list. Additionally, the distribution of predicted outcomes across minor land-use categories for the full sample of CI properties is provided in Table 4.22. In general, the patterns for the predicted outcomes in Table 4.22 appear to follow what is observed in Table 4.21.

Chapter 6 will discuss how the predicted outcomes generated by the OPFS model are incorporated into hedonic property value models to determine the extent to which they emit negative externality effects on neighboring CI properties.

Table 4.1. Description of Explanatory Variables

Variable Name	Variable Description
Property Characteristics	
lu1	dummy = 1 if apartment, vacant land
lu2	dummy = 1 if commercial, vacant land
lu3	dummy = 1 if industrial, vacant land
lu4	dummy = 1 if exempt, vacant land
lu5	dummy = 1 if utility/other, vacant land
lu6	dummy = 1 if mixed residential/commercial
lu7	dummy = 1 if misc commercial
lu8	dummy = 1 if apartments
lu9	dummy = 1 if hotel/motel
lu10	dummy = 1 if nursing home/boarding home/day care
lu11	dummy = 1 if food and beverage place
lu12	dummy = 1 if automotive - non parking related
lu13	dummy = 1 if parking - parking deck/garage
lu14	dummy = 1 if retail, multi occupancy - non food related
lu15	dummy = 1 if retail single occupancy - non food related
lu16	dummy = 1 if retail, food related
lu17	dummy = 1 if other misc. retail
lu18	dummy = 1 if office
lu19	dummy = 1 if sport/health/fitness/recreation
lu20	dummy = 1 if golf
lu21	dummy = 1 if cold storage
lu22	dummy = 1 if lumber storage
lu23	dummy = 1 if warehouse, general
lu24	dummy = 1 if warehouse, office
lu25	dummy = 1 if misc warehouse/storage
lu26	dummy = 1 if general manufacturing/processing
lu27	dummy = 1 if research and development
lu28	dummy = 1 if food related manufacturing/processing
lu29	dummy = 1 if clothing related manufacturing/processing
lu30	dummy = 1 if parts and equipment manufacturing
lu31	dummy = 1 if glass/metal/plastic/etc products manufacturing/processing
lu32	dummy = 1 if concrete/cement/asphalt etc plant
lu33	dummy = 1 if natural gas/mining
lu34	dummy = 1 if misc. manufacturing/processing
lu35	dummy = 1 if public building/school/university/hospital/etc
lu36	dummy = 1 if religious/cemetery

Table 4.1 Continued

Variable Name	Variable Description
lu37	dummy = 1 if police/fire station/correctional facility/improved gov't owned
lu38	dummy = 1 if transportation/communication/utilities
lu39	dummy = 1 if parking - paved parking lot
$biguse_1$	dummy = 1 if major land-use category is Retail
$biguse_2$	dummy = 1 if major land-use category is Office
$biguse_3$	dummy = 1 if major land-use category is Industrial
$biguse_4$	dummy = 1 if major land-use category is Apartment/Hotel/Motel
$biguse_5$	dummy = 1 if major land-use category is Auto Related
$biguse_{6v}$	dummy = 1 if major land-use category is Vacant (excludes paved parking lot)
$biguse_{6p}$	dummy = 1 if major land-use category is Vacant - paved parking lot
$biguse_7$	dummy = 1 if major land-use category is Public/Exempt
acre	land area of parcel in acres
acre2	acre squared
$acrebig_x$	acre×$biguse_x$ for x=1, 2, 3, 4, 5, 7
$acre2big_x$	acre2×$biguse_x$ for x=1, 2, 3, 4, 5, 7
Neighborhood and Spatial Variables	
big_1dens	number of Retail parcels within half mile
big_2dens	number of Office parcels within half mile
big_3dens	number of Industrial parcels within half mile
big_4dens	number of Apartment/Hotel/Motel parcels within half mile
big_5dens	number of Auto Related parcels within half mile
$big_{6v}dens$	number of Vacant (excludes paved parking lot) parcels within half mile
$big_{6p}dens$	number of Vacant - paved parking lot parcels within half mile
big_7dens	number of Public/Exempt parcels within half mile
cbd	distance to CBD in miles
cbd2	cbd×cbd
north	dummy = 1 if parcel is located in north Fulton County
northeast	dummy = 1 if parcel is located in northeast Fulton County
northwest	dummy = 1 if parcel is located in northwest Fulton County
southeast	dummy = 1 if parcel is located in southeast Fulton County
southwest	dummy = 1 if parcel is located in southwest Fulton County
cbdne	cbd×northeast
cbdnw	cbd×northwest
cbdse	cbd×southeast
cbdsw	cbd×southwest
cbdne2	cbdne×cbdne
cbdnw2	cbdnw×cbdnw

Table 4.1. Continued

Variable Name	Variable Description
cbdse2	cbdse×cbdse
cbdsw2	cbdsw×cbdsw
pdens	population density of census tract (1990)
nwhite	percent non-white population of census tract (1990)
pnwhite	percentage change in non-white population of census tract (1980-1996)
rminc	real median income of census tract (1990)
princ	percentage change in real median income of census tract (1980-1996)
cretemp	change in retail sector employment in census tract (1996-1980)
cservemp	change in service sector employment in census tract (1996-1980)
cindemp	change in industrial sector employment in census tract (1996-1980)
cgovemp	change in government sector employment in census tract (1996-1980)
martahm	dummy = 1 if parcel is located within half mile of MARTA transit station
exit1m	dummy = 1 if parcel is located within one mile of highway exit
harts5m	dummy = 1 if parcel is located within five miles Hartsfield Atlanta Airport
jursi1	dummy = 1 if property is located in Alpharetta
jursi2	dummy = 1 if property is located in Atlanta
juris3	dummy = 1 if property is located in College Park
juris4	dummy = 1 if property is located in East Point
juris5	dummy = 1 if property is located in Fairburn
juris6	dummy = 1 if property is located in Fulton
juris7	dummy = 1 if property is located in Hapeville
juris8	dummy = 1 if property is located in Palmetto
juris9	dummy = 1 if property is located in Roswell
$big_y densbig_x$	$big_y dens \times biguse_x$ for y=1, 2, 3, 4, 5, 6v, 6p, 7 and for x=1, 2, 3, 4, 5, 7
$cbdbig_x$	$cbd \times biguse_x$ for x=1, 2, 3, 4, 5, 7
$northbig_x$	$north \times biguse_x$ for x=1, 2, 3, 4, 5, 7
$ncbdbig_x$	$north \times cbd \times biguse_x$ for x=1, 2, 3, 4, 5, 7
$pdensbig_x$	$pdens \times biguse_x$ for x=1, 2, 3, 4, 5, 7
$nwhitebig_x$	$nwhite \times biguse_x$ for x=1, 2, 3, 4, 5, 7
$pnwhitebig_x$	$pnwhite \times biguse_x$ for x=1, 2, 3, 4, 5, 7
$rmincbig_x$	$rminc \times biguse_x$ for x=1, 2, 3, 4, 5, 7
$princbig_x$	$princ \times biguse_x$ for x=1, 2, 3, 4, 5, 7
$cretempbig_x$	$cretemp \times biguse_x$ for x=1, 2, 3, 4, 5, 7
$cservempbig_x$	$cservemp \times biguse_x$ for x=1, 2, 3, 4, 5, 7
$cindempbig_x$	$cindemp \times biguse_x$ for x=1, 2, 3, 4, 5, 7
$cgovempbig_x$	$cgovemp \times biguse_x$ for x=1, 2, 3, 4, 5, 7
$martahmbig_x$	$martahm \times biguse_x$ for x=1, 2, 3, 4, 5, 7

Table 4.1. Continued

Variable Name	Variable Description
exit1mbig$_x$	exit1m×biguse$_x$ for x=1, 2, 3, 4, 5, 7
harts5mbig$_x$	harts5m×biguse$_x$ for x=1, 2, 3, 4, 5, 7
Proximity to Contaminated Site Variables	
highdens	number of sites with high level of contamination within one mile
lowdens	number of sites with low level of contamination within one mile
invdhigh	inverse distance to nearest site with high level of contamination
invdlow	inverse distance to nearest site with low level of contamination
highdensbig$_x$	highdens×biguse$_x$ for x=1, 2, 3, 4, 5, 7
lowdensbig$_x$	lowdens×biguse$_x$ for x=1, 2, 3, 4, 5, 7
invdhighbig$_x$	invdhigh×biguse$_x$ for x=1, 2, 3, 4, 5, 7
invdlowbig$_x$	invdlow×biguse$_x$ for x=1, 2, 3, 4, 5, 7
imr	Inverse Mills Ratio calculated from sample-selection probit

Table 4.2. Sample-Selection Model

Observations	15,360
Log Likelihood	-9,696.3642
Wald chi2 (155)	1,436.10
Prob > chi2	0.00

Variable	Coefficient	Robust Std. Error	z	P > z
biguse1	-0.3345008	0.1619	-2.07	0.039
biguse2	-0.7566218	0.2936	-2.58	0.010
biguse3	0.0831713	0.2004	0.42	0.678
biguse5	-0.6452931	0.2739	-2.36	0.018
biguse7	-0.8907735	0.2216	-4.02	0.000
acrebig1	-0.0288128	0.0093	-3.08	0.002
acrebig2	-0.0097795	0.0139	-0.71	0.481
acrebig3	-0.0140673	0.0055	-2.54	0.011
acrebig4	-0.0205740	0.0049	-4.23	0.000
acrebig5	-0.0264208	0.0224	-1.18	0.238
acrebig7	-0.0261143	0.0078	-3.33	0.001
acre2big1	0.0000968	0.0001	1.14	0.253
acre2big2	0.0000102	0.0003	0.04	0.969
acre2big3	0.0000145	0.0001	0.26	0.797
acre2big4	0.0001144	0.0001	2.16	0.031
acre2big5	0.0006503	0.0004	1.60	0.109
acre2big7	0.0000955	0.0000	2.13	0.033
big1densbig1	-0.0009605	0.0011	-0.89	0.374
big2densbig2	0.0069977	0.0027	2.58	0.010
big3densbig3	0.0036157	0.0012	3.09	0.002
big4densbig4	0.0018420	0.0006	3.34	0.001
big7densbig7	-0.0029215	0.0025	-1.16	0.247
big1densbig2	-0.0000641	0.0017	-0.04	0.971
big1densbig3	-0.0001878	0.0018	-0.10	0.918
big1densbig4	-0.0027415	0.0011	-2.39	0.017
big1densbig5	0.0047768	0.0026	1.82	0.068
big1densbig7	-0.0049500	0.0023	-2.18	0.029
big2densbig1	-0.0058979	0.0026	-2.23	0.026
big2densbig3	-0.0005121	0.0036	-0.14	0.887
big2densbig4	-0.0015616	0.0026	-0.60	0.545
big2densbig5	-0.0081873	0.0048	-1.69	0.091
big2densbig7	0.0077436	0.0045	1.73	0.084

Table 4.2. Continued

Variable	Coefficient	Robust Std. Error	z	P > z
big3densbig1	-0.0009968	0.0014	-0.72	0.469
big3densbig2	0.0030761	0.0023	1.31	0.190
big3densbig4	0.0017640	0.0014	1.27	0.205
big3densbig5	-0.0013123	0.0025	-0.51	0.607
big3densbig7	0.0044555	0.0027	1.63	0.103
big4densbig1	0.0011763	0.0007	1.77	0.077
big4densbig2	0.0026857	0.0012	2.15	0.031
big4densbig3	0.0002171	0.0011	0.19	0.849
big4densbig5	0.0020908	0.0016	1.30	0.193
big4densbig7	0.0033838	0.0012	2.94	0.003
big6vdensbig1	0.0031654	0.0011	2.76	0.006
big6vdensbig2	-0.0020458	0.0023	-0.90	0.366
big6vdensbig3	-0.0037137	0.0015	-2.55	0.011
big6vdensbig4	-0.0006077	0.0011	-0.57	0.572
big6vdensbig5	-0.0036051	0.0020	-1.82	0.069
big6vdensbig7	0.0008962	0.0017	0.54	0.588
big6pdensbig1	0.0084140	0.0021	4.04	0.000
big6pdensbig2	-0.0047721	0.0026	-1.83	0.068
big6pdensbig3	0.0032620	0.0030	1.08	0.279
big6pdensbig4	0.0040615	0.0020	2.03	0.043
big6pdensbig5	0.0104099	0.0040	2.62	0.009
big6pdensbig7	0.0018403	0.0025	0.75	0.454
big7densbig1	-0.0045083	0.0019	-2.41	0.016
big7densbig2	0.0042782	0.0028	1.51	0.131
big7densbig3	-0.0041624	0.0028	-1.47	0.141
big7densbig4	-0.0015242	0.0020	-0.75	0.452
big7densbig5	-0.0151691	0.0041	-3.70	0.000
northbig1	-0.0163848	0.1097	-0.15	0.881
northbig2	0.1365708	0.2736	0.50	0.618
northbig3	-0.3113548	0.1616	-1.93	0.054
northbig4	-0.4271635	0.1107	-3.86	0.000
northbig5	-0.1361987	0.2425	-0.56	0.574
northbig7	0.4491405	0.1648	2.73	0.006
cbdbig1	-0.0151346	0.0238	-0.63	0.525
cbdbig2	0.0362418	0.0539	0.67	0.501
cbdbig3	-0.0854358	0.0304	-2.81	0.005

Table 4.2. Continued

Variable	Coefficient	Robust Std. Error	z	P > z
cbdbig4	0.0166187	0.0245	0.68	0.498
cbdbig5	0.0217106	0.0481	0.45	0.652
cbdbig7	-0.0217617	0.0399	-0.55	0.585
cbd2big1	0.0010097	0.0011	0.92	0.359
cbd2big2	-0.0013097	0.0025	-0.53	0.599
cbd2big3	0.0029724	0.0015	2.03	0.043
cbd2big4	-0.0007157	0.0012	-0.61	0.544
cbd2big5	-0.0005756	0.0023	-0.25	0.805
cbd2big7	-0.0015877	0.0019	-0.83	0.404
ncbdbig1	0.0182499	0.0296	0.62	0.537
ncbdbig2	-0.0525734	0.0594	-0.89	0.376
ncbdbig3	0.0503555	0.0405	1.24	0.214
ncbdbig4	0.0363275	0.0317	1.15	0.252
ncbdbig5	0.0022177	0.0656	0.03	0.973
ncbdbig7	-0.1145296	0.0443	-2.59	0.010
ncbd2big1	-0.0008875	0.0014	-0.62	0.536
ncbd2big2	0.0034992	0.0028	1.26	0.207
ncbd2big3	-0.0004673	0.0020	-0.23	0.819
ncbd2big4	-0.0001441	0.0016	-0.09	0.927
ncbd2big5	0.0000656	0.0031	0.02	0.983
ncbd2big7	0.0042138	0.0022	1.94	0.053
pnwhitebig1	-0.0000974	0.0001	-1.09	0.274
pnwhitebig2	0.0000075	0.0001	0.08	0.937
pnwhitebig3	-0.0001907	0.0001	-1.37	0.172
pnwhitebig4	-0.0002134	0.0001	-2.42	0.016
pnwhitebig5	0.0002503	0.0002	1.51	0.131
pnwhitebig7	0.0002666	0.0002	1.69	0.092
princbig1	0.0012915	0.0011	1.18	0.240
princbig2	0.0004491	0.0016	0.28	0.781
princbig3	0.0022089	0.0015	1.45	0.146
princbig4	0.0039596	0.0011	3.56	0.000
princbig5	-0.0046478	0.0024	-1.93	0.054
princbig7	-0.0028719	0.0016	-1.79	0.073
cretempbig1	0.0000296	0.0000	1.42	0.156
cretempbig2	-0.0000833	0.0000	-3.12	0.002
cretempbig3	-0.0000616	0.0000	-2.41	0.016

Table 4.2. Continued

Variable	Coefficient	Robust Std. Error	z	P > z
cretempbig4	-0.0000217	0.0000	-1.07	0.284
cretempbig5	0.0000050	0.0000	0.12	0.903
cretempbig7	0.0001170	0.0000	3.04	0.002
cservempbig1	-0.0000184	0.0000	-1.78	0.075
cservempbig2	0.0000227	0.0000	1.64	0.101
cservempbig3	0.0000231	0.0000	1.42	0.155
cservempbig4	0.0000137	0.0000	1.41	0.158
cservempbig5	-0.0000607	0.0000	-2.89	0.004
cservempbig7	-0.0000357	0.0000	-1.49	0.137
cindempbig1	-0.0000588	0.0000	-2.50	0.012
cindempbig2	0.0000355	0.0000	1.05	0.295
cindempbig3	0.0000179	0.0000	0.65	0.517
cindempbig4	0.0000072	0.0000	0.33	0.739
cindempbig5	0.0000550	0.0000	1.24	0.213
cindempbig7	-0.0001098	0.0000	-2.50	0.013
cgovempbig1	0.0000276	0.0000	0.57	0.570
cgovempbig2	-0.0000138	0.0001	-0.17	0.862
cgovempbig3	0.0001066	0.0001	1.78	0.074
cgovempbig4	-0.0000666	0.0001	-1.21	0.227
cgovempbig5	0.0001931	0.0001	1.86	0.064
cgovempbig7	0.0001296	0.0001	1.86	0.063
highdensbig1	0.0166475	0.0195	0.85	0.394
highdensbig2	0.0135415	0.0313	0.43	0.666
highdensbig3	-0.0418534	0.0197	-2.13	0.033
highdensbig4	0.0009634	0.0177	0.05	0.957
highdensbig5	0.0183712	0.0382	0.48	0.631
highdensbig7	-0.0916577	0.0339	-2.70	0.007
lowdensbig1	-0.0158717	0.0062	-2.57	0.010
lowdensbig2	0.0019936	0.0094	0.21	0.832
lowdensbig3	0.0085008	0.0058	1.46	0.144
lowdensbig4	0.0085134	0.0058	1.47	0.142
lowdensbig5	0.0223958	0.0129	1.74	0.082
lowdensbig7	-0.0432103	0.0115	-3.77	0.000
invdhighbig1	0.0000126	0.0000	1.72	0.086
invdhighbig2	-0.0000637	0.0001	-0.92	0.355
invdhighbig3	-0.0000021	0.0000	-0.12	0.904

Table 4.2. Continued

Variable	Coefficient	Robust Std. Error	z	P > z
invdhighbig4	0.0000178	0.0000	0.43	0.671
invdhighbig5	0.0000497	0.0001	0.92	0.355
invdhighbig7	0.0000771	0.0000	1.95	0.051
invdlowbig1	0.0000279	0.0000	2.46	0.014
invdlowbig2	0.0000166	0.0000	0.79	0.430
invdlowbig3	-0.0000132	0.0000	-1.09	0.278
invdlowbig4	0.0000152	0.0000	0.78	0.434
invdlowbig5	0.0000386	0.0000	1.51	0.131
invdlowbig7	0.0000582	0.0000	1.79	0.073
constant	0.2944093	0.1123	2.62	0.009

Table 4.3. Ordered Probit Probability of Contamination Model

Observations	6,434
Log Likelihood	-885.8554
Wald chi2 (92)	12,291.84
Prob > chi2	0.00

Variable	Coefficient	Robust Std. Error	z	P > z
lu7	1.6844090	0.4269	3.95	0.000
lu8	0.6230616	0.3964	1.57	0.116
lu9	1.3760270	0.3886	3.54	0.000
lu10	-5.9980810	0.5510	-10.88	0.000
lu11	0.9816973	0.8380	1.17	0.241
lu12	1.9994220	0.9766	2.05	0.041
lu13	2.5048290	1.0473	2.39	0.017
lu14	1.1911290	0.8392	1.42	0.156
lu15	1.1485480	0.8240	1.39	0.163
lu16	0.5756635	0.8846	0.65	0.515
lu17	0.9650584	0.9655	1.00	0.318
lu18	0.2808363	1.2479	0.23	0.822
lu21	-6.6085920	0.8381	-7.89	0.000
lu22	2.2214750	0.9540	2.33	0.020
lu23	1.1425690	0.8155	1.40	0.161
lu24	1.3950380	0.9650	1.45	0.148
lu25	1.3452200	0.8630	1.56	0.119
lu26	1.8343410	0.8223	2.23	0.026
lu27	-6.9299800	0.8675	-7.99	0.000
lu28	1.2340220	0.8928	1.38	0.167
lu29	2.5539070	1.1825	2.16	0.031
lu30	1.5507930	0.9610	1.61	0.107
lu31	2.1131820	0.8269	2.56	0.011
lu32	2.3519970	0.8488	2.77	0.006
lu33	-5.4241350	0.8498	-6.38	0.000
lu35	2.3700220	1.1594	2.04	0.041
lu36	1.8781250	1.1300	1.66	0.096
lu37	2.7013960	1.2010	2.25	0.024
lu38	1.4220340	0.8730	1.63	0.103
acrebig1	0.1388794	0.0393	3.53	0.000
acrebig2	0.5524897	0.1634	3.38	0.001
acrebig3	0.0520279	0.0122	4.28	0.000

Table 4.3. Continued

Variable	Coefficient	Robust Std. Error	z	P > z
acrebig4	0.0626127	0.0170	3.69	0.000
acrebig5	0.1189551	0.0493	2.41	0.016
acrebig7	0.1466782	0.0351	4.18	0.000
acre2big1	-0.0017163	0.0020	-0.85	0.393
acre2big2	-0.0293144	0.0121	-2.42	0.016
acre2big3	-0.0002659	0.0001	-1.80	0.071
acre2big4	-0.0003366	0.0001	-2.71	0.007
acre2big5	-0.0019301	0.0013	-1.46	0.145
acre2big7	-0.0015649	0.0004	-3.56	0.000
cbdnw	0.2127424	0.0684	3.11	0.002
cbdne	0.1833821	0.0466	3.94	0.000
cbdse	0.2774348	0.1326	2.09	0.036
cbdsw	0.1094237	0.0462	2.37	0.018
cbdne2	-0.0084169	0.0018	-4.81	0.000
cbdnw2	-0.0148629	0.0069	-2.17	0.030
cbdse2	-0.0469750	0.0239	-1.96	0.050
cbdsw2	-0.0058171	0.0024	-2.42	0.015
nwhitebig1	-0.6551904	0.2632	-2.49	0.013
nwhitebig2	-1.4261770	1.0002	-1.43	0.154
nwhitebig3	0.1659241	0.2149	0.77	0.440
nwhitebig4	0.2186244	0.3837	0.57	0.569
nwhitebig5	-0.5694593	0.3393	-1.68	0.093
nwhitebig7	0.0181673	0.5190	0.04	0.972
pdensbig1	0.0262991	0.0183	1.44	0.150
pdensbig2	-0.0618924	0.0308	-2.01	0.044
pdensbig3	0.0289998	0.0264	1.10	0.272
pdensbig4	-0.0324869	0.0376	-0.87	0.387
pdensbig5	0.0084385	0.0470	0.18	0.857
pdensbig7	-0.0632046	0.0461	-1.37	0.170
rmincbig1	-0.0000046	0.0000	-0.49	0.621
rmincbig2	-0.0000635	0.0000	-2.61	0.009
rmincbig3	-0.0000122	0.0000	-1.26	0.209
rmincbig4	-0.0000257	0.0000	-1.42	0.155
rmincbig5	-0.0000288	0.0000	-1.35	0.176
rmincbig7	-0.0000645	0.0000	-1.53	0.125
highdensbig1	-0.0579546	0.0462	-1.25	0.210

Table 4.3. Continued

Variable	Coefficient	Robust Std. Error	z	P > z
highdensbig2	-0.0778414	0.1295	-0.60	0.548
highdensbig3	0.0476920	0.0348	1.37	0.171
highdensbig4	-0.0185607	0.0623	-0.30	0.766
highdensbig5	-0.0010369	0.1158	-0.01	0.993
highdensbig7	0.1654803	0.0958	1.73	0.084
lowdensbig1	0.0303390	0.0118	2.56	0.010
lowdensbig2	0.1173828	0.0259	4.54	0.000
lowdensbig3	0.0150574	0.0084	1.79	0.074
lowdensbig4	0.0323042	0.0162	2.00	0.046
lowdensbig5	-0.0159230	0.0201	-0.79	0.429
lowdensbig7	0.0244323	0.0191	1.28	0.202
invdhighbig1	-0.0005091	0.0022	-0.23	0.818
invdhighbig2	-0.0158697	0.0216	-0.73	0.463
invdhighbig3	0.0000408	0.0000	1.77	0.077
invdhighbig4	0.0000947	0.0001	1.40	0.162
invdhighbig5	-0.0314716	0.0407	-0.77	0.440
invdhighbig7	-0.1438380	0.0456	-3.16	0.002
invdlowbig1	0.0000223	0.0000	1.11	0.266
invdlowbig2	0.0000713	0.0000	1.82	0.069
invdlowbig3	0.0000618	0.0000	3.45	0.001
invdlowbig4	0.0001229	0.0000	3.74	0.000
invdlowbig5	-0.0020264	0.0047	-0.43	0.664
invdlowbig7	0.0000603	0.0000	1.43	0.154
imr	-0.2138257	0.2738	-0.78	0.435
alpha1	3.3703810	0.7941	-	-
alpha2	4.2362880	0.7994	-	-

Table 4.4. Predicted Outcomes for Ordered Probit Probability of Contamination Model (Estimating Sample only)

	k=0.05			*k*=0.10			*k*=0.15		
	No ($\hat{c}=0$)	Low ($\hat{c}=1$)	High ($\hat{c}=2$)	No ($\hat{c}=0$)	Low ($\hat{c}=1$)	High ($\hat{c}=2$)	No ($\hat{c}=0$)	Low ($\hat{c}=1$)	High ($\hat{c}=2$)
No = 6,172 obs (95.9)[a]	5,100 (82.6)[b]	931 (15.1)	141 (2.3)	5,839 (94.6)	279 (4.5)	54 (0.9)	6,001 (97.2)	146 (2.4)	25 (0.4)
Low = 203 obs (3.2)[a]	45 (22.2)	79 (38.9)	79 (38.9)	91 (44.8)	60 (29.6)	52 (25.6)	118 (58.1)	57 (28.1)	28 (13.8)
High = 59 obs (0.9)[a]	8 (13.6)	23 (39.0)	28 (47.5)	21 (35.6)	17 (28.8)	21 (35.6)	30 (50.8)	13 (22.0)	16 (27.1)
Total = 6,434	5,153 (80.1)	1,033 (16.1)	248 (3.9)	5,951 (92.5)	356 (5.5)	127 (2.0)	6,149 (95.6)	216 (3.4)	69 (1.1)

[a] Number in parentheses is the percentage of properties in the estimating sample which are classified as not contaminated, low level of contamination (on NFRAP/NonHSI lists), and high level of contamination (on CERCLIS/HSI list).
[b] Number is parentheses is the percentage of properties in the observed category that are predicted as not contaminated, low level of contamination, and high level of contamination.

Table 4.5. Predicted Outcomes for Ordered Probit Probability of Contamination Model (Full Sample)

	k=0.05			k=0.10			k=0.15		
	No ($\hat{c}$ = 0)	Low ($\hat{c}$ = 1)	High ($\hat{c}$ = 2)	No ($\hat{c}$ = 0)	Low ($\hat{c}$ = 1)	High ($\hat{c}$ = 2)	No ($\hat{c}$ = 0)	Low ($\hat{c}$ = 1)	High ($\hat{c}$ = 2)
No = 15,098 obs (98.3)[a]	11,797 (78.1)[b]	2,668 (17.7)	633 (4.2)	13,837 (91.6)	968 (6.4)	293 (1.9)	14,360 (95.1)	548 (3.6)	190 (1.3)
Low = 203 obs (1.3)[a]	45 (22.2)	79 (38.9)	79 (38.9)	91 (44.8)	60 (29.6)	52 (25.6)	118 (58.1)	57 (28.1)	28 (13.8)
High = 59 obs (0.4)[a]	8 (13.6)	23 (39.0)	28 (47.5)	21 (35.6)	17 (28.8)	21 (35.6)	30 (50.8)	13 (22.0)	16 (27.1)
Total = 15,360 obs	11,850 (77.2)	2,770 (18.0)	740 (4.8)	13,949 (90.8)	1,045 (6.8)	366 (2.4)	14,508 (94.5)	618 (4.0)	234 (1.5)

[a] Number in parentheses is the percentage of properties in the full sample which are classified as not contaminated, low level of contamination (on NFRAP/NonHSI lists), and high level of contamination (on CERCLIS/HSI list).
[b] Number is parentheses is the percentage of properties in the observed category that are predicted as not contaminated, low level of contamination, and high level of contamination.

Table 4.6. Probit Probability of Contamination Model

Observations	6,310
Log Likelihood	-734.8956
Wald chi2 (88)	639.35
Prob > chi2	0.00

Variable	Coefficient	Robust Std. Error	z	P > z
lu7	1.7648720	0.4225	4.18	0.000
lu8	0.7643049	0.3906	1.96	0.050
lu9	1.5070630	0.3977	3.79	0.000
lu11	1.1875790	0.8325	1.43	0.154
lu12	2.3985040	0.9368	2.56	0.010
lu13	2.8591160	1.0501	2.72	0.006
lu14	1.3166580	0.8268	1.59	0.111
lu15	1.3414580	0.8153	1.65	0.100
lu16	0.7426376	0.8800	0.84	0.399
lu17	1.1417370	0.9745	1.17	0.241
lu18	0.7237638	1.3033	0.56	0.579
lu22	2.2801980	0.9219	2.47	0.013
lu23	1.2209100	0.8032	1.52	0.129
lu24	1.5318920	0.9969	1.54	0.124
lu25	1.4080210	0.8565	1.64	0.100
lu26	1.9491770	0.8123	2.40	0.016
lu28	1.3386210	0.8965	1.49	0.135
lu29	2.3662260	1.1094	2.13	0.033
lu30	1.6136950	0.9176	1.76	0.079
lu31	2.3556110	0.8134	2.90	0.004
lu32	2.6317280	0.8476	3.10	0.002
lu35	2.2669230	1.0433	2.17	0.030
lu36	1.8128440	1.0897	1.66	0.096
lu37	2.5423400	1.1176	2.27	0.023
lu38	1.3165350	0.8590	1.53	0.125
acrebig1	0.1834550	0.0402	4.57	0.000
acrebig2	0.6179180	0.2103	2.94	0.003
acrebig3	0.0729731	0.0129	5.64	0.000
acrebig4	0.0535036	0.0162	3.30	0.001
acrebig5	0.1205912	0.0424	2.84	0.004
acrebig7	0.1487055	0.0409	3.63	0.000
acre2big1	-0.0034983	0.0019	-1.81	0.070

Table 4.6. Probit Probability of Contamination Model

Variable	Coefficient	Robust Std. Error	z	P > z
acre2big2	-0.0322885	0.0157	-2.06	0.040
acre2big3	-0.0004052	0.0001	-3.05	0.002
acre2big4	-0.0002475	0.0001	-1.85	0.064
acre2big5	-0.0018233	0.0007	-2.55	0.011
acre2big7	-0.0013764	0.0006	-2.28	0.022
cbdnw	0.1825995	0.0610	3.00	0.003
cbdne	0.1777025	0.0478	3.72	0.000
cbdse	0.2820158	0.1348	2.09	0.036
cbdsw	0.1055876	0.0480	2.20	0.028
cbdne2	-0.0084298	0.0018	-4.64	0.000
cbdnw2	-0.0119108	0.0052	-2.31	0.021
cbdse2	-0.0465438	0.0238	-1.96	0.050
cbdsw2	-0.0064900	0.0027	-2.39	0.017
nwhitebig1	-0.6266226	0.2709	-2.31	0.021
nwhitebig2	-1.6720570	1.1097	-1.51	0.132
nwhitebig3	0.1676907	0.2091	0.80	0.423
nwhitebig4	0.2930543	0.3844	0.76	0.446
nwhitebig5	-0.6631608	0.3316	-2.00	0.046
nwhitebig7	0.1210771	0.5854	0.21	0.836
pdensbig1	0.0278584	0.0189	1.48	0.140
pdensbig2	-0.0814831	0.0406	-2.01	0.045
pdensbig3	0.0243674	0.0244	1.00	0.319
pdensbig4	-0.0344859	0.0387	-0.89	0.373
pdensbig5	-0.0043115	0.0518	-0.08	0.934
pdensbig7	-0.0890023	0.0562	-1.58	0.113
rmincbig1	-0.0000037	0.0000	-0.38	0.704
rmincbig2	-0.0000757	0.0000	-2.49	0.013
rmincbig3	-0.0000121	0.0000	-1.21	0.227
rmincbig4	-0.0000182	0.0000	-1.04	0.300
rmincbig5	-0.0000295	0.0000	-1.42	0.155
rmincbig7	-0.0000521	0.0000	-1.43	0.153
highdensbig1	-0.0526309	0.0491	-1.07	0.283
highdensbig2	-0.1113839	0.1497	-0.74	0.457
highdensbig3	0.0548474	0.0379	1.45	0.147
highdensbig4	-0.0223997	0.0654	-0.34	0.732
highdensbig5	-0.0479128	0.1027	-0.47	0.641

Table 4.6. Probit Probability of Contamination Model

Variable	Coefficient	Robust Std. Error	z	P > z
highdensbig7	0.2567195	0.1061	2.42	0.016
lowdensbig1	0.0289933	0.0124	2.34	0.019
lowdensbig2	0.1261338	0.0324	3.89	0.000
lowdensbig3	0.0212437	0.0088	2.41	0.016
lowdensbig4	0.0324292	0.0164	1.98	0.048
lowdensbig5	-0.0125004	0.0211	-0.59	0.554
lowdensbig7	0.0338750	0.0206	1.64	0.101
invdhighbig1	-0.0007810	0.0023	-0.34	0.736
invdhighbig2	-0.0080877	0.0125	-0.65	0.519
invdhighbig3	0.0000299	0.0000	1.19	0.234
invdhighbig4	0.0000746	0.0001	1.30	0.195
invdhighbig5	-0.0258017	0.0332	-0.78	0.437
invdhighbig7	-0.1657165	0.0599	-2.77	0.006
invdlowbig1	0.0000246	0.0000	1.16	0.245
invdlowbig2	0.0000879	0.0000	1.89	0.058
invdlowbig3	0.0000691	0.0000	3.53	0.000
invdlowbig4	0.0001268	0.0000	3.61	0.000
invdlowbig5	-0.0017710	0.0043	-0.42	0.678
invdlowbig7	0.0000960	0.0000	1.92	0.055
imr	-0.2117177	0.2816	-0.75	0.452
constant	-3.5729550	0.7842	-4.56	0.000

Table 4.7. Predicted Outcomes for Probit Probability of Contamination Model (Estimating Sample Only)

	k=0.05		k=0.10		k=0.15	
	Not Contaminated ($\hat{c}$ = 0)	Contaminated ($\hat{c}$ = 1)	Not Contaminated ($\hat{c}$ = 0)	Contaminated ($\hat{c}$ = 1)	Not Contaminated ($\hat{c}$ = 0)	Contaminated ($\hat{c}$ = 1)
No = 6,048 obs (95.8)[a]	4,936 (81.6)[b]	1,112 (18.4)	5,614 (92.8)	434 (7.2)	5,789 (95.7)	259 (4.3)
Low = 203 obs (3.2)[a]	42 (20.7)	161 (79.3)	82 (40.4)	121 (59.6)	103 (50.7)	100 (49.3)
High = 59 obs (0.9)[a]	7 (11.9)	52 (88.1)	22 (37.3)	37 (62.7)	27 (45.8)	32 (54.2)
Total = 6,310 obs	4,985 (79.0)	1,325 (21.0)	5,718 (90.6)	592 (9.4)	5,934 (93.8)	391 (6.2)

[a] Number in parentheses is the percentage of properties in the estimating sample which are classified as not contaminated, low level of contamination (on NFRAP/NonHSI lists), and high level of contamination (on CERCLIS/HSI list).
[b] Number is parentheses is the percentage of properties in the observed category that are predicted as not contaminated and contaminated.

Table 4.8. Predicted Outcomes for Probit Probability of Contamination Model (Full Sample)

	$k = 0.05$		$k = 0.10$		$k = 0.15$	
	Not Contaminated ($\hat{c} = 0$)	Contaminated ($\hat{c} = 1$)	Not Contaminated ($\hat{c} = 0$)	Contaminated ($\hat{c} = 1$)	Not Contaminated ($\hat{c} = 0$)	Contaminated ($\hat{c} = 1$)
No = 14,856 obs (98.3)[a]	11,399 (76.7)[b]	3,457 (23.3)	13,288 (89.4)	1,568 (10.6)	13,804 (92.9)	1,052 (7.1)
Low = 203 obs (1.3)[a]	42 (20.7)	161 (79.3)	82 (40.4)	121 (59.6)	103 (50.7)	100 (49.3)
High = 59 obs (0.4)[a]	7 (11.9)	52 (88.1)	22 (37.3)	37 (62.7)	27 (45.8)	32 (54.2)
Total = 15,118 obs	11,448 (75.7)	3,670 (24.3)	13,392 (88.6)	1,726 (11.4)	13,934 (92.2)	1,184 (7.8)

[a] Number in parentheses is the percentage of properties in the full sample which are classified as not contaminated, low level of contamination (on NFRAP/NonHSI lists), and high level of contamination (on CERCLIS/HSI list).

[b] Number is parentheses is the percentage of properties in the observed category that are predicted as not contaminated and contaminated.

Table 4.9. Cross Tabulation of Predicted Outcomes for Ordered Probit and Probit Probability of Contamination Models (Estimating Sample Only)

			Predicted Outcomes from Probit Model					
			k =0.05		k =0.10		k =0.15	
			Not Contaminated	Contaminated	Not Contaminated	Contaminated	Not Contaminated	Contaminated
Predicted Outcomes from Ordered Probit Model	k = 0.05	No [a] (5,029)	4,933 (98.1)	96 (1.9)	-	-	-	-
		Low (1,033)	52 (5.0)	981 (95.0)	-	-	-	-
		High (248)	0 (0.0)	248 (100)	-	-	-	-
	k = 0.10	No [a] (5,827)	-	-	5,712 (98.0)	115 (2.0)	-	-
		Low (356)	-	-	6 (1.7)	350 (98.3)	-	-
		High (127)	-	-	0 (0.0)	127 (100)	-	-
	k = 0.15	No [a] (6,025)	-	-	-	-	5,919 (98.2)	106 (1.8)
		Low (216)	-	-	-	-	0 (0.0)	216 (100)
		High (69)	-	-	-	-	0 (0.0)	69 (100)
		Total (6,310)	4,985 (79.0)	1,325 (21.0)	5,718 (90.6)	592 (9.4)	5,919 (93.8)	391 (6.2)

[a] An additional 124 properties were predicted to be not contaminated in the ordered probit model where a predicted outcome in the probit model could not be computed.

Table 4.10. Cross Tabulation of Predicted Outcomes for Ordered Probit and Probit Probability of Contamination Models (Full Sample)

			Predicted Outcomes from Probit Model					
			k =0.05		k =0.10		k =0.15	
			Not Contaminated	Contaminated	Not Contaminated	Contaminated	Not Contaminated	Contaminated
Predicted Outcomes from Ordered Probit Model	k = 0.05	No [a] (11,608)	11,242 (96.8)	366 (3.2)	-	-	-	-
		Low (2,770)	205 (7.4)	2,565 (92.6)	-	-	-	-
		High (740)	1 (0.1)	739 (99.9)	-	-	-	-
	k = 0.10	No [a] (13,707)	-	-	13,352 (97.4)	355 (2.6)	-	-
		Low (1,045)	-	-	40 (3.8)	1,005 (96.2)	-	-
		High (366)	-	-	0 (0.0)	366 (100)	-	-
	k = 0.15	No [a] (14,266)	-	-	-	-	13,926 (97.6)	340 (2.4)
		Low (618)	-	-	-	-	7 (1.1)	611 (98.9)
		High (234)	-	-	-	-	1 (0.4)	233 (99.6)
		Total (15,118)	11,448 (75.7)	3,670 (24.3)	13,392 (88.6)	1,726 (11.4)	13,934 (92.2)	1,184 (7.8)

[a] An additional 242 properties were predicted to be not contaminated in the ordered probit model where a predicted outcome in the probit model could not be computed.

Table 4.11. Ordered Probit Probability of Contamination Model Using Random Sample

Observations	1,180
Log Likelihood	-510.1398
Wald chi2 (90)	10,387.57
Prob > chi2	0.00

Variable	Coefficient	Robust Std. Error	z	P > z
lu7	2.8840800	0.7277	3.96	0.000
lu8	0.9553100	0.6234	1.53	0.125
lu9	1.9330430	0.6132	3.15	0.002
lu10	-6.3684290	0.6252	-10.19	0.000
lu11	0.4312879	1.0846	0.40	0.691
lu12	2.9981760	1.5179	1.98	0.048
lu13	3.8329080	1.4936	2.57	0.010
lu14	0.5406966	1.1030	0.49	0.624
lu15	0.5223565	1.0860	0.48	0.631
lu16	-0.3452722	1.2014	-0.29	0.774
lu17	0.2704840	1.2817	0.21	0.833
lu18	-3.6518930	2.6864	-1.36	0.174
lu22	3.0242460	1.3113	2.31	0.021
lu23	0.9957615	1.0483	0.95	0.342
lu24	1.4297390	1.1333	1.26	0.207
lu25	1.1534250	1.1320	1.02	0.308
lu26	1.8315280	1.0652	1.72	0.086
lu28	1.4674820	1.1605	1.26	0.206
lu29	10.8581200	0.9949	10.91	0.000
lu30	1.7113230	1.2803	1.34	0.181
lu31	1.9232230	1.0741	1.79	0.073
lu32	2.1939280	1.0711	2.05	0.041
lu33	-6.0298050	1.1197	-5.39	0.000
lu35	2.3963920	1.6267	1.47	0.141
lu36	1.7902560	1.4884	1.20	0.229
lu37	2.8099620	1.6574	1.70	0.090
lu38	1.7906460	1.2082	1.48	0.138
acrebig1	0.0944461	0.0469	2.01	0.044
acrebig2	1.4406560	0.3202	4.50	0.000
acrebig3	0.0232075	0.0139	1.68	0.094
acrebig4	0.1942157	0.0328	5.92	0.000

Table 4.11. Continued

Variable	Coefficient	Robust Std. Error	z	P > z
acrebig5	0.2970337	0.1987	1.49	0.135
acrebig7	0.1419577	0.0414	3.43	0.001
acre2big1	-0.0002525	0.0021	-0.12	0.902
acre2big2	-0.0910570	0.0236	-3.86	0.000
acre2big3	-0.0000862	0.0001	-0.58	0.565
acre2big4	-0.0023107	0.0004	-5.67	0.000
acre2big5	-0.0097745	0.0097	-1.01	0.311
acre2big7	-0.0017142	0.0005	-3.14	0.002
cbdnw	0.2747055	0.1028	2.67	0.008
cbdne	0.2058011	0.0687	3.00	0.003
cbdse	0.2569955	0.1860	1.38	0.167
cbdsw	0.1405009	0.0635	2.21	0.027
cbdne2	-0.0091125	0.0027	-3.41	0.001
cbdnw2	-0.0196406	0.0102	-1.92	0.055
cbdse2	-0.0345287	0.0318	-1.08	0.278
cbdsw2	-0.0067483	0.0031	-2.17	0.030
nwhitebig1	-0.5657352	0.3481	-1.63	0.104
nwhitebig2	-2.5953530	1.4302	-1.81	0.070
nwhitebig3	0.1883037	0.3252	0.58	0.563
nwhitebig4	-0.6096904	0.6236	-0.98	0.328
nwhitebig5	-1.9834300	0.6712	-2.95	0.003
nwhitebig7	-0.0220131	0.6504	-0.03	0.973
pdensbig1	0.0236195	0.0287	0.82	0.410
pdensbig2	0.0778384	0.0968	0.80	0.421
pdensbig3	0.0468460	0.0379	1.24	0.216
pdensbig4	-0.0076633	0.0517	-0.15	0.882
pdensbig5	0.0199593	0.0721	0.28	0.782
pdensbig7	-0.0233082	0.0439	-0.53	0.595
rmincbig1	0.0000079	0.0000	0.58	0.564
rmincbig2	-0.0000748	0.0000	-2.09	0.037
rmincbig3	-0.0000102	0.0000	-0.66	0.511
rmincbig4	-0.0000844	0.0000	-2.27	0.023
rmincbig5	-0.0000604	0.0000	-1.59	0.111
rmincbig7	-0.0000810	0.0001	-1.48	0.139
highdensbig1	-0.0690784	0.0723	-0.96	0.339
highdensbig2	0.7003614	0.2418	2.90	0.004

Table 4.11. Continued

Variable	Coefficient	Robust Std. Error	z	P > z
highdensbig3	0.0173677	0.0485	0.36	0.720
highdensbig4	0.0271000	0.0936	0.29	0.772
highdensbig5	0.1733174	0.1689	1.03	0.305
highdensbig7	0.2863728	0.1671	1.71	0.087
lowdensbig1	0.0495699	0.0163	3.05	0.002
lowdensbig2	0.2048713	0.0494	4.14	0.000
lowdensbig3	0.0247870	0.0131	1.90	0.058
lowdensbig4	0.0362893	0.0220	1.65	0.099
lowdensbig5	-0.0583187	0.0460	-1.27	0.205
lowdensbig7	-0.0129440	0.0305	-0.42	0.671
invdhighbig1	0.0079447	0.0146	0.55	0.585
invdhighbig2	-0.2505595	0.1441	-1.74	0.082
invdhighbig3	0.0000106	0.0000	0.35	0.730
invdhighbig4	0.0022971	0.0005	4.86	0.000
invdhighbig5	-0.0324848	0.0577	-0.56	0.573
invdhighbig7	-0.2049910	0.0882	-2.32	0.020
invdlowbig1	0.0000386	0.0000	1.15	0.252
invdlowbig2	-0.0000380	0.0000	-1.01	0.315
invdlowbig3	0.0000465	0.0000	2.09	0.037
invdlowbig4	0.0002516	0.0001	4.12	0.000
invdlowbig5	-0.0023690	0.0062	-0.38	0.701
invdlowbig7	0.0001006	0.0001	1.73	0.084
imr	0.0177020	0.3742	0.05	0.962
alpha1	2.5566960	1.0191	-	-
alpha2	3.9070000	1.0232	-	-

Table 4.12. Predicted Outcomes for Ordered Probit Probability of Contamination Model Estimated Using Random Sample (Estimating Sample Only)

	k=0.20			k=0.25			k=0.30		
	No ($\hat{c}$ = 0)	Low ($\hat{c}$ = 1)	High ($\hat{c}$ = 2)	No ($\hat{c}$ = 0)	Low ($\hat{c}$ = 1)	High ($\hat{c}$ = 2)	No ($\hat{c}$ = 0)	Low ($\hat{c}$ = 1)	High ($\hat{c}$ = 2)
No = 918 obs (77.8)[a]	683 (74.4)[b]	226 (24.6)	9 (1.0)	743 (80.9)	170 (18.5)	5 (0.5)	783 (85.3)	133 (14.5)	2 (0.2)
Low = 203 obs (17.2)[a]	31 (15.3)	122 (60.1)	50 (24.6)	43 (21.2)	119 (58.6)	41 (20.2)	56 (27.6)	123 (60.6)	24 (11.8)
High = 59 obs (5.0)[a]	4 (6.8)	30 (50.8)	25 (42.4)	8 (13.6)	29 (49.2)	22 (37.3)	8 (13.6)	33 (55.9)	18 (30.5)
Total = 1,180 obs	718 (60.8)	378 (32.3)	84 (7.1)	794 (67.3)	318 (26.9)	68 (5.8)	847 (71.8)	289 (24.5)	44 (3.7)

[a] Number in parentheses is the percentage of properties in the estimating sample which are classified as not contaminated, low level of contamination (on NFRAP/NonHSI lists), and high level of contamination (on CERCLIS/HSI list).

[b] Number is parentheses is the percentage of properties in the observed category that are predicted as not contaminated, low level of contamination, and high level of contamination.

Table 4.13. Cross Tabulation of Predicted Outcomes for OPFS Model and OPRS Model (Estimating Sample for OPFS Only)

			Predicted Outcomes from OPRS Model								
			k = 0.20			k = 0.25			k = 0.30		
			No	Low	High	No	Low	High	No	Low	High
Predicted Outcomes from OPFS Model	k = 0.05	No (5,153)	4,542 (88.1)	598 (11.6)	13 (0.3)	-	-	-	-	-	-
		Low (1,033)	31 (3.0)	949 (91.9)	53 (5.1)	-	-	-	-	-	-
		High (248)	2 (0.8)	102 (41.1)	144 (58.1)	-	-	-	-	-	-
	k = 0.10	No (5,951)	-	-	-	4,927 (82.8)	999 (16.8)	25 (0.4)	-	-	-
		Low (356)	-	-	-	3 (0.8)	318 (89.3)	35 (9.8)	-	-	-
		High (127)	-	-	-	1 (0.8)	37 (29.1)	89 (70.1)	-	-	-
	k = 0.15	No (6,149)	-	-	-	-	-	-	5,243 (85.3)	875 (14.2)	31 (0.5)
		Low (216)	-	-	-	-	-	-	1 (0.5)	191 (88.4)	24 (11.1)
		High (69)	-	-	-	-	-	-	1 (1.4)	16 (23.2)	52 (75.4)
		Total (6,434)	4,575 (71.1)	1,649 (25.6)	210 (3.3)	4,931 (76.6)	1,354 (21.0)	149 (2.3)	5,245 (81.5)	1,082 (16.8)	107 (1.7)

Table 4.14. Cross Tabulation of Predicted Outcomes for OPFS Model and OPRS Model (Full Sample)

			Predicted Outcomes from OPRS Model								
			k = 0.20			k = 0.25			k = 0.30		
			No	Low	High	No	Low	High	No	Low	High
Predicted Outcomes from OPFS Model	k = 0.05	No (11,850)	10,232 (86.3)	1,581 (13.3)	37 (0.3)	-	-	-	-	-	-
		Low (2,770)	118 (4.3)	2,502 (90.3)	150 (5.4)	-	-	-	-	-	-
		High (740)	6 (0.8)	298 (40.3)	436 (58.9)	-	-	-	-	-	-
	k = 0.10	No (13,949)	-	-	-	11,190 (80.2)	2,695 (19.3)	64 (0.5)	-	-	-
		Low (1,045)	-	-	-	22 (2.1)	917 (87.8)	106 (10.1)	-	-	-
		High (366)	-	-	-	3 (0.8)	81 (22.1)	282 (77.0)	-	-	-
	k = 0.15	No (14,508)	-	-	-	-	-	-	12,064 (83.2)	2,363 (16.3)	81 (0.6)
		Low (618)	-	-	-	-	-	-	4 (0.6)	542 (87.7)	72 (11.7)
		High (234)	-	-	-	-	-	-	0 (0.0)	43 (18.4)	189 (80.8)
		Total (15,360)	10,356 (67.4)	4,381 (28.5)	623 (4.1)	11,215 (73.0)	3,693 (24.0)	452 (3.0)	12,070 (78.6)	2,948 (19.2)	342 (2.2)

Table 4.15. Probit Probability of Contamination Model Using Random Sample

Number of obs	1,142
Log likelihood	-354.83458
Wald chi2(85)	376.27
Prob > chi2	0.00

Variable	Coefficient	Robust Std. Error	z	P > z
lu7	3.4092820	1.0506	3.25	0.001
lu8	1.5002690	0.9050	1.66	0.097
lu9	2.5175190	0.9228	2.73	0.006
lu11	0.9031289	1.2181	0.74	0.458
lu12	3.5188330	1.5633	2.25	0.024
lu13	4.3707530	1.5955	2.74	0.006
lu14	0.7676138	1.2218	0.63	0.530
lu15	0.8941594	1.2153	0.74	0.462
lu16	0.0081567	1.3500	0.01	0.995
lu17	0.5915047	1.4403	0.41	0.681
lu18	-3.3668170	3.7339	-0.90	0.367
lu23	1.2212880	1.1637	1.05	0.294
lu24	2.1140930	1.3036	1.62	0.105
lu25	1.4096910	1.2497	1.13	0.259
lu26	2.2291150	1.1953	1.86	0.062
lu28	1.9074450	1.4106	1.35	0.176
lu30	1.9853790	1.3678	1.45	0.147
lu31	2.6508880	1.2083	2.19	0.028
lu35	1.8299970	1.8102	1.01	0.312
lu36	1.4343300	1.6865	0.85	0.395
lu37	2.0108760	1.8911	1.06	0.288
lu38	1.4235480	1.2478	1.14	0.254
acrebig1	0.1967383	0.0567	3.47	0.001
acrebig2	2.3642180	0.9356	2.53	0.012
acrebig3	0.0602460	0.0178	3.39	0.001
acrebig4	0.1943002	0.0440	4.41	0.000
acrebig5	-0.1919649	0.4573	-0.42	0.675
acrebig7	0.1440668	0.0552	2.61	0.009
acre2big1	-0.0040792	0.0022	-1.87	0.061
acre2big2	-0.1452200	0.0651	-2.23	0.026
acre2big3	-0.0003653	0.0001	-2.48	0.013

Table 4.15. Continued

Variable	Coefficient	Robust Std. Error	z	P > z
acre2big4	-0.0024719	0.0009	-2.70	0.007
acre2big5	0.0395094	0.0391	1.01	0.312
acre2big7	-0.0012632	0.0009	-1.33	0.183
cbdnw	0.2008626	0.0799	2.51	0.012
cbdne	0.1996158	0.0737	2.71	0.007
cbdse	0.2053873	0.2014	1.02	0.308
cbdsw	0.1077797	0.0693	1.56	0.120
cbdne2	-0.0096109	0.0030	-3.25	0.001
cbdnw2	-0.0137407	0.0049	-2.82	0.005
cbdse2	-0.0227822	0.0322	-0.71	0.479
cbdsw2	-0.0064241	0.0037	-1.71	0.087
nwhitebig1	-0.4091646	0.3659	-1.12	0.263
nwhitebig2	-5.0101280	2.9632	-1.69	0.091
nwhitebig3	0.2112857	0.3350	0.63	0.528
nwhitebig4	-0.5147672	0.6862	-0.75	0.453
nwhitebig5	-1.9705920	0.7483	-2.63	0.008
nwhitebig7	0.2123608	0.8183	0.26	0.795
pdensbig1	0.0245277	0.0296	0.83	0.408
pdensbig2	0.0306120	0.1292	0.24	0.813
pdensbig3	0.0341875	0.0345	0.99	0.322
pdensbig4	-0.0158649	0.0536	-0.30	0.767
pdensbig5	0.0163628	0.0865	0.19	0.850
pdensbig7	-0.0779019	0.0538	-1.45	0.148
rmincbig1	0.0000115	0.0000	0.70	0.484
rmincbig2	-0.0001583	0.0001	-2.10	0.036
rmincbig3	-0.0000129	0.0000	-0.75	0.450
rmincbig4	-0.0000788	0.0000	-1.92	0.054
rmincbig5	-0.0000388	0.0000	-1.09	0.278
rmincbig7	-0.0000380	0.0001	-0.64	0.524
highdensbig1	-0.0336696	0.0791	-0.43	0.671
highdensbig2	0.8738296	0.4013	2.18	0.029
highdensbig3	0.0335156	0.0598	0.56	0.575
highdensbig4	0.0112216	0.0996	0.11	0.910
highdensbig5	0.0412068	0.1830	0.23	0.822
highdensbig7	0.6765503	0.2202	3.07	0.002
lowdensbig1	0.0438689	0.0172	2.54	0.011

Table 4.15. Continued

Variable	Coefficient	Robust Std. Error	z	P > z
lowdensbig2	0.2616260	0.0699	3.74	0.000
lowdensbig3	0.0415642	0.0149	2.79	0.005
lowdensbig4	0.0336738	0.0235	1.44	0.151
lowdensbig5	-0.0480235	0.0510	-0.94	0.346
lowdensbig7	-0.0114773	0.0399	-0.29	0.774
invdhighbig1	0.0031255	0.0140	0.22	0.823
invdhighbig2	-0.1340382	0.0755	-1.77	0.076
invdhighbig3	-0.0000082	0.0000	-0.24	0.811
invdhighbig4	0.0029081	0.0013	2.23	0.026
invdhighbig5	-0.0091967	0.0118	-0.78	0.437
invdhighbig7	-0.2442781	0.1212	-2.02	0.044
invdlowbig1	0.0000460	0.0000	1.07	0.284
invdlowbig2	-0.0000327	0.0001	-0.43	0.668
invdlowbig3	0.0000673	0.0000	2.24	0.025
invdlowbig4	0.0002852	0.0001	3.49	0.000
invdlowbig5	-0.0015891	0.0057	-0.28	0.781
invdlowbig7	0.0001776	0.0001	2.21	0.027
imr	0.0301584	0.4173	0.07	0.942
constant	-3.0167350	1.1524	-2.62	0.009

Table 4.16. Predicted Outcomes for Probit Probability of Contamination Model Estimated Using Random Sample (Estimating Sample Only)

	k=0.20		k=0.25		k=0.30	
	Not Contaminated ($\hat{c}$ = 0)	Contaminated ($\hat{c}$ = 1)	Not Contaminated ($\hat{c}$ = 0)	Contaminated ($\hat{c}$ = 1)	Not Contaminated ($\hat{c}$ = 0)	Contaminated ($\hat{c}$ = 1)
No = 895 obs (78.4)[a]	685 (76.5)[b]	210 (23.5)	729 (81.5)	166 (18.5)	766 (85.6)	129 (14.4)
Low = 193 obs (16.9)[a]	25 (13.0)	168 (87.0)	40 (20.7)	153 (79.3)	51 (26.4)	142 (73.6)
High = 54 obs (4.7)[a]	6 (11.1)	48 (88.9)	8 (14.8)	46 (85.2)	10 (18.5)	44 (81.5)
Total = 1,142obs	716 (62.7)	426 (37.3)	777 (68.0)	365 (32.0)	827 (72.4)	315 (27.6)

[a] Number in parentheses is the percentage of properties in the estimating sample which are classified as not contaminated, low level of contamination (on NFRAP/NonHSI lists), and high level of contamination (on CERCLIS/HSI list).

[b] Number is parentheses is the percentage of properties in the observed category that are predicted as not contaminated and contaminated.

Table 4.17. Cross Tabulation of Predicted Outcomes for OPFS Model and PRS Model (Estimating Sample for OPFS Only)

			Predicted Outcomes from PRS Model					
			k = 0.20		k = 0.25		k = 0.30	
			Not Contaminated	Contaminated	Not Contaminated	Contaminated	Not Contaminated	Contaminated
Predicted Outcomes from OPFS Model	k = 0.05	No (5,028)	4,526 (90.2)	502 (9.8)	-	-	-	-
		Low (1,028)	51 (5.0)	977 (95.0)	-	-	-	-
		High (219)	1 (0.5)	218 (99.5)	-	-	-	-
	k = 0.10	No (5,825)	-	-	4,859 (83.4)	966 (16.6)	-	-
		Low (344)	-	-	4 (1.2)	340 (98.8)	-	-
		High (106)	-	-	1 (0.9)	105 (99.1)	-	-
	k = 0.15	No (6,019)	-	-	-	-	5,095 (84.6)	924 (15.4)
		Low (200)	-	-	-	-	0 (0.0)	200 (100)
		High (56)	-	-	-	-	1 (1.8)	55 (98.2)
		Total (6,275)[a]	4,578 (73.0)	1,697 (27.0)	4,864 (77.5)	1,411 (22.5)	5,096 (81.2)	1,179 (18.8)

[a] Predicted outcomes for 159 properties could not be computed using the results for the probit model estimated with random sample.

Table 4.18. Cross Tabulation of Predicted Outcomes for OPFS Model and PRS Model (Full Sample)

			Predicted Outcomes from PRS Model					
			k = 0.20		k = 0.25		k = 0.30	
			Not Contaminated	Contaminated	Not Contaminated	Contaminated	Not Contaminated	Contaminated
Predicted Outcomes from OPFS Model	k = 0.05	No (11,606)	10,162 (87.6)	1,444 (12.4)	-	-	-	-
		Low (2,760)	186 (6.7)	2,574 (93.3)	-	-	-	-
		High (683)	7 (1.0)	676 (99.0)	-	-	-	-
	k = 0.10	No (13,700)	-	-	11,071 (80.8)	2,629 (19.2)	-	-
		Low (1,022)	-	-	21 (2.1)	1,001 (97.9)	-	-
		High (327)	-	-	3 (0.9)	324 (99.1)	-	-
	k = 0.15	No (14,254)	-	-	-	-	11,688 (82.0)	2,566 (18.0)
		Low (586)	-	-	-	-	10 (1.7)	576 (98.3)
		High (209)	-	-	-	-	3 (1.4)	206 (98.6)
		Total (15,049)[a]	10,355 (68.8)	4,694 (31.2)	11,095 (73.7)	3,954 (26.3)	11,701 (77.7)	3,348 (22.3)

[a] Predicted outcomes for 311 properties could not be computed using the results for the probit model estimated with random sample.

Table 4.19. Predicted Outcomes Across Major Land-use Categories for OPFS Model (Estimating Sample Only)

	Not Contaminated				Low Level of Contamination				High Level of Contamination			
Major Land-use	Observed	k=0.05	k=0.10	k=0.15	Observed	k=0.05	k=0.10	k=0.15	Observed	k=0.05	k=0.10	k=0.15
Retail (1,585)	1,526	1,290	1,504	1,542	51	263	63	32	8	32	18	11
Office (701)	692	671	687	695	9	24	11	4	0	6	3	2
Industrial (1,196)	1,057	450	875	995	99	570	239	163	40	176	82	38
Apartment/Hotel/Motel (2,272)	2,246	2,154	2,243	2,262	22	108	21	5	4	10	8	5
Auto-Related (402)	391	370	395	398	9	28	4	2	2	4	3	2
Public/Exempt (278)	260	218	247	257	13	40	18	10	5	20	13	11
Total (6,434)	6,172	5,153	5,951	6,149	203	1,033	356	216	59	248	127	69

[a] Number in parentheses is the number of properties in the estimating sample in that major land-use category.

Table 4.20. Predicted Outcomes Across Major Land-use Categories for OPFS Model (Full Sample)

Major Land-use	Not Contaminated			Low Level of Contamination			High Level of Contamination		
	k = 0.05	k = 0.10	k = 0.15	k = 0.05	k = 0.10	k = 0.15	k = 0.05	k = 0.10	k = 0.15
Retail (3,834)	3,074	3,634	3,731	679	161	76	81	39	27
Office (1,468)	1,408	1,440	1,454	47	19	11	13	9	3
Industrial (2,787)	1,069	2,063	2,324	1,316	545	369	402	179	94
Apartment/Hotel/Motel (4,268)	4,051	4,217	4,253	202	39	7	15	12	8
Auto-Related (975)	896	951	966	71	20	7	8	4	2
Public/Exempt (2,028)	1,352	1,644	1,780	455	261	148	221	123	100
Total (15,360)	11,850	13,949	14,508	2,770	1,045	618	740	366	234

[a] Number in parentheses is the number of properties in the full sample in that major land-use category.

Table 4.21. Predicted Outcomes Across Minor Land-use Categories for OPFS Model (Estimating Sample Only)

	Not Contaminated				Low Level of Contamination				High Level of Contamination			
Land-use	Observed	k=0.05	k=0.10	k=0.15	Observed	k=0.05	k=0.10	k=0.15	Observed	k=0.05	k=0.10	k=0.15
mixed res/com lu6 (627)	626	621	626	627	0	6	1	0	1	0	0	0
misc com lu7 (82)	74	33	70	76	5	43	6	1	3	6	6	5
apartments lu8 (1,354)	1,342	1,319	1,342	1,353	12	34	11	1	0	1	1	0
hotel/motel lu9 (97)	92	69	93	94	5	25	3	3	0	3	1	0
nursing, boarding home/day care lu10 (112)	112	112	112	112	0	0	0	0	0	0	0	0
food and beverage place lu11 (304)	295	261	300	303	9	42	4	1	0	1	0	0
automotive, non parking related lu12 (369)	360	347	364	366	7	19	3	2	2	3	2	1
parking deck/parking garage lu13 (33)	31	23	31	32	2	9	1	0	0	1	1	1
retail multi occ, non food related lu14 (569)	537	411	504	531	25	129	47	27	7	29	18	11
retail single occ, non food related lu15 (545)	529	456	535	542	15	87	10	3	1	2	0	0
retail, food related lu16 (120)	119	118	120	120	1	2	0	0	0	0	0	0
other misc retail lu17 (47)	46	44	45	46	1	3	2	1	0	0	0	0

Table 4.21. Continued

Land-use	Not Contaminated				Low Level of Contamination				High Level of Contamination			
	Observed	k=0.05	k=0.10	k=0.15	Observed	k=0.05	k=0.10	k=0.15	Observed	k=0.05	k=0.10	k=0.15
office lu18 (701)	692	671	687	695	9	24	11	4	0	6	3	2
cold storage lu21 (8)	8	8	8	8	0	0	0	0	0	0	0	0
lumber storage lu22 (8)	6	1	1	1	1	0	5	7	1	7	2	0
general warehouse lu23 (855)	791	385	737	806	47	428	105	45	17	42	13	4
office warehouse lu24 (16)	15	11	14	14	1	3	2	2	0	2	0	0
misc warehouse/storage lu25 (56)	51	23	44	50	4	29	11	6	1	4	1	0
general manu./proc. lu26 (90)	69	7	15	39	14	38	59	44	7	45	16	7
research and development lu27 (3)	3	3	3	3	0	0	0	0	0	0	0	0
food related manu./proc. lu28 (17)	15	4	10	16	2	12	7	1	0	1	0	0
clothing related manu./proc. lu29 (4)	3	0	0	2	0	2	2	1	1	2	2	1
parts and equipment manu. lu30 (8)	6	1	4	5	1	5	2	1	1	2	2	2

Table 4.21. Continued

Land-use	Not Contaminated Observed	k=0.05	k=0.10	k=0.15	Low Level of Contamination Observed	k=0.05	k=0.10	k=0.15	High Level of Contamination Observed	k=0.05	k=0.10	k=0.15
glass/metal/plastic/etc products manu./proc. lu31 (70)	44	0	5	13	20	21	37	46	6	49	28	11
concrete/cement/ asphalt etc plant lu32 (23)	11	0	1	3	9	3	5	8	3	20	17	12
natural gas/mining lu33 (1)	1	1	1	1	0	0	0	0	0	0	0	0
public building/school/university/ hospital/etc lu35 (79)	73	54	67	72	5	19	9	5	1	6	3	2
religious/cemetery lu36 (107)	105	102	105	105	2	3	0	0	0	2	2	2
police/fire station/correctional facility/ improved gov't owned lu37 (92)	82	62	75	80	6	18	9	5	4	12	8	7
trans/communication/ utilities lu38 (37)	34	6	32	34	0	29	4	2	3	2	1	1
Total (6,434)	6,172	5,153	5,951	6,149	203	1,033	356	216	59	248	127	69

[a] Number in parentheses is the number of properties in the estimating sample with that particular minor land-use.

Table 4.22. Predicted Outcomes Across Minor Land-use Categories for OPFS Model (Full Sample)

	Not Contaminated			Low Level of Contamination			High Level of Contamination		
Land-use	k = 0.05	k = 0.10	k = 0.15	k = 0.05	k = 0.10	k = 0.15	k = 0.05	k = 0.10	k = 0.15
mixed res/com lu6 (1,158)	1,149	1,157	1,158	9	1	0	0	0	0
misc com lu7 (198)	96	176	190	94	14	1	8	8	7
apartments lu8 (2,510)	2,454	2,489	2,509	55	20	1	1	1	0
hotel/motel lu9 (185)	135	178	179	44	4	5	6	3	1
nursing, boarding home/day care lu10 (217)	217	217	217	0	0	0	0	0	0
food and beverage place lu11 (779)	668	770	777	109	9	2	2	0	0
automotive, non parking related lu12 (904)	847	892	898	51	10	5	6	2	1
parking deck/parking garage lu13 (71)	49	59	68	20	10	2	2	2	1
retail multi occ, non food related lu14 (1,314)	955	1,181	1,239	301	101	52	58	32	23
retail single occ, non food related lu15 (1,305)	1,037	1,252	1,282	249	48	21	19	5	2

Table 4.22. Continued

Land-use	Not Contaminated k = 0.05	k = 0.10	k = 0.15	Low Level of Contamination k = 0.05	k = 0.10	k = 0.15	High Level of Contamination k = 0.05	k = 0.10	k = 0.15
retail, food related lu16 (287)	284	287	287	3	0	0	0	0	0
other misc retail lu17 (149)	130	144	146	17	3	1	2	2	2
office lu18 (1,468)	1,408	1,440	1,454	47	19	11	13	9	3
cold storage lu21 (12)	12	12	12	0	0	0	0	0	0
lumber storage lu22 (15)	2	3	3	1	9	12	12	3	0
general warehouse lu23 (1,834)	884	1,603	1,731	866	205	93	84	26	10
office warehouse lu24 (38)	23	30	34	11	8	4	4	0	0
misc warehouse/storage lu25 (115)	36	82	100	69	28	14	10	5	1
general manu./proc. lu26 (172)	11	29	70	73	117	89	88	26	13
research and development lu27 (9)	9	9	9	0	0	0	0	0	0

Table 4.22. Continued

Land-use	Not Contaminated k = 0.05	k = 0.10	k = 0.15	Low Level of Contamination k = 0.05	k = 0.10	k = 0.15	High Level of Contamination k = 0.05	k = 0.10	k = 0.15
food related manu./proc. lu28 (36)	9	25	31	23	9	3	4	2	2
clothing related manu./proc. lu29 (8)	0	1	3	3	2	4	5	5	1
parts and equipment manu. lu30 (21)	5	10	15	12	7	4	4	4	2
glass/metal/plastic/etc products manu./proc. lu31 (170)	3	17	35	45	96	108	122	57	27
concrete/cement/ asphalt etc plant lu32 (46)	0	3	6	6	12	16	40	31	24
natural gas/mining lu33 (4)	4	4	4	0	0	0	0	0	0
misc manu./proc. lu34 (3)	3	3	3	0	0	0	0	0	0
public building/school/university/ hospital/etc lu35 (601)	361	474	516	166	88	54	74	39	31

Table 4.22. Continued

Land-use	Not Contaminated k = 0.05	k = 0.10	k = 0.15	Low Level of Contamination k = 0.05	k = 0.10	k = 0.15	High Level of Contamination k = 0.05	k = 0.10	k = 0.15
religious/cemetery lu36 (679)	639	661	664	26	10	11	14	8	4
police/fire station/correctional facility/ improved gov't owned lu37 (748)	352	509	600	263	163	83	133	76	65
trans/communication/ utilities lu38 (304)	68	232	268	207	52	22	29	20	14
Total (15,360)	11,850	13,949	14,508	2,770	1,045	618	740	366	234

[a] Number in parentheses is the number of properties in the full sample with that particular minor land-use.

CHAPTER 5

ESTIMATING THE EFFECTS OF KNOWN ENVIRONMENTALLY CONTAMINATED SITES ON COMMERCIAL AND INDUSTRIAL PROPERTY VALUES

Introduction

In this chapter, the extent to which environmentally contaminated properties affect commercial and industrial (CI) property markets is investigated. The effects of severely contaminated properties, such as the Environmental Protection Agency's (EPA) National Priority List (NPL) of contaminated sites, are well documented in previous research (Michaels and Smith, 1990, Kohlhase, 1991, Kiel, 1995, Kiel and Zabel, 2001). However, the vast majority of contaminated sites are not so severe as to warrant placement on the NPL or other federal and state lists of "priority" sites. Unlike previous research, this study utilizes a comprehensive list of less severely contaminated sites (i.e. sites not found on the NPL) generated from two federal registries (EPA's CERCLIS and NFRAP) and two state registries (Georgia EPD's HSI and NonHSI) of contaminated sites.[48] Furthermore, this research is unique in that a data set of CI property sales is used for the analysis, compared to previous studies that primarily examined that impacts of contaminated sites on residential property values.

[48] See Chapter 3 for a complete description of the sites found on the CERCLIS, NFRAP, HSI, and NonHSI registries of contaminated sites.

Hedonic property value models are estimated to determine the effects that properties known to be contaminated have on neighboring CI property values. In general, CI property values are expected to be negatively affected by proximity to a contaminated site, and these negative effects are expected to decline as distance to a contaminated site increases. Several issues are addressed in the development of the hedonic models. Of primary concern are the following:

1. The relationship between price and proximity to a contaminated site,
2. The specification of the set independent variables other than those used to control for the externality effects of contaminated sites,
3. The relationship between price and other effects of contaminated sites (e.g. density of sites nearby and/or characteristics of contaminated sites),
4. Testing and correcting for spatial error correlation.

First, due to the assumed nature of the externality effects of contaminated sites, the marginal effect of distance on price is expected to decrease as distance increases. Functional forms that satisfy this condition are explored, such as a reciprocal relationship, semi-log and double-log models. Second, the specifications of the hedonic models are carefully considered since there are over fifty variables available to describe each particular CI property (see Chapter 3 for a description of these variables). Third, it is possible that negative impacts on CI property values may not only be a consequence of proximity to the nearest site, but also from the density of sites nearby. Furthermore, the impacts may vary according to the characteristics of the sites, such as their size. Therefore, different measures that control for the density and characteristics of contaminated sites in close proximity are incorporated into the hedonic models. Finally, because the presence of spatial error correlation is likely in a hedonic property value model, the models are tested and, when necessary, corrected for spatial error correlation.

The specification of a "Base" hedonic model will be presented first followed by a discussion of the estimated results. Next, other functional forms are explored and their results are compared to the Base model. A preferred model is determined and investigated further by incorporating controls for the density of sites nearby and characteristics of the nearest site. Lastly, the final set of preferred models are tested for spatial error correlation for which appropriately specified spatial models are then estimated.

The purpose of this chapter is to present the results of hedonic property value models estimated to examine the effects of environmentally contaminated properties on neighboring CI property values. The set of preferred models developed in this chapter will be replicated in Chapter 6 where additional "potentially contaminated" properties identified by the probability of contamination model estimated in Chapter 4 are incorporated into the analysis. The results reported in this chapter and Chapter 6 will form the basis for the analysis presented in Chapter 7, which will discuss the economic importance of the estimated models (i.e. comparisons are made between the hedonic models estimated in Chapters 5 and 6, marginal impacts are computed, and total impacts on CI property values are calculated).

Estimating the Externality Effects of Environmentally Contaminated Properties

This study utilizes a comprehensive list of less severely contaminated sites (i.e. sites not found on the NPL) generated from two federal registries (EPA's CERCLIS and NFRAP) and two state registries (Georgia EPD's HSI and NonHSI) of contaminated sites. Similar to Chapter 4, sites on CERCLIS and HSI were combined to form a single list of sites ("List1" sites). The listing date assigned to the List1 sites was the earlier of either the HSI or CERCLIS listing date. Different from Chapter 4, NFRAP and NonHSI sites were not combined into one list. This is due to the temporary classification of NFRAP sites as CERCLIS sites before they are "de-listed" (i.e. site classification has changed from CERCLIS to NFRAP). Although the level of risks associated with NFRAP sites to nearby property owners may be similar to NonHSI sites, this may only be apparent once the NFRAP site has been formally de-listed. As such, nearby property owners may have risk perceptions of NFRAP sites similar to List1 sites after discovery, but before de-listing (i.e. the period of time the NFRAP site was classified as a CERCLIS site). Therefore, it would be important to investigate if these differences between NFRAP ("List2" sites) and NonHSI ("List3" sites) sites are reflected in CI property markets.

Furthermore, because the EPA and the EPD use different methods to determine the severity and potential threat to nearby residents of properties with contaminant releases, sites on CERCLIS may also be listed on the NonHSI and sites on the HSI may simultaneously appear on NFRAP. For analysis purposes, CERCLIS or HSI sites also found on the NonHSI or NFRAP will be identified as CERCLIS or HSI sites only because it is assumed that investors associate properties with the list that signifies the more severe level of contamination present.[49, 50]

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[49] Table 3.11 in Chapter 3 provides a cross-tabulation of the number of sites found concurrently on a federal (CERCLIS or NFRAP) and state (HSI or NonHSI) list.

[50] Although this can not be known with certainty, it is believed to be a reasonable assumption because the differences between the underlying methods used by the EPA and EPD to determine the severity of contamination present are not known in great detail.

The Base Hedonic Model

The general specification of the Base hedonic model estimated to investigate the externality effects of List1, List2 and List3 sites can be expressed as follows:

$$P_{it} = c + \sum_{t=1}^{T} \alpha_t\, YR_t + \sum_{j=1}^{J} \beta_j\, X_{ijt} + \delta_1\, invl1d_i^A + \delta_2\, invl1d_i^B + \gamma_1\, invl2d_i^A$$
$$+ \gamma_2\, invl2d_i^D + \gamma_3\, invl2d_i^B + \lambda_1\, invl3d_i^A + \lambda_2\, invl3d_i^B + \epsilon_{it} \tag{5.1}$$

where:

P_{it}	the sales price of CI property i at time t,
c	constant,
YR_t	dummy variables indicating the year the property was last sold,
X_{jit}	the J property characteristics that include location and neighborhood oriented variables for property i at time t,
$invl1d^A$	inverse distance of property i to nearest List1 site if sale occurred after the site was listed, 0 otherwise,
$invl1d^B$	inverse distance of property i to nearest List1 site if sale occurred before the site was listed, 0 otherwise,
$invl2d^A$	inverse distance of property i to nearest List2 site if sale occurred after the site was de-listed (i.e. site was listed as NFRAP), 0 otherwise,
$invl2d^D$	inverse distance of property i to nearest List2 site if sale occurred after the site was listed on CERCLIS but before it was de-listed, 0 otherwise,
$invl2d^B$	inverse distance of property i to nearest List2 site if sale occurred before the site was listed, 0 otherwise,
$invl3d^A$	inverse distance of property i to nearest List3 site if sale occurred after the site was listed, 0 otherwise,
$invl3d^B$	inverse distance of property i to nearest List3 site if sale occurred before the site was listed, 0 otherwise,
ε_{it}	unobserved random error.

Equation 5.1 assumes the price-distance relationship can be described by the reciprocal of distance to the nearest List1, List2, and List3 site. Negative coefficients estimated for the distance variables indicate that price will increase with distance at a decreasing rate, while nearing an asymptotically constant level. Additionally, the price-

distance relationship is allowed to vary before and after listing for List1 and List3 sites, and for List2 sites, it is allowed to vary before listing on CERCLIS, after listing on CERCLIS but before de-listing, and after de-listing (i.e. site was classified as NFRAP).

The functional form expressed by Equation 5.1 was chosen as the Base model because it is consistent with the assumed nature of the negative externality effects of contaminated sites. Risks of contaminated sites to nearby property owners include potential contaminant migration to surrounding properties, fouling of nearby air quality, and potential hazards to those who inadvertently cross property boundaries (Ihlanfeldt and Taylor, 2004). It is expected that the size of these negative effects will continuously decline as distance from a contaminated site increases, and these effects are expected to disappear beyond some point. This implies that the price of CI properties will increase at a decreasing rate as distance to a contaminated site increases, but price will not be affected after some distance, suggesting the function should have an asymptote. The reciprocal relationship is the only functional form that specifically demonstrates a relationship between price and distance that is consistent with the assumed nature of the externality effects of contaminated sites.

Equation 5.1 is estimated separately for CI properties in six major land-use categories: Retail, Office, Industrial, Apartment/Hotel/Model, Auto-Related, and Vacant.[51] Each of the categories are assumed to represent separate property markets, such that potential property owners in the Retail category do not consider purchasing

[51] See Chapter 3 for a complete description of the six major land-use categories. Also, note that the hedonic models estimated for the vacant major land-use category will not include property characteristics associated with structural improvements.

properties in the Apartment/Hotel/Motel or Office categories, and vice versa.[52]

In addition to the distance measures used to measure the externality effects of List1, List2 and List3 sites, there are over fifty variables that comprise the full set of independent variables used to control for the property, location-oriented, and neighborhood-oriented characteristics of CI properties.[53] Table 5.1 provides the full set of variables considered for $\sum_{j=1}^{J} \beta_j X_{jit}$. However, briefly they include the following:

ret1-ret8	dummy variables for aggregated minor land-use categories specific to Retail land-use
off1-off5	dummy variables for aggregated minor land-use categories specific to Office land-use
ind1-ind4	dummy variables for aggregated minor land-use categories specific to Industrial land-use
ahm1-ahm7	dummy variables for aggregated minor land-use categories specific to Apartment/Hotel/Motel land-use,
auto1-auto4	dummy variables for aggregated minor land-use categories specific to Auto-Related land-use
vac1-vac4	dummy variables for aggregated minor land-use categories specific to Vacant land-use
sqft	square feet of floor space of all improvements
age	age of the primary structural improvement
acre	size of the property in acres
numimp	number of structural improvements on property
building grade	dummy variables indicating the building quality of the primary structure as assigned by the tax assessor
exterior wall	dummy variables indicating the exterior wall type of the primary structure as assigned by the tax assessor
frontage	dummy variables indicating the type of street the property fronts as assigned by the tax assessor
location	dummy variables indicating the location description of the property as assigned by the tax assessor
parking	dummy variable indicating the type and quantity of parking as assigned by the tax assessor
rmedinc	real median income of the census tract the property is

[52] It should be noted that this may not always be the case since an investor may demolish an existing facility/building on a property and construct a new facility/building associated with a different major land-use category. However, the extent that this has occurred is not known.

[53] Chapter 3 provides a complete description of all the data.

	located at the time of sale
minority	percent minority population of the census tract the property is located at the time of sale
popdens	population density of the census tract the property is located at the time of sale
empdens	total employment density of the census tract the property is located at the time of sale
north	dummy variable indicating if the property is located in North Fulton County
cbd	distance (miles) to the central business district of the property
martahm	dummy variable indicating if the property is located within one-half mile of a MARTA transit station
exit	distance to nearest major highway exit
harts	distance to Hartsfield-Jackson Atlanta Airport
juris1-juris9	dummy variables indicating the tax jurisdiction in which the property is located

Increases in land area and square feet of floor space are expected to positively affect the value of CI properties, as are better construction quality and adequacy/availability of parking. The effects on property values that variables controlling for exterior wall types, property frontage, and general location indicators are likely to vary by major land-use categories. Finally, indicators for minor land-use types are important to control for differences in property types within major land-use categories.

Neighborhood characteristics include: real median income, percent minority population, population density, and employment density of the census tract a property is located. Racial composition and median income levels may control for the type and/or quality of the surrounding area or neighborhood. Census tract population density may describe the potential employee base available for firms nearby or the accessability to potential customers. Employment density may be used to control for agglomeration economies and/or other spillover effects of being located near other firms. The census data was obtained from the Atlanta Regional Commission (ARC) and Donnelly, Inc. The above variables vary by year (from 1980 to 1997) and are based on 1980 and 1990 census tract information, but summarized according to 1980 census tract geography.[54] The ARC and Donnelly, Inc. interpolate each variable for the years between 1980 and 1997. As such, the census data could be appended to the property data according to its 1980 census tract location and by matching the census data year to the year of sale for each property.[55]

Location-oriented characteristics include: distance to CBD, distance to nearest major highway exit, distance to Hartsfield-Jackson Atlanta Airport, a variable indicating if the property is located in North Fulton County, a variable indicating if the property is located within one-half mile of an existing MARTA transit station at the time of sale, and variables indicating the tax jurisdiction of Fulton County a property is located. It is expected that as distance to the CBD increases, CI property values will decrease. However, Bollinger, Ihlanfeldt and Bowes (1998) provide evidence for differences in price gradients for office rental space in north or south Fulton County. Therefore, it is reasonable to also control for the location of a CI property's location in north/south Fulton County.[56] Properties near a MARTA transit station may benefit from easier means of access for employees, thereby leading to increased property values. Similar to the benefits of a MARTA station, properties located in close proximity to highway exits may benefit from easier means of access for their employees and customers. In addition,

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[54]The 1990 census tract numbers were converted to 1980 tract numbers to merge the data. It is expected that using 1980 census tract geography will not affect the estimated models.

[55]All properties with a sale date prior to 1980 were given 1980 census data and all properties with a sale date after 1996 were given 1996 data as a result of incomplete data for 1997.

[56]North (south) Fulton is specified as north (south) of the CBD reference point. The CBD reference point is defined as the Five Points MARTA transit station in downtown Atlanta.

benefits can stem from easier means of accessibility for receiving inputs and/or delivering outputs. Finally, it is likely that proximity to Hartsfield Atlanta International Airport can have an effect on CI property values, but it can be argued that the effect may be positive or negative. Properties near the airport may benefit from lower transportation costs through better accessibility to distribution networks, therefore resulting in higher property values. However, airport noise and airplane exhaust may be viewed as nuisances, thereby negatively affecting property values.

Base Hedonic Model Results

The results of the Base hedonic model (given by Equation 5.1) estimated for the six major land-use categories (Retail, Office, Industrial, Apartment/Hotel/Motel, Auto-related and Vacant) are provided in Table 5.2, where the model estimated for each category used sales greater than $10 thousand over the period of 1980-2000. The minimum sale price of $10 thousand was chosen under the assumption that properties with sales greater than $10 thousand represent "arms length transactions".

To obtain the results given in Table 5.2, three estimation issues were addressed. The first issue involved the exclusion of five List1 sites from the set used to calculated the distance measures. Initially, distance to the nearest List1 site was based on the original set of fifty-eight geocoded sites. However, preliminary model estimations indicated that the results were very sensitive to the inclusion of five sites in the distance calculations. Four of these List1 sites were classified as HSI and one as CERCLIS. All four HSI sites were originally listed in 1999, but were subsequently removed from the

EPD's list of HSI sites published in 2000. The single CERCLIS site was listed in 1998 and involved an emergency removal of spilled contaminants. There is good reason to believe that these five sites do not represent the same risks to nearby property owners as the other List1 sites due to their quick de-listing or quick removal of contaminants. The characteristics of these five sites suggest that any potential threats to nearby property owners were likely to have been quickly negated. In general, these sites appear to be similar to the sites that are classified NFRAP. As such, it is assumed that these sites would not represent the same information to CI property markets as the other List1 sites and it would not be appropriate to include them when calculating distance to the nearest List1 site.

The second issue addressed was whether observations used in the estimating sample should be restricted to only those sales which lie within some maximum distance of a contaminated site. It is expected that the externality effects of contaminated sites will be highly localized given their assumed nature. Ihlanfeldt and Taylor (2004) explain that "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." Similar to the approach that Ihlanfeldt and Taylor followed, models for each major land-use category were estimated where the assumed impact area around contaminated sites was increased in quarter mile increments until a decline in the precision of the estimated gradient was observed. This occurred at 1.50 miles for the Retail, Industrial, Apartment/Hotel/Motel, and Vacant categories and 1.25 miles for the Office and Auto-related models.

The final issue concerned whether a correction for heteroskedasticity is necessary. In all preliminary model estimations for each major land-use category, the null hypothesis of homoskedasticity was rejected. As a result, White's (1980) heteroskedastic-consistent covariance matrix estimator was used to correct the estimated standard errors for an unknown form of heteroskedasticity.

The overall results given in Table 5.2 indicate the functional form expressed by Equation 5.1 performs reasonably well for all six major land-use categories. The Office, Industrial, Apartment/Hotel/Motel, and Auto-Related models each explain at least 48 percent of the variation in sales price. The Retail and Vacant categories perform less well, explaining 37 percent and 36 percent of the variation in sales price, respectively. In comparison to Ihlanfeldt and Taylor (2004), the models for Office, Industrial, Apartment/Hotel/Motel, and Vacant perform better in terms of a higher R^2. However, the R^2 for Retail is lower than that of Ihlanfeldt and Taylor. Comparison can not be made for the results for Auto-Related since Ihlanfeldt and Taylor do not estimate this model. Also, in general, the overall results of these models compare favorably to the results reported in the literature that estimate hedonic models for residential properties. Before discussing the coefficient estimates for the variables used to investigate the externality effects of List1, List2 and List3 sites, the results obtained for the other property characteristics will be briefly covered first.

Dummy variables for minor land-use types specific to each major land-use category were used to control for differences in property types that may exist. In general, the results for these variables indicate that controlling for minor land-use types within each major category is important. For Retail, all types of properties except fast food (ret8) exhibit higher sales prices when compared to the reference category, single occupancy retail (ret2). However, only the coefficient for multi-occupancy retail (ret1) is statistically significant (0.10 level). Properties classified as multi-occupancy retail also have the highest sales prices among all land-use types in the Retail category. Not surprisingly, high rise office buildings (off4) have the highest sales prices for the Office category, while medical (off1) and banking (off2) office buildings display the lowest sales prices. However, none of the coefficients for minor land-use dummies in the Office category were statistically significant. Properties associated with warehouse/storage (ind1) facilities and heavy manufacturing/processing (ind3) in the Industrial category both sell for a greater value when compared to light manufacturing/processing (ind2). Only the coefficient for warehouse/storage was statistically significant (0.10 level). Three of the five coefficients for the land-use dummies in the Apartment/Hotel/Motel category were significant at the 0.05 level (loft/mid-rise apartments (ahm2), high rise apartments (ahm4), and luxury/first class hotels (ahm5)). As may be expected, luxury/first class hotels (ahm5) exhibited significantly higher sales prices than all other property types. Interestingly, high-rise apartments (ahm4) sell for slightly over $5 million less than properties in the reference category, garden apartments (ahm3). When compared to service stations (auto3) in the Auto-Related category, both auto service garages (auto2) and car washes (auto4) have lower sales prices, while full-service auto dealers sell for a higher price. However, the coefficients for these three dummy variables were insignificant. For the Vacant category, vacant apartment land (vac1), vacant industrial land (vac4) and other vacant land (vac5) sell for up to$391.1 thousand more than vacant commercial land (vac2). Although, only the coefficient for vacant apartment land was statistically significant (0.10 level) in the estimated model.

The primary property characteristics included in the models were square feet of floor space for all improvements (sqft), age of the primary structure (age), size of property (acre), and the number of structural improvements on the property (numimp).[57] Squared terms for sqft (sqft2), age (age2), and acre (acre2) were also used in the models to allow for a non-linear relationship with sales price. In general, the signs of the coefficients for sqft, sqft2, age, age2, acre and acre2 were as expected. However, only sqft and sqft2 were found to be consistently statistically significant (0.10 level) across all major land-use categories (excluding Vacant). Although the coefficient sign for acre was contrary to expectations in the Office and Auto-Related models, it was never significant. Interestingly, the estimate for number of structural improvements (numimp) is negative and insignificant in all models. This may be a result of sqft and numimp measuring similar characteristics of CI properties, since sqft is defined as the sum of the square feet of floor space for all structural improvements located on a property. Finally, the variables used to control for other property characteristics related to building quality, exterior wall types, and adequacy of parking were mostly not statistically significant for any of the major land-use categories, where many of the t-statistics were less than one.

Additional characteristics from the property data incorporated into the models included dummy variables to describe a property's frontage and indicators for a

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[57] Note, "sqft", "age", and "numimp" do not apply to the model estimated for the Vacant category.

property's general location.[58] The coefficient signs and levels of significance for these dummy variables varied across land-use categories. As such, a more detailed description of these results will not be given.

The variables used to control for neighborhood characteristics included real median family income (rmedinc), percent minority population (minority), population density (popdens), and employment density (empdens) of the census tract a property is located. The estimated models also included the interaction between each the four neighborhood characteristics and a north/south Fulton County indicator variable. As stated earlier, Bollinger, Ihlanfeldt and Bowes (1998) provide evidence for differences in price gradients for office rental space in north and south Fulton County. Therefore, it may be reasonable to assume that there are also similar differences between neighborhood characteristics and CI property values.

Higher median census tract income (rmedinc) is found to have a positive and significant (0.05 level) effect on Industrial property values. The coefficient in the Vacant model was also positive, but not significant. For both models, the positive effects are offset for properties located in north Fulton County. Median tract income is also found to have negative and significant (0.05 level) effect on Apartment/Hotel/Motel properties located in north Fulton County. Increases in percent minority population (minority) is only found to have a negative and significant (0.05 level) effect on Retail properties. Interestingly, a higher percentage of minority population is found to have a significant (0.05 level) negative effect on Apartment/Hotel/Motel properties located in north Fulton,

[58]The specific codes for these variables are assigned by the Fulton County Tax Assessor.

but a significant (0.10 level) positive effect for Office properties. Higher population density (popdens) only has a positive and significant (0.10 level) effect on Retail property values, while population density and population density interacted with the north/south Fulton indicator variable (npopdens) were not statistically significant in any of the other models. Coefficients for employment density (empdens) or employment density interacted with the north/south Fulton indicator variable (nempdens) are not found to be statistically significant in any of the estimated models.

The effects of a CI property's spatial location on property value, relative to the central business district, varied by major land-use category. The coefficient for the variable controlling for a property's location in north Fulton (north) was positive for all land-use categories except Vacant, but the coefficient was only significant (0.05 level) for Apartment/Hotel/Motel. Surprisingly, an increase in distance to the central business district (cbd) is only found to have a significant (0.10 level) negative effect on Apartment/Hotel/Motel property values in south Fulton. Property values are shown to increase for Apartment/Hotel/Motel properties as distance to the central business district increases. This is a result of the coefficient for distance to the central business district interacted with the north Fulton dummy variable (ncbd) being positive, significant (0.05 level) and of greater magnitude than the estimated coefficient for cbd.

The effects of proximity to transportation or accessibility nodes varies by major land-use category. Property values for Vacant and Auto-Related properties are observed to be significantly negatively affected by proximity to a MARTA transit station for all Vacant properties (martahm) and Auto-Related properties located in north Fulton (nmartahm), at 0.05 and 0.10 levels respectively. Proximity to a highway exit is found to be a significant factor for determining property values in the Retail and Apartment/Hotel/Motel categories. Although, only the coefficients estimates for distance to nearest highway exit interacted with the north/south Fulton indicator variable (nexit) were statistically significant (0.05 level) in the two models. And consistent with expectations, these coefficients estimates were negative, indicating that greater access to highway exits is associated with higher property values. Finally, access to Hartsfield-Jackson Atlanta International Airport only has a statistically significant (0.10 level) relationship with property values in the Auto-Related category, where property values are found to increase at decreasing rate as distance increases to approximately 11.30 miles from the airport. While distance to Hartsfield-Jackson Airport (harts) and distance squared (harts2) is not statistically significant for any of the other models, the signs of these coefficients were opposite to what was observed to Auto-Related model.

The estimated coefficients for the variables used to examine the externality effects of List1, List2 and List3 sites on CI property values are reported at the bottom of Table 5.2. The results for List1 sites will be discussed first followed by List2 and List3 sites.

The coefficients for the inverse distance to nearest List1 site listed at the time of sale ("post-listing distance" or $invl1d^{A}$) and not listed at the time of sale ("pre-listing distance" or $invl1d^{B}$) are estimated to have negative signs for all major land-use categories. Specifying distance to enter the models inversely implies that an increase in the distance to the nearest List1 site leads to an increase in the sales price of CI properties (i.e. there is a positive relationship between price and distance to nearest List1 site).

Although the sign of the coefficient for the pre-listing distance variable ($invl1d^B$) is negative for each land-use category, none of them are statistically significant. The coefficients for the post-listing distance variable ($invl1d^A$) are negative and statistically significant (0.10 level or higher) for the Retail, Office, Industrial, and Auto-Related. Furthermore, the post-listing coefficient is greater (in absolute value) than the pre-listing coefficient in each of these four models. Even though the post-listing distance coefficient was negative for the Apartment/Hotel/Motel and Vacant models, it was not statistically significant. Also, the pre-listing coefficient was slightly greater (in absolute value) than the post-listing coefficient in these two models. Table 5.3 computes the difference between the pre- and post-listing coefficients and tests whether the difference is statistically significant. The difference between the pre- post-listing coefficients is found to be statistically significant (0.10 level) for the Office and Industrial models only. However, it is not surprising that the difference between these coefficients is not significant for all the models. This is primarily a result of either the large standard errors associated with the pre-listing coefficient or, in the case of the Apartment/Hotel/Motel and Vacant models, the insignificance of both pre- and post-listing coefficients.

The effects of List2 sites differ from what is observed for List1 sites. Although the pre-listing coefficient for List2 sites ($invl2d^B$) is negative for five land-use categories (Retail, Office, Industrial, Apartment/Hotel/Motel, and Vacant), it is not statistically significant in any of the models. More importantly, the coefficient for inverse distance to the nearest List2 site after listing and before de-listing ($invl2d^D$) is only negative for Industrial and Apartment/Hotel/Motel. Although not statistically significant, positive signs for the post-delisting coefficient ($invl2d^A$) are estimated for the Industrial, Apartment/Hotel/Motel, Auto-Related, and Vacant models. In general, the overall results suggest that List2 sites may not generate negative externality effects for neighboring CI property owners, even for the period of time List2 sites are temporarily classified as CERCLIS sites.

The estimated distance coefficients for List3 sites are similar to the results obtained for List2 sites. The estimates are not statistically significant for any of the six models and only a negative post-listing distance coefficient ($invl3d^A$) is observed for Office, Apartment/Hotel/Motel, Auto-Related, and Vacant. These results are not necessarily surprising as List3 sites do not represent properties with any form of serious contamination and they are not on any publically published list.[59]

The results of the Base model estimated for the six major land-use categories contain a large set of control variables (see Table 5.2). Following Ihlanfeldt and Taylor (2004), additional models were estimated where restrictions were made on the set of control variables used for estimation (other than the List1, List2 and List3 distance measures). The coefficient estimates for the List1, List2 and List3 distance measures for models estimated when variables from the Base model with t-statistics less than 0.50 and 1.0 were dropped are reported in Table 5.4 and 5.5, respectively.

The results in Table 5.4 demonstrate that very little changes in the magnitude of the coefficient estimates for List1 sites when variables from the Base model with t-

[59] The Georgia EPD's record of NonHSI sites comprise the set of List3 sites. The GA EPD does not officially publish a list of NonHSI sites, but does keep files of these sites at their office. The list used for this study was manually generated by entering the information contained in these files into a database. See Chapter 3 for additional details.

statistics less than 0.50 are dropped. This is observed for both the pre- and post-listing distance coefficients (i.e. $invl1d^B$ and $invl1d^A$). Only for Auto-Related is there an increase in the magnitude (in absolute value terms) of the post-listing coefficient. However, this is offset with a similar increase (in absolute value terms) in the pre-listing distance coefficient. Table 5.4 also indicates that the standard errors for post-listing distance coefficients for List1 sites are lower (i.e. the absolute value of the t-statistics are higher). But, the difference between the pre- and post-listing coefficient is still only statistically significant in the Office (0.05 level) and Industrial (0.10 level) models (see Table 5.5).

In general, this restriction does not affect the results obtained for the distance coefficients for List2 and List3 sites. This further supports the initial findings from the Base model that distance to the nearest List2 and List3 site does not appear to negatively affect neighboring CI property values. Finally, there is also very little difference between R^2 values for the Base models and the models reported in Table 5.4. Overall, dropping variables from the Base model with t-statistics less than 0.50 reduced the standards errors for the coefficient estimates of the inverse distance measures, but had little effect on their magnitude. These results suggest that greater efficiency was obtained while not biasing the estimates.

Table 5.6 reports the results for models estimated when variables from the Base model with t-statistics less than 1.0 are dropped. Compared to the Base model, the most noticeable differences are observed for the post-listing coefficient for List1 sites for the Retail and Office categories, where there is a reduction in the magnitude of the post-listing estimate (in absolute value terms). While still statistically significant for Office, the estimate for Retail is now nearly identical to the pre-listing coefficient and not statistically significant. There is also less of a difference between the pre- and post-listing distance coefficients for the Auto-Related category, even though both are still individually statistically significant. These differences are also observed in Table 5.7. Only for the Office category is there a greater statistical significance for the difference between the pre- and post-listing distance coefficients when compared to the Base model, while noticeable reductions in the level of significance are observed for Retail and Auto-Related. Industrial and Vacant remain relatively unchanged in terms of both magnitude of difference and level of significance. Interestingly, the post-listing distance coefficient for Apartment/Hotel/Motel becomes larger than the pre-listing coefficient (in absolute value terms). However, neither coefficient is individually statistically significant and as such, the difference between coefficients is not statistically significant.

The only noticeable change in the distance coefficients for List2 and List3 sites occurs for the Industrial and Vacant models where the pre-listing distance coefficient for List2 sites ($invl2d^B$) is negative and statistically significant (0.10 level). However, the coefficient for inverse distance to nearest List2 site after listing and before delisting ($invl2d^D$) and the after delisting coefficient ($invl2d^A$) are both not statistically significant. Similar to the models presented in Table 5.4, it appears that the restriction of dropping variables from the Base model with t-statistics less than 1.0 also does not affect the results obtained for the inverse distance coefficients for List2 and List3 sites.

Although the results for List2 and List3 sites do not change when variables in the

Base model with t-statistics less than 0.50 or 1.0 are dropped, the latter restriction does affect the results for List1 sites. Using a cut-off of 1.0 may be too restrictive, leading to bias of the distance coefficients for List1 sites, particularly for Retail. As such, only the models used to generate the results presented in Tables 5.2 (the Base model) and 5.4 (variables with t-statistics less than 0.50 are dropped from the Base model) will continue to be considered as appropriate specifications. For ease of exposition, the latter model will be referred to as the Reduced Base Model (RBM).

The results for the Base model (Table 5.2) and for the RBM (Table 5.4) indicate that only distance to the nearest List1 site negatively affects CI property values. It is reasonable to expect that distance to the nearest List3 site would not have any negative effect on CI properties. It is likely that the market does not necessarily perceive these sites to be very dangerous because they represent sites that were tested by the Georgia EPD, but were not found to be contaminated enough to be placed on Georgia's HSI list. Typically, these sites are characterized by a small release of contaminants (e.g. cleaning agents used by a dry cleaner) where there are not expected to be any long term impacts or risks to nearby property owners. Furthermore, these sites are not on any list publically published by the Georgia EPD. Therefore, any information or knowledge about any these sites can only be acquired by reviewing records kept on file at the Georgia EPD's offices.

Unlike List3 sites, it may not be reasonable to expect List2 sites to be treated different in the market than List1 sites since, List2 sites are temporarily classified as CERCLIS sites. However, it is possible that differences in perceived risks between List2 and List1 sites can explain the results observed. As Ihlanfeldt and Taylor (2004) indicate, List2 sites do appear on CERCLIS after initial discovery, but the EPA records generally show that most of the sites were delisted quickly after a site assessment had taken place (sites are initially listed on CERCLIS prior to the site assessment that determines the severity of contamination present). Ihlanfeldt and Taylor (2004) suggest that CI property investors may place a low probability on a site's potential for future risks until the assessment has been completed. Different from List2 sites (i.e. NFRAP sites), the List1 sites that continue to remain on CERCLIS after site assessments may provide a signal to the market that these sites have significant contamination present. This is also evident for the List1 sites found on the HSI since the Georgia EPD only places a site on the HSI if they determine there has been significant release of contaminants. As such, CI property investors may not perceive the long term risks associated with being located in close proximity to a List1 site in a similar way for List2 sites.

Other Functional Forms of the Hedonic Model

The functional form expressed by Equation 5.1 (Base model) is the only functional form that specifically demonstrates a relationship between price and distance that is consistent with the assumed nature of the externality effects of contaminated sites. Other functional forms do allow price to increase at a decreasing rate as distance to a contaminated site increases over some range. However, some of these forms may not be appropriate because they assume that after a certain point, price will decline with distance to a contaminated site or even increase at an increasing rate. Due to these drawbacks, functional forms that exhibit this relationship would not be appropriate to consider.

In addition to the functional form expressed by Equation 5.1, three other forms that are consistent with the assumed relationship of price continuously increasing at a decreasing rate are considered. These three forms can be described in general as follows:

$$Price = c + \delta \; Ln(Dist) \tag{5.2}$$

$$Ln(Price) = c + \delta \; Ln(Dist) \tag{5.3}$$

$$Ln(Price) = c + \delta_1 \frac{1}{Dist} \tag{5.4}$$

Equations 5.2 - 5.4 are estimated separately for the six major land-use categories and compared to the Base model using goodness of fit criterion.[60] When comparing the four functional forms, the set of independent variables other than distance to a contaminated site remain consistent across each of the models estimated. Therefore, the only variation between models is the manner in which sales price is transformed and how the distance measures are specified.

Tables 5.8 and 5.9 provide results for goodness-of-fit measures computed for the Base model (Equation 5.1) and the functional forms given by Equations 5.2 - 5.4. The goodness-of-fit measures in Table 5.8 are based on models estimated with the full set of independent variables, while those in Table 5.9 are based on models estimated using a reduced set of independent variables (i.e. variables in Table 5.2 with t-statistics less than 0.50 were dropped).

Table 5.8 indicates that functional forms where the dependent variable is equal to sale price (Equations 5.1 and 5.2) perform better than when the dependent variable is

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[60] The R^2 of the functional forms given in equations (5.3) and (5.4) are not directly comparable to the R^2 for (5.1) and (5.2). A method presented in Wooldridge (2003) is used to obtain an alternative R^2 value for equations (5.3) and (5.4) to enable comparison between goodness of fit values across models.

equal to the natural log of sale price (Equations 5.3 and 5.4) for the Retail, Office, Industrial, and Apartment/Hotel/Motel categories. The differences between R^2 values range from 0.072 (Office) to 0.151 (Retail). However, when comparing R^2 values for the models that use sales price as the dependent variable, there is virtually no difference across these four land-uses (i.e. comparing R^2 values for Equations 5.1 and 5.2). Only for Auto-Related and Vacant do the goodness-of-fit estimates suggest that functional forms given by Equations 5.4 (Auto-Related) and 5.3 (Vacant) could be considered as the preferred model. Nearly identical results are obtained when models are estimated with the reduced set of independent variables (see Table 5.9). The only difference observed is that now the goodness-of-fit measures suggest Equation 5.3 may be the preferred model for Auto-Related and Equation 5.4 as the preferred model for Vacant.

In general, the comparisons of goodness-of-fit measures indicate the Base model (i.e. Equation 5.1) is an appropriate functional form for the Retail, Office, Industrial, and Apartment/Hotel/Motel categories. Although this is not necessarily the case for the Auto-Related and Vacant models, one could question whether it is appropriate to estimate a model according to Equation 5.3 or 5.4 for only these two categories. This would imply that the assumed nature of the externality effects of contaminated sites differs by major land-use. Because the goodness-of-fits values indicate that the natural log of sales price should be used as the dependent variable for the Auto-Related and Vacant models, the externality effects of contaminated sites will vary by sales price. Ihlanfeldt and Taylor (2004) point out that property value losses associated with proximity to a contaminated site reflect expected clean-up costs and any expected costs resulting from liability for damages, such that these costs would be independent of the value of the land. The models given by Equations 5.3 and 5.4 are not consistent with this relationship and therefore, may not necessarily be appropriate to estimate for only the Auto-Related and Vacant categories. The overall results indicate that the Base model fits well for all major land-use categories. Furthermore, given that it is the only functional form that is consistent with the assumed nature of the externality effects of contaminated sites, it is assumed to be reasonable to use the Base model as the preferred functional form for all major land-use categories.

Other Externality Effects of Contaminated Sites

Density of Contaminated Sites

To further examine the negative externalities of contaminated sites, the effects of the density of List1, List2, and List3 sites on CI property values is investigated. An increase in the number of contaminated sites within a certain distance could be expected to have a negative effect on property values, and not accounting for density could result in an understatement of their full externality effects. Furthermore, a negative correlation between the distance to nearest site and density of sites within a certain distance would suggest that contaminated sites are spatially clustered. If contaminated sites are spatially clustered and if density effects are important, then not controlling for them would bias the distance coefficients indicating that the negative effects associated with the nearest site will be more severe than they actually are (Ihlanfeldt and Taylor, 2004).

The density of contaminated sites is expressed as the count of List1, List2, and

List3 sites within a certain distance. The maximum distance for the count of List1 and List2 sites was based on the maximum distance specified for the inverse distance measures in the Base hedonic models. Therefore, the number of List1 and List2 within 1.50 miles (not including the nearest site) is computed for Retail, Industrial, Apartment/Hotel/Motel and Vacant properties, and within 1.25 miles for Office and Auto-Related. A distance of 0.50 miles was chosen for List3 sites. Any negative externality effects of List3 sites are expected to be even more localized than the effects of List1 and List2 sites. Therefore, it was assumed that 1.50 miles and 1.25 miles was too great of a distance to capture any potential density effects of List3 sites. This was not assumed for List2 sites since they are temporarily classified as CERCLIS sites. Finally, the density variables are defined in a similar way as the inverse distance variables, and are given as follows:

$l1den1hm^{A}$	number of List1 sites within 1.50 miles of a property listed at the time of sale (Retail, Industrial, Apartment/Hotel/Motel and Vacant models)
$l1den1hm^{B}$	number of List1 sites within 1.50 miles of a property not listed at the time of sale (Retail, Industrial, Apartment/Hotel/Motel and Vacant models)
$l1den1qm^{A}$	number of List1 sites within 1.25 miles of a property listed at the time of sale (Office and Auto-Related models)
$l1den1qm^{B}$	number of List1 sites within 1.25 miles of a property not listed at the time of sale (Office and Auto-Related models)
$l2den1hm^{A}$	number of List2 sites within 1.50 miles of a property delisted at the time of sale (Retail, Industrial, Apartment/Hotel/Motel and Vacant models)
$l2den1hm^{D}$	number of List2 sites within 1.50 miles of a property listed on CERCLIS, and before delisting, at the time of sale (Retail, Industrial, Apartment/Hotel/Motel and Vacant models)
$l2den1hm^{B}$	number of List2 sites within 1.50 miles of a property not listed at the time of sale (Retail, Industrial, Apartment/Hotel/Motel and Vacant models)
$l2den1qm^{A}$	number of List2 sites within 1.25 miles of a property delisted at the

	time of sale (Office and Auto-Related models)
l2den1qm^D	number of List2 sites within 1.25 miles of a property listed on CERCLIS, and before delisting, at the time of sale (Office and Auto-Related models)
l2den1qm^B	number of List2 sites within 1.25 miles of a property not listed at the time of sale (Office and Auto-Related models)
l3denhm^A	number of List3 sites within 0.50 miles of a property listed at the time of sale (all models)
l3denhm^B	number of List3 sites within 0.50 miles of a property not listed at the time of sale (all models)

Table 5.10 gives the coefficient estimates for the density variables listed above. The models use the identical set of explanatory variables used in the Base models estimated for each land-use, including the inverse distance measures for List1, List2, and List3 sites. Only one of the List1 density variables is negative and statistically significant, l1den1hm^B (List1 pre-list count) for Apartment/Hotel/Motel. However, l1den1hm^A (List1 post-list count) was positive and not statistically significant in the same model. Similar results were observed for the List2 and List3 density variables. Table 5.10 indicates that l2den1hm^D (List2 post-list and pre-delist count) is only statistically significant and negative for Retail, while l2den1hm^A (List2 post-delist count) is negative and statistically significant in the Office model. Interestingly, l3denhm^B (List3 pre-list count) is statistically significant and negative in the Apartment/Hotel/Motel, while l3denhm^A (List3 post-list count) is positive and statistically significant in the Vacant model. Models including the density variables were also estimated for each major land-use using the RBM specification (i.e. variables in the Base model with t-statistics less than 0.50 were dropped). The results given in Table 5.11 indicate that little changes when using the reduced set of explanatory variables.

Although the density variables were generally not found to have any negative effect on property values, it is important to determine if they have affected the coefficient estimates for the inverse distance measures. The results in Table 5.10 and 5.11 indicate that the coefficients for the List1, List2, and List3 distance measures and their levels of significance are relatively unchanged compared to those reported in Table 5.2. There is small variation in the estimates for the List1 pre- and post-listing distance coefficients (i.e. $invl1d^B$ and $invl1d^A$) in the Retail models. When the density variables are included, the magnitude of the List1 post-listing gradient ($invl1d^A$) increases (i.e. becomes more negative). Furthermore, the estimate for the pre-listing ($invl1d^B$) coefficient becomes either less negative or positive, but is still not significant. This suggests that the effects of the nearest List1 site on property values are greater when the density variables are included in the Retail models. Overall, the results indicate that the negative effects of the nearest site on CI property values are not necessarily overstated in the models when the List1, List2 and List3 density variables are not included. Therefore, the negative impacts of contaminated sites on CI property values are mainly a consequence of proximity to the nearest site and not from the density of sites.

Size of Nearest Contaminated Site

The results up to now suggest that the negative impacts of contaminated sites on CI property values are primarily caused by proximity to the nearest site. Furthermore, the estimated hedonic models indicate that negative impacts are only observed for properties in close proximity to the most severely contaminated sites, or List1 sites. Although these results support the hypothesis that contaminated sites negatively affect nearby property values, the models estimated do not account for the possibility that the impacts may vary by certain characteristics of contaminated sites. In particular, the "size" of the nearest site, measured as the property acreage of the nearest site, may affect the magnitude of the impacts. "Larger" contaminated sites may be viewed as a greater threat to nearby property owners since the larger structural facilities on these properties may be more likely to produce higher amounts of contaminants. Therefore, in may be reasonable to assume that larger contaminated sites could have stronger negative externality effects than smaller sites, holding distance to the site constant. However, it is possible that the opposite conclusion could be drawn. A more expansive lot size could serve as a buffer between contaminated sites and nearby property owners, lessening the risk of exposure to contamination. As a result, the negative effects of contaminated sites on property values may be dampened the larger the property.

To control for the potential differences in impacts of List1, List2, and List3 sites of different sizes, the Base hedonic model (Equation 5.1) was estimated where variables for the acreage of the nearest site and variables interacting acreage and the inverse distance measures were included. Briefly, the variables are defined as:

$l1acre^A$	acreage of nearest List1 site if sale occurred after the site was listed, 0 otherwise,
$l1acre^B$	acreage of nearest List1 site if sale occurred before the site was listed, 0 otherwise,
$l2acre^A$	acreage of nearest List2 site if sale occurred after the site was delisted (i.e. site was listed as NFRAP), 0 otherwise,
$l2acre^D$	acreage of nearest List2 site if sale occurred after the site was listed on CERCLIS but before it was delisted, 0 otherwise,
$l2acre^B$	acreage of nearest List2 site if sale occurred before the site was listed, 0 otherwise,
$l3acre^A$	acreage of nearest List3 site if sale occurred after the site was listed, 0 otherwise,

$l3acre^B$	acreage of nearest List3 site if sale occurred before the site was listed, 0 otherwise,
$invl1d^Aacre$	$invl1d^A \times$ acreage of nearest List1 site
$invl1d^Bacre$	$invl1d^B \times$ acreage of nearest List1 site
$invl2d^Aacre$	$invl2d^A \times$ acreage of nearest List2 site
$invl2d^Dacre$	$invl2d^D \times$ acreage of nearest List2 site
$invl2d^Bacre$	$invl2d^B \times$ acreage of nearest List2 site
$invl3d^Aacre$	$invl3d^A \times$ acreage of nearest List3 site
$invl3d^Bacre$	$invl3d^B \times$ acreage of nearest List3 site

The Base model was re-estimated for each land-use category where the variables listed above were used in addition to the inverse distance variables. The interaction variables will test whether the acreage of the nearest site affects the steepness of the gradient for the distance measures. Table 5.12 reports the coefficients estimates for the six land-use categories. The pre-listing acreage of the nearest List1 site ($l1acre^B$) is negative and statistically significant for the Apartment/Hotel/Motel model, but the post-listing acreage of the nearest List1 site ($l1acre^A$) is not statistically significant in any of the estimated models. The List1 site post-listing distance interaction variables ($invl1d^Aacre$) is only estimated to be negative in three of the six models (Office, Apartment/Hotel/Motel, and Vacant), but similarly, they were not statistically significant for any of them. The List1 pre-listing distance interaction coefficient ($invl1d^Bacre$) in the Industrial, Auto-Related, and Vacant models were also negative, but again, were never statistically significant.

Similar results were obtained for List1 sites in the hedonic models that use the reduced set of independent variables (i.e. RBM or variables in Table 5.2 with t-statistics less than 0.50 were dropped). As shown in Table 5.13, the magnitude of the coefficients and levels of significance only vary very slightly when compared to Table 5.12. The results for the List2 and List3 acreage variables and interaction terms in Tables 5.12 and

5.13 were also consistent with the results from the previous hedonic models estimated. In general, they indicate that List2 and List3 do not negatively affect nearby CI property values.

Although the List1, List2,and List3 acreage variables and interaction terms were not found to have any negative effect on property values, their inclusion did lead to some minor changes in the coefficient estimates for the inverse distance measures. Including the additional variables mainly resulted in a slight change in the estimates for the List1 pre- and post-listing distance coefficients (i.e. $invl1d^B$ and $invl1d^A$) for the Retail models. When the acreage variables and interaction terms are included, the magnitude of the List1 post-listing gradient ($invl1d^A$) decreases (i.e. becomes less negative). Furthermore, the estimate for the pre-listing ($invl1d^B$) coefficient becomes more negative, but is still not significant. As such, the difference between the List1 pre- and post-listing distance coefficients are not as great when compared to the Base model. The difference between the List1 pre- and post-listing distance coefficients in the Office, Industrial, and Auto-Related models were very similar to the results obtained in the Base models. However, the List1 post-listing distance coefficient in the Office model was not significant at the 0.10 level (t-statistic equal to -1.59) when the full set of independent variables were used (see Table 5.12), but it was significant at the 0.05 level (t-statistic equal to -2.35) in the model using the reduced set of independent variables (see Table 5.13). The List1 pre- and post-listing distance coefficients were still not statistically significant in Apartment/Hotel/Motel and Vacant models. In addition, the coefficient estimates for the List2 and List3 inverse distance measures and their levels of significance are relatively unchanged compared to those reported in Table 5.2 (i.e. Base model). Overall, the results of the hedonic models estimated continue to indicate that the negative effects of contaminated sites on CI property values are primarily due to proximity to the nearest List1 site, and the magnitude of the negative effects do not vary according to the size of the nearest site.

Land-use of Nearest Contaminated Site

The effect that proximity to the nearest contaminated site has on nearby CI property values is investigated further to determine if spillover effects vary by the major land-use category of the nearest site. It may be reasonable to assume that the magnitude of the spillover effects of contaminated sites could be greater for industrial type properties than for non-industrial properties. Industrial sites are likely to have aesthetic characteristics that may enhance the risks perceptions of nearby property owners regarding the potential for contaminant migration or exposure to contamination through other pathways (i.e. air, water, or direct exposure through inadvertent crossing of property lines). Therefore, the perceived risks of contaminated industrial sites may be greater than for other land-use types, even though there may not necessarily be a higher level of contamination present. As such, contaminated industrial sites may have a larger negative effect on nearby CI property values than non-industrial sites.

To address this issue, the Base hedonic model (Equation 5.1) estimated for each major land-use category is re-estimated to account for the land-use type of the nearest List1 site. It was assumed that accounting for the land-use type of the nearest List2 and

List3 site was not necessary because the analysis up to this point has not shown any clear evidence that List2 and List3 sites have a negative effect on nearby CI property values. Therefore, the focus will be on any potential differences in the price impacts of List1 sites only. In the Base model specification, pre- and post-listing inverse distance variables were used to control for the effects of the nearest List1 site. To account for the major land-use type of the nearest List1 site, the pre- and post-listing distance variables were modified as follows:

$invl1d^{A}ind$	inverse distance of property *i* to nearest List1 site if sale occurred after the site was listed and if the nearest List1 site is an industrial site, 0 otherwise
$invl1d^{B}ind$	inverse distance of property *i* to nearest List1 site if sale occurred before the site was listed and if the nearest List1 site is an industrial site, 0 otherwise
$invl1d^{A}oth$	inverse distance of property *i* to nearest List1 site if sale occurred after the site was listed and if the nearest List1 site is a non-industrial site, 0 otherwise
$invl1d^{B}oth$	inverse distance of property *i* to nearest List1 site if sale occurred before the site was listed and if the nearest List1 site is a non-industrial site, 0 otherwise

The industrial vs non-industrial specification of the inverse distance variables was assumed to be most appropriate since 60.38 percent of List1 sites used in calculating the distance measures are sites with primary land-use types in the Industrial category. All other independent variables used in estimation are the same as those used for the Base models, including the inverse distance variables for List2 and List3 sites (see Table 5.2).

Table 5.14 provides the results of the models estimated for each major land-use that control for land-use type of the nearest List1 site. In four of the six models estimated (Retail, Industrial, Apartment/Hotel/Motel, and Auto-Related), the magnitude of the post-listing distance coefficient for industrial List1 sites ($invl1d^{A}ind$) is greater than the post-listing distance coefficient for non-industrial sites (invl1d^Aoth). Furthermore, invl1d^Aind was statistically significant in the Retail, Industrial, and Auto-Related, while invl1d^Aoth (post-listing distance coefficient for non-industrial sites) was only statistically significant for Office and Auto-Related. Wald tests indicate that the difference between the post-listing distance coefficients (i.e. the difference between invl1d^Aind and invl1d^Aoth) is not statistically significant in any of these models. This is likely a result of there not being a very large difference between the two post-listing distance coefficients. Compared to the results of the Base models for Retail, Industrial, and Auto-Related given in Table 5.2, the magnitude of the two post-listing distance coefficients compare favorably. In general, the post-listing distance coefficient for industrial List1 sites (invl1d^Aind) is greater (in absolute value) than the simple List1 site inverse distance coefficient (invl1d^A) estimated in the Base model (see Table 5.2), while the post-listing distance coefficient for non-industrial List1 sites (invl1d^Aoth) is lower (in absolute value).

A surprising result was obtained for Office model. Here, the post-listing distance coefficient for non-industrial List1 sites (invl1d^Aoth) was negative and statistically significant, while invl1d^Aind was negative and not significant. Additionally, the coefficient estimate for invl1d^Aoth is over 5.5 times larger than the estimate for invl1d^Aind. This was easily the largest difference between the post-listing distance coefficients when comparing all models. However, a Wald test indicates the difference in the post-listing distance coefficients (i.e. the difference between invl1d^Aind and invl1d^Aoth) for the Office model is not statistically significant. This is likely a result of the large standard errors for invl1d^Aind. Finally, only the pre-listing distance coefficient for industrial List1 sites (invl1d^{B}ind) in the Vacant model was found to be statistically significant. were observed to be statistically significant for any major land-use category.

A more conservative method of comparing the negative effects of industrial and non-industrial List1 sites is to compare the magnitude of the difference between the pre- and post-listing distance coefficients (i.e. compare invl1d^{B}ind - invl1d^{A}ind and invl1d^{B}oth - invl1d^{A}oth). For the land-uses in which one of the post-listing distance coefficients was statistically significant, the difference between the pre- and post-listing coefficients was greatest for industrial sites in the Retail and Industrial models, but greatest for non-industrial sites in the Office and Auto-Related models. Interestingly, in the Office model the magnitude of the difference for non-industrial sites was over eight times greater than that for industrial sites. Although the difference in coefficient estimates for non-industrial sites was also greatest in the Auto-Related model, it was only slightly larger than the difference for industrial sites. As for the Industrial model, the magnitude for industrial sites was just over 2.5 times larger than for non-industrial sites. The difference in magnitudes was less apparent in the Retail model where the difference in the pre- post-listing coefficients for industrial sites was only 1.6 times greater. This comparison was not made for Apartment/Hotel/Motel and Vacant since the post-listing distance coefficient for industrial and non-industrial sites was not statistically significant.

As was expected, the results for List2 and List3 sites are consistent to the results for the Base model given in Table 5.2. In addition to the models discussed above, hedonic models that use a reduced set of independent variables (i.e. variables in Table 5.2 with t-statistics less than 0.50 were dropped) were also estimated (see Table 5.15). Only a slight change in the pre- and post-listing distance coefficients for List1 sites was observed. This also applies for List2 and List3 sites. The results given in Table 5.14 and 5.15 suggest there may be some differences between the magnitude of the spillover effects of industrial and non-industrial List1 sites, but the general conclusion that industrial List1 sites have a greater negative effect on nearby CI property values than non-industrial sites cannot necessarily be made for all major land-use categories. However, the results of these models will be utilized in Chapter 7 to investigate the losses in CI property values associated with being located in close proximity to industrial and non-industrial List1 sites, and to compare to the total losses computed when not distinguishing between industrial and non-industrial sites.

Hedonic Property Models and Spatial Error Correlation

The presence of spatial error correlation is likely in a hedonic property value model since the relative location of properties throughout a geographic area is an important determinant of price. Spatial error correlation is described as spatial dependence across the errors terms. As Bell and Bockstael (2000) note, properties in close proximity to each other will have similar unobservable characteristics in hedonic models, which will likely result in spatial error correlation. Additionally, the neighborhood characteristics themselves may be spatially correlated, such as when using Census data to control for neighborhood attributes in the estimated model. Not accounting for spatial error correlation will lead to unbiased, but inefficient parameter estimates. Correlation matrix estimators that do not account for spatial error correlation are inconsistent, so that inference may be misleading.

In spatial econometrics, the method of capturing the spatial relationship between the observations within the study area is through the specification of a spatial weights matrix. A spatial weights matrix, W, is an $N \times N$ matrix that describes the relative spatial relationship between observations in the same "neighborhood". A simple example of a binary weights matrix can be given as follows. If an element in W equals zero, $w_{ij} = 0$, then this indicates that property j is not in the same "neighborhood" as property i, for $i \neq j$. When an element in W equals 1, $w_{ij} = 1$, then property j is considered to be in the same "neighborhood" as property i, for $i \neq j$. The diagonal elements in a spatial weights matrix are always set equal to zero. In application, a spatial weights matrix is commonly normalized or row-standardized so that the elements in each row sum to one.

Some important issues to consider when constructing the spatial weights matrix include how a property's "neighborhood" is defined (i.e. within what distance are other properties considered to be in the same neighborhood) and the use of uniform or nonuniform weights (i.e. incorporating the distance between properties). An example of a row-standardized weights matrix utilizing uniform weights is given below. Here, the neighborhood is described as all properties within a one mile radius. In this instance, non-zero elements in W are defined as $w_{ij} = 1/n_i$, indicating that property j is within one mile of property i and that there are n total properties within one mile of property i, for $i \neq j$. When $w_{ij} = 0$, then property j is not within one mile of property i, for $i \neq j$.

$$W = \begin{bmatrix} 0 & 0 & \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ 0 & 0 & \frac{1}{2} & \frac{1}{2} & 0 \\ \frac{1}{3} & \frac{1}{3} & 0 & \frac{1}{3} & 0 \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

The first row shows that properties $j = 3, 4, 5$ are the only properties within one mile of property $i = 1$ and therefore, $n_1 = 3$. Rows $i = 2, \ldots, 5$ of the weights matrix are interpreted in the same manner. There are several ways in which a spatial weights matrix can be specified, but in general, the construction of the spatial weights matrix should take into consideration the nature of the problem being modeled (LeSage 1998).

For this application, the spatial weights matrix is defined by a distance-decay matrix. Bell and Bockstael (2000) indicate that distance-decay type of spatial weights matrix is applicable to microeconomic data since it suggests that neighbors are less closely related when distance between them increases. The general form of the weights matrix used here defines the elements of the weights matrix equal to the inverse distance between properties raised to a power for distances less than or equal to some maximum distance. Specifically, the elements of a distance-decay weights matrix are defined as:

$$\begin{aligned} w_{ij} &= \frac{1}{(d_{ij})^p} \qquad if\ d_{ij} \le c \\ w_{ij} &= 0 \qquad\quad if\ d_{ij} > c, \end{aligned} \tag{5.5}$$

where d_{ij} is the distance between property i and property j, c is some maximum distance, and p is the power in which the distances are raised. When d_{ij} is greater than the distance cut-off, it is assumed that there is no dependence between the errors. Here, the distance cut-off is chosen to equal 3.25 miles and the power to raise the distances is set to one. Following Ihlanfeldt and Taylor (2004), this cut-off was selected to allow for all observations to have a least one neighbor, where they indicate that choosing the cut-off in this manner is likely to allow for nearly all types of spatial error correlation.

A linear hedonic model that incorporates spatial error correlation is given by the following:

$$\begin{aligned} P_j &= X_j \beta_j + \varepsilon_j \\ \varepsilon_j &= \lambda_j W_j \varepsilon_j + \mu_j \\ \mu_j &\sim N(0, \sigma^2 I), \end{aligned} \tag{5.6}$$

where, P_j is an $N\times1$ vector of sales prices for major land-use j, X_j is an $N\times K$ matrix of explanatory variables, β_j is a $K\times1$ vector of parameters associated with X_j, and λ_j is the coefficient in a spatial autoregressive structure for the error term ϵ_j, and W_j is an $N\times N$ spatial weight matrix associated with a spatial autoregressive process in the error term for land-use j. Equation 5.6 can further be rewritten as:

$$P_j = X_j \beta_j + (I - \lambda_j W_j)^{-1} \mu_j . \tag{5.7}$$

Models where $\lambda_j = 0$ simply describe the classical linear regression model without spatial effects.

A Lagrange multiplier (LM) test based on Burridge (1980) is used to test for spatial error correlation in the hedonic models estimated for the six major land-use categories. The test statistic is defined as:

$$LM_{\lambda} = \frac{\left[\frac{\hat{\varepsilon}' W \hat{\varepsilon}}{\hat{\sigma}^2}\right]^2}{T} \tag{5.8}$$

where

$$T = tr\left[(W' + W)W\right],$$

and where $\hat{\varepsilon}$ and $\hat{\sigma}^2$ are based on ordinary least squares (OLS) estimation of the model under the null of no spatial error correlation. Anselin et al. (1996) demonstrate that this statistic provides asymptotically the same inference to the Anselin (1988) LM test statistic for spatial error correlation in the presence of heteroskedasticity. This is beneficial because one can test for spatial error correlation in the presence of heteroskedasticity using Equation 5.8 without the computational difficulties associated with LM statistics in Anselin (1988).

The LM test statistics were generated using the results of the Base model specification (Equation 5.1) given in Table 5.2. The null hypothesis of no spatial error correlation was not rejected (0.05 level) for the Retail, Office and Apartment/Hotel/Motel categories. However, the null hypothesis was rejected (0.05 level) for the Industrial, Auto-Related, and Vacant models. To address the spatial error correlation present in the Industrial, Auto-Related and Vacant models, four spatial hedonic models following Equation 5.7 were estimated for each of these major land-uses. The four model specifications are based on whether the full set independent variables (i.e. variables in Base model) or the reduced set (i.e. RBM or variables in Base model with t-statistics less than 0.50 are dropped) are used and whether the pre- and post-listing inverse distance variables for List1 sites varies by the major land-use of the nearest site.[61]

The results of the spatial hedonic models estimated for the Industrial, Auto-Related, and Vacant land-uses are given in Table 5.16. For List1 sites, the results generated from the spatial models were generally consistent with those obtained from non-spatially corrected models (i.e. models estimated using OLS). The post-listing distance coefficient ($invl1d^{A}$) or the post-listing distance coefficient for industrial and non-industrial List1 sites ($invl1d^{A}ind$ and $invl1d^{A}oth$) were statistically significant for all of the Auto-Related spatial models estimated. Furthermore, very little difference between the spatial and OLS models was observed regarding the magnitude of the post-listing distance coefficients estimated for the Auto-Related models. In general, the spatial model estimates were slightly lower than the estimates from the OLS models.

Some differences were observed for the Industrial models. The post-listing distance coefficient ($invl1d^{A}$) and the post-listing distance coefficients for industrial and non-industrial List1 sites ($invl1d^{A}ind$ and $invl1d^{A}oth$) were close in magnitude for all the models, but were not statistically significant (0.10 level) in the models that use the full set of independent variables (see column one and two of Table 5.16). However, the post-listing distance coefficient ($invl1d^{A}$) and the post-listing distance coefficient for industrial List1 sites ($invl1d^{A}ind$) were statistically significant (0.10 level) in the models that use the reduced set of independent variables (see column three and four of Table 5.16). The post-listing distance coefficient for non-industrial List1 sites ($invl1d^{A}oth$) was not statistically

[61] As expected, the null hypothesis was also rejected (0.05 level) for the additional models estimated for Industrial, Auto-Related, and Vacant, while the null hypothesis could not be rejected (0.05 level) for Retail, Office, and Apartment/Hotel/Motel.

significant for either of the models. Although, this was also observed for similar models estimated using OLS. The pre-listing distance coefficient ($invl1d^B$) and pre-listing distance coefficient for industrial List1 sites ($invl1d^Bind$) were only statistically significant in the Auto-Related models. Finally, similar to the Vacant non-spatially corrected hedonic models, the List1 inverse distance coefficients were never statistically significant in the spatial hedonic models.

The correction for spatially correlated errors did not affect the conclusions that can be made about proximity to List2 and List3 sites. The results in Table 5.16 continue to suggest that List2 and List3 sites do not negatively affect the values of nearby CI properties. The estimates for the List1 site distance measures support the previous findings that CI properties in close proximity to a List1 site are negatively affected after the site has been listed. Furthermore, the negative effect on property values may be greater for industrial List1 sites compared to non-industrial List1 sites. Although the correction for spatially correlated errors was necessary for the Industrial, Auto-Related, and Vacant categories, the spatial hedonic models result in coefficient estimates that are similar in magnitude to the Base model and RBM. This is not surprising since the coefficient estimates for the OLS hedonic models are consistent in the presence of spatial error correlation.

Conclusion

This chapter focused on the estimation of hedonic property value models to investigate the negative effects that known contaminated sites have on nearby CI property values. First, a base hedonic model (Base) was developed where the variables used to control for the externality effects of contaminated sites were specified according to theoretical priors. Variations of the Base model were then estimated where the models estimated utilized a reduced set of independent variables (RBM - the Base model where certain variables not associated with contaminated sites are not included). Comparisons of goodness-of-fit criterion between the Base model and other specifications of hedonic models indicated that the Base model was an appropriate functional form. The robustness of the Base model and RBM were tested based on assumptions about the size of the nearest contaminated site, the land-use type of the nearest site, and the form of spatial error correlation present in the models. The results indicate that proximity to a List1 site has a negative effect on nearby property values for properties in the Retail, Office, Industrial, and Auto-Related land-use categories. Additionally, the magnitude of the effects may differ for List1 sites with industrial and non-industrial land-uses. These models will be replicated in Chapter 6, but the models estimated will consider both known contaminated sites and sites that are predicted to be contaminated, but do not have a documented record of a contaminant release. Chapter 7 will discuss the size of the total impacts on CI property markets in Fulton County, Georgia, where the results from Chapter 5 will be used to compute the reduction in property value associated with being located in close proximity to a List1 site, and the results from Chapter 6 will be used to determine the potential effects from being located in close proximity to a site that may be perceived to be contaminated.

Table 5.1. Description of Explanatory Variables

Variable Name	Description
Property Characteristics	
ret1	dummy variable indicating if property is retail, multi-occupancy
ret2	dummy variable indicating if property is retail, single-occupancy
ret3	dummy variable indicating if property is retail, row
ret6	dummy variable indicating if property is retail, food
ret7	dummy variable indicating if property is retail, eating and drinking
ret8	dummy variable indicating if property is retail, fast food
off1	dummy variable indicating if property is office, medical
off2	dummy variable indicating if property is office, banking
off3	dummy variable indicating if property is office, low-rise
off4	dummy variable indicating if property is office, high-rise
off5	dummy variable indicating if property is office, condo
ind1	dummy variable indicating if property is warehouse/storage
ind2	dummy variable indicating if property is manufacturing/processing - light
ind3	dummy variable indicating if property is manufacturing/processing - heavy
ahm1	dummy variable indicating if property is mixed residential/commercial
ahm2	dummy variable indicating if property is apartment, loft/mid-rise
ahm3	dummy variable indicating if property is garden apartment
ahm4	dummy variable indicating if property is high-rise apartment
ahm5	dummy variable indicating if property is luxury/first class hotel
ahm6	dummy variable indicating if property is economy/budget model
ahm7	dummy variable indicating if property is nursing home/boarding house/day care
auto1	dummy variable indicating if property is auto dealer, full service
auto2	dummy variable indicating if property is auto service garage
auto3	dummy variable indicating if property is service station/truck stop
auto4	dummy variable indicating if property is car wash
vac1	dummy variable indicating if property is vacant, apartment
vac2	dummy variable indicating if property is vacant, commercial
vac3	dummy variable indicating if property is vacant, industrial
vac5	dummy variable indicating if property is vacant, other
sqft	square feet of floor space for all improvements
sqft2	sqft × sqft
age	age of primary structural improvement on property
age2	age × age
acre	size of property
acre2	acre × acre
numimp	number of improvements

Table 5.1 Continued

Variable Name	Description
bgradeaave	dummy variable indicating if primary structure on property is of above-average quality
bgradeave	dummy variable indicating if primary structure on property is of average quality
bgradebave	dummy variable indicating if primary structure on property is of below-average quality
extframe	dummy variable indicating if exterior wall of the primary structure is frame
extbrick	dummy variable indicating if exterior wall of the primary structure is brick
extconc	dummy variable indicating if exterior wall of the primary structure is concrete
extmetal	dummy variable indicating if exterior wall of the primary structure is metal
extglass	dummy variable indicating if exterior wall of the primary structure is glass
extmisc	dummy variable indicating if exterior wall of the primary structure is other
pqadeq	dummy variable indicating if property has adequate parking available
front1	dummy variable indicating if property fronts CBD street
front2	dummy variable indicating if property fronts major strip
front34	dummy variable indicating if property fronts secondary artery or street
front56	dummy variable indicating if property fronts frontage or private road
front9	dummy variable indicating if property fronts residential street
loc12	dummy variable indicating if the type of location for the property is CBD or permanent CBD
loc3	dummy variable indicating if the type of location for the property is business cluster
loc4	dummy variable indicating if the type of location for the property is major strip
loc5	dummy variable indicating if the type of location for the property is secondary strip
loc6	dummy variable indicating if the type of location for the property is neighborhood or spot
loc7	dummy variable indicating if the type of location for the property is commercial/industrial park
loc8	dummy variable indicating if the type of location for the property is industrial site
loc9	dummy variable indicating if the type of location for the property is apartment/condominium complex
yr80 - yr00	dummy variables indicating the year the property sold for years 1980 to 2000
Neighborhood and Spatial Variables	
north	dummy = 1 if property is located in north Fulton County
cbd	distance to CBD
ncbd	north × cbd
martahm	dummy = 1 if property is located within ½ mile of a MARTA transit station

Table 5.1 Continued

Variable Name	Description
nmartahm	north × martahm
exit	distance to nearest major highway exit
nexit	north × exit
harts	distance to Hartsfield International Airport
harts2	harts × harts
jursi1	dummy = 1 if property is located in Alpharetta
jursi2	dummy = 1 if property is located in Atlanta
juris3	dummy = 1 if property is located in College Park
juris4	dummy = 1 if property is located in East Point
juris5	dummy = 1 if property is located in Fairburn
juris6	dummy = 1 if property is located in Fulton
juris7	dummy = 1 if property is located in Hapeville
juris8	dummy = 1 if property is located in Palmetto
juris9	dummy = 1 if property is located in Roswell
rmedinc	real median income, by year, of the census tract the property is located
nrmedinc	north × rmedinc
minority	percent non-white population, by year, of the census tract the property is located
nminority	north × minority
popdens	population density, by year, of the census tract the property is located
npopdens	north × popdens
empdens	employment density, by year, of the census tract the property is located
nempdens	north × empdens
Proximity to Contaminated Site Variables	
$invl1d^A$	inverse distance of property *i* to nearest List1 site if sale occurred after the site was listed, 0 otherwise
$invl1d^B$	inverse distance of property *i* to nearest List1 site if sale occurred before the site was listed, 0 otherwise
$invl2d^A$	inverse distance of property *i* to nearest List2 site if sale occurred after the site was de-listed (i.e. site was classified as NFRAP), 0 otherwise
$invl2d^D$	inverse distance of property *i* to nearest List2 site if sale occurred after the site was listed on CERCLIS but before it was de-listed, 0 otherwise
$invl2d^B$	inverse distance of property *i* to nearest List2 site if sale occurred before the site was listed, 0 otherwise
$invl3d^A$	inverse distance of property *i* to nearest List3 site if sale occurred after the site was listed, 0 otherwise
$invl3d^B$	inverse distance of property *i* to nearest List3 site if sale occurred before the site was listed, 0 otherwise

Table 5.2. Results of Base Hedonic Models

	Retail		Office		Industrial		Apartment/ Hotel/Motel		Auto-Related		Vacant	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
constant	732,235.80	3.04	4,133,232.00	0.85	1,250,319.00	1.05	-717,397.90	-0.56	-479,541.40	-1.00	1,168,919.00	1.98
yr80	-256,920.70	-1.71	-3,198,799.00	-0.82	-208,583.00	-1.42	-543,275.90	-1.92	-32,049.09	-0.26	-578,636.60	-1.46
yr81	-191,394.30	-1.44	-2,026,226.00	-1.04	-156,467.10	-1.19	-707,366.50	-1.98	-201,446.70	-1.64	-743,271.40	-2.59
yr82	-278,223.10	-1.89	-1,853,988.00	-1.28	87,533.51	0.35	-267,207.30	-0.74	115,311.20	0.32	-346,793.00	-1.67
yr83	-199,490.50	-1.23	-3,346,719.00	-1.12	-107,736.90	-0.73	-389,470.10	-1.46	-144,463.30	-1.50	-518,853.40	-2.50
yr84	-110,729.60	-1.00	-6,970,053.00	-1.10	-451,877.30	-1.22	-313,838.20	-1.43	-430,530.90	-2.88	-121,948.20	-0.46
yr86	-135,970.30	-0.99	148,173.30	0.15	20,824.39	0.21	-273,498.40	-1.03	2,101.58	0.02	-391,464.00	-2.08
yr87	-160,650.90	-1.03	-106,585.10	-0.07	-56,358.56	-0.25	303,274.10	0.68	-120,991.30	-0.92	-129,606.50	-0.50
yr88	-3,708.44	-0.03	57,612.86	0.04	144,716.80	0.63	-612,677.50	-1.92	12,780.06	0.10	-301,115.30	-1.19
yr89	-13,495.25	-0.09	-226,372.10	-0.18	729,979.60	2.72	-312,996.80	-0.95	-69,767.99	-0.36	-13,668.37	-0.05
yr90	-76,160.90	-0.77	-1,436,160.00	-0.95	46,453.69	0.31	259,221.00	0.67	5,564.71	0.05	-170,589.10	-0.89
yr91	-29,893.34	-0.31	3,251,990.00	1.45	-235,424.70	-1.08	-115,680.70	-0.44	-326,250.90	-1.28	-1,226,229.00	-1.73
yr92	-77,224.35	-0.63	-4,462,984.00	-1.41	231,391.70	1.11	-255,613.30	-1.20	-75,771.59	-0.18		
yr93	25,633.01	0.25	-730,414.40	-0.26	291,841.80	1.17	-354,036.40	-1.52	-2,898.13	-0.01	-414,091.50	-2.02
yr94	28,789.03	0.27	467,612.90	0.17	-57,325.81	-0.12	-220,619.30	-0.83	244,071.80	1.18	-913,697.80	-2.22
yr95	221,662.50	1.20	-328,350.40	-0.19	351,204.60	1.49	-321,202.90	-1.12	-6,352.14	-0.05	545,122.50	1.55
yr96	-56,123.40	-0.48	-318,811.10	-0.17	290,609.80	1.44	-267,967.40	-1.03	77,974.09	0.40	-111,701.80	-0.39
yr97	16,040.11	0.15	2,369,132.00	0.90	479,535.90	2.06	-162,978.10	-0.68	83,650.89	0.61	166,817.20	0.64
yr98	84,234.00	0.70	6,643,503.00	1.66	561,838.40	2.13	-426,699.00	-1.20	288,361.30	2.05	163,843.30	0.77
yr99	48,825.92	0.42	4,405,659.00	1.66	112,878.80	0.59	175,801.90	0.44	218,077.20	1.57	-176,008.80	-0.90
yr00	98,774.90	1.03	2,959,384.00	1.49	2,030,972.00	1.21	219,376.20	0.58			-45,129.66	-0.17

Table 5.2. Continued

	Retail		Office		Industrial		Apartment/ Hotel/Motel		Auto-Related		Vacant	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
ret1	148,680.10	1.84										
ret3	39,889.26	0.64										
ret6	91,738.09	1.02										
ret7	138,205.40	1.21										
ret8	-83,305.94	-0.71										
off1			-695,871.50	-1.01								
off2			-1,955,068.00	-1.21								
off4			2,214,543.00	1.51								
off5			781,179.60	0.22								
ind1					273,188.70	1.88						
ind3					198,688.50	1.05						
ahm1							222,823.30	1.48				
ahm2							1,813,566.00	2.12				
ahm4							-5,398,759.00	-2.62				
ahm5							14,900,000.00	3.89				
ahm6							1,027,709.00	1.60				
ahm7							190,534.90	1.00				
auto1									332,458.70	1.05		
auto2									-111,633.50	-1.49		
auto4									-136,144.20	-1.02		
vac1											391,053.90	1.87

Table 5.2. Continued

	Retail		Office		Industrial		Apartment/ Hotel/Motel		Auto-Related		Vacant	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
vac3											270,181.90	0.81
vac5											150,998.80	0.91
sqft	23,904.08	2.83	61,900.05	1.93	16,861.35	5.49	21,730.53	1.55	29,704.77	3.51		
sqft2	-54.03	-3.33	-9.83	-0.37	-14.40	-6.56	-17.88	-1.94	-219.88	-3.59		
age	-6,482.46	-2.46	-102,704.60	-1.32	-7,293.89	-0.96	-17,299.24	-1.16	-6,519.33	-1.00		
age2	45.93	2.20	514.10	0.64	55.12	0.66	140.74	1.35	24.14	0.33		
acre	158,377.70	1.91	-416,901.20	-0.43	13,172.04	0.33	143,329.50	0.91	-205,503.20	-1.18	22,315.05	1.46
acre2	-5,215.28	-1.38	34,576.14	0.34	421.08	0.84	5,371.53	1.31	48,575.41	1.50	-195.35	-1.18
numimp	-63,666.97	-1.28	-219,685.40	-0.32	-51,968.77	-1.38	-57,434.13	-0.52	-25,971.92	-0.40		
bgradeaave	161,871.00	1.03	401,875.90	0.32	-787,521.50	-1.41	-751.30	0.00	-11,797.85	-0.09		
bgradebave	9,575.33	0.24	-173,771.10	-0.20	16,036.02	0.16	43,351.51	0.62	-25,014.81	-0.45		
extframe	95,397.76	0.78	49,371.52	0.05	-168,107.10	-0.83	-194,812.40	-1.69	-315,309.50	-1.83		
extconc	-29,678.58	-0.58	113,198.60	0.06	100,438.00	0.78	740,872.60	2.15	25,587.59	0.38		
extmetal	-14,254.40	-0.20	-416,884.30	-0.26	-142,858.50	-1.39	-7,083,094.00	-4.88	-110,060.40	-1.28		
extglass	-31,400.97	-0.32	-6,866,333.00	-1.27	2,673,438.00	2.35	501,316.10	0.24	-437,005.80	-1.31		
extmisc	-29,065.86	-0.28	-150,901.30	-0.16	96,132.88	0.36	-69,249.99	-0.45	2,319.65	0.02		
pqadeq	31,940.24	0.63	575,765.50	0.47	102,089.40	0.85	-33,441.63	-0.38	64,672.47	0.57		
front1	-361,314.10	-1.22	2,856,602.00	1.08	-564,054.40	-0.57	2,943,495.00	1.77	381,417.10	1.78	102,293.50	0.17
front34	-189,741.40	-1.58	1,201,388.00	0.78	-774,044.80	-1.04	1,908,814.00	2.38	-97,090.43	-0.91	-1,286.94	-0.01
front56	160,384.70	1.11	3,195,144.00	0.69	146,138.20	0.20	430,155.50	0.30	-181,448.70	-0.58	-453,719.40	-1.24
front9	-236,214.60	-1.90	184,890.60	0.08	-768,975.90	-1.07	1,973,282.00	2.48	15,622.24	0.15	-144,814.80	-0.72

Table 5.2. Continued

	Retail		Office		Industrial		Apartment/ Hotel/Motel		Auto-Related		Vacant	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
loc12	445,034.80	1.66	1,115,285.00	0.69	388,560.60	0.63	-472,873.30	-0.34	5,208.10	0.02	1,047,621.00	1.73
loc3	92,686.42	0.91	2,848,678.00	0.87	860,655.00	1.10	2,616,831.00	1.10	373,311.40	0.86	-65,405.52	-0.35
loc5	-5,118.16	-0.11	-1,303,744.00	-1.12	-151,283.60	-0.46	139,636.50	0.49	18,017.97	0.18	-299,174.40	-1.98
loc6	40,517.57	0.54	-1,762,690.00	-1.39	-2,072.97	-0.01	21,804.36	0.07	36,044.38	0.37	-98,834.08	-0.61
loc7	-34,964.08	-0.51	-2,277,620.00	-1.02	132,930.20	0.36	-976,737.00	-2.11	-9,043.77	-0.08	154,014.60	0.92
loc8	-129,556.40	-1.07	-3,114,768.00	-1.02	50,894.49	0.13	-1,231,085.00	-0.69	624,182.00	1.90	-106,047.90	-0.59
loc9	-14,496.56	-0.07	-4,370,284.00	-1.07			248,403.40	0.78			80,319.75	0.44
rmedinc	-0.20	-0.03	-15.84	-0.12	35.51	2.06	18.78	1.22	-0.35	-0.03	12.91	1.23
nrmedinc	17.62	1.50	62.26	0.40	-36.57	-1.64	-66.52	-2.12	10.10	0.79	-58.31	-1.82
minority	-284,780.60	-2.44	-3,049,729.00	-1.22	-48,820.60	-0.08	237,150.80	0.60	136,150.70	0.58	-464,655.70	-0.96
nminority	124,154.50	0.72	10,100,000.00	1.88	-2,645.20	0.00	-1,445,121.00	-2.45	27,060.43	0.11	-380,230.00	-0.56
popdens	14,792.76	1.67	277,565.70	0.77	6,931.90	0.25	4,400.29	0.14	13,230.20	0.49	12,245.48	0.74
npopdens	-9,316.64	-0.81	-850,051.00	-1.50	-1,208.12	-0.03	49,819.04	1.55	503.19	0.02	2,837.47	0.11
empdens	1,103.55	0.72	-5,885.28	-0.14	-91.61	-0.02	-11,021.04	-1.27	172.39	0.06	-8,275.08	-2.68
nempdens	-1,407.23	-0.84	-5,639.32	-0.12	3,858.89	0.69	-12,754.34	-1.20	507.62	0.10	36,304.04	2.50
north	270,331.10	1.31	1,555,677.00	0.30	198,407.10	0.26	2,255,560.00	2.64	55,894.64	0.15	-46,858.29	-0.05
cbd	-7,207.29	-0.24	416,469.30	0.98	-80,551.08	-1.07	-129,415.20	-1.67	44,278.50	1.62	-46,189.14	-1.16
ncbd	-12,741.45	-0.45	-858,357.40	-0.73	69,233.51	0.93	207,954.80	2.02	-15,962.84	-0.38	71,225.90	1.13
martahm	-50,625.94	-1.13	-368,553.80	-0.41	-192,166.00	-1.41	-24,306.28	-0.17	140,515.80	1.61	-301,382.20	-2.63
nmartahm	-85,886.04	-0.80	-797,512.80	-0.47	177,050.40	0.63	274,924.50	1.17	-271,579.20	-1.78	166,766.60	0.62
exit	72,637.53	1.26	-691,378.90	-0.51	-88,635.91	-0.40	116,822.40	1.01	-32,531.27	-0.40	-45,450.82	-0.37

Table 5.2. Continued

	Retail		Office		Industrial		Apartment/ Hotel/Motel		Auto-Related		Vacant	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
nexit	-365,168.90	-2.44	310,530.20	0.18	-358,354.40	-1.31	-1,095,742.00	-3.54	-81,713.45	-0.48	58,927.50	0.21
harts	-60,317.38	-1.35	-376,861.10	-0.42	-312,118.40	-0.94	-267,346.50	-1.58	117,898.70	1.97	-155,754.20	-0.99
harts2	2,309.51	1.20	31,377.90	0.64	26,127.40	1.20	17,953.90	1.47	-5,207.16	-1.81	17,757.03	1.82
juris1												
juris3	-158,288.60	-0.90	-3,443,433.00	-0.91	243,294.80	0.42	428,264.70	0.75	226,859.60	1.12	213,629.30	0.54
juris4	-271,800.30	-2.18	-2,894,552.00	-0.86	-97,965.58	-0.19	-54,221.76	-0.17	176,378.00	1.04	-248,752.50	-1.01
juris5	-169,094.40	-0.41	-5,529,601.00	-1.06	342,589.70	0.36	1,506,456.00	1.49	-335,873.90	-0.72	-621,628.50	-1.02
juris6	-272,757.50	-1.14	-4,798,879.00	-1.32	91,848.98	0.16	615,013.30	1.12	475,661.40	2.15	39,479.40	0.10
juris7	-272,932.10	-1.59	-1,420,446.00	-0.34	-59,444.19	-0.08	-25,855.77	-0.06	306,803.30	1.00	-368,355.30	-1.02
juris8	-58,715.19	-0.08	-9,870,443.00	-0.96	-2,241,790.00	-1.40	974,740.70	0.48	-1,442,720.00	-1.51	-1,987,537.00	-2.39
juris9							-4,720,910.00	-1.33			-6,680,296.00	-2.21
$invl1d^{A}$	-11,424.04	-1.93	-894,023.20	-1.75	-33,661.13	-2.26	-17,167.13	-0.35	-44,137.37	-2.34	-8,353.59	-0.65
$invl1d^{B}$	-3,477.60	-0.47	-130,800.80	-0.37	-2,577.02	-0.21	-20,751.47	-0.81	-25,204.34	-1.51	-16,089.66	-1.22
$invl2d^{A}$	-2,567.62	-0.48	-81,903.82	-0.33	7,914.31	0.81	2,117.59	0.12	7,722.25	0.50	6,532.66	0.62
$invl2d^{D}$	18,059.43	0.88	103,668.00	0.64	-5,911.73	-0.54	-3,996.63	-0.15	12,435.69	0.70	2,546.71	0.16
$invl2d^{B}$	-10,985.64	-0.94	-1,198,286.00	-1.27	-34,534.77	-1.46	-26,329.34	-0.92	18,451.26	0.77	-24,053.93	-1.06
$invl3d^{A}$	4,012.95	0.62	-81,176.58	-1.11	34,372.07	1.11	-2,035.00	-0.12	-10,326.89	-0.99	-9,455.78	-0.73
$invl3d^{B}$	1,343.17	0.94	119,446.70	1.23	7,009.28	1.01	-4,880.32	-0.22	7,408.19	0.89	-3,736.43	-0.72
N	916		230		730		1,433		208		711	
R^2	0.370		0.666		0.480		0.639		0.759		0.358	

Table 5.3. Difference Between Pre- and Post-listing Inverse Distance Coefficients for List1 Sites[a]

	Retail	Office	Industrial	Apartment/ Hotel/Motel	Auto-Related	Vacant
Post-listing	-11,424.04	-894,023.20	-33,661.13	-17,167.13	-44,137.37	-8353.59
($invl1d^A$)	(-1.93)	(-1.75)	(-2.26)	(-0.35)	(-2.34)	(-0.65)
Pre-listing	-3,477.60	-130,800.80	-2,577.02	-20,751.47	-25,204.34	-16,089.66
($invl1d^B$)	(-0.47)	(-0.37)	(-0.21)	(-0.81)	(-1.51)	(-1.22)
Difference[b]	-7,946.44	-763,222.40	-31,084.12	3,584.34	-18,933.03	7,736.07
	(-0.87)	(-1.64)	(-1.70)	(0.07)	(-1.21)	(-0.45)

[a] t-statistics in parentheses

[b] The coefficient is determined from a separate regressions in which $invl1d^A$ and $invl1d^B$ are combined to form *invl1d* (defined as the inverse distance to nearest List1 site), where the regression models estimated include both *invl1d* and $invl1d^A$. The coefficient reported is for the variable $invl1d^A$ from these models, which shows the difference between the coefficients for $invl1d^A$ and $invl1d^B$ and whether the difference is statistically significant.

Table 5.4. Results After Dropping Variables With t-statistics Less Than 0.50 from Base Models

	Retail	Office	Industrial	Apartment/ Hotel/Motel	Auto-Related	Vacant
$\mathit{invl1d}^{A}$	-10,597.61	-856,675.20	-33,189.59	-11,565.63	-46,735.51	-9,045.60
	(-2.03)	(-2.60)	(-2.30)	(-0.23)	(-2.85)	(-0.73)
$\mathit{invl1d}^{B}$	-3,503.09	-108,553.00	-2,537.17	-25,842.53	-30,962.60	-15,296.87
	(-0.48)	(-0.47)	(-0.21)	(-1.10)	(-2.28)	(-1.12)
$\mathit{invl2d}^{A}$	-1,470.60	-93,054.92	6,986.66	6,283.80	6,809.99	5,234.47
	(-0.36)	(-0.53)	(0.66)	(0.38)	(0.73)	(0.48)
$\mathit{invl2d}^{D}$	18,783.01	96,379.68	-7,136.48	-5,845.47	12,344.10	3,583.39
	(0.95)	(0.87)	(-0.69)	(-0.22)	(1.01)	(0.21)
$\mathit{invl2d}^{B}$	-9,835.97	-1,093,902.00	-35,216.15	-25,938.45	17,768.11	-23,824.76
	(-0.97)	(-1.47)	(-1.83)	(-0.88)	(1.53)	(-1.23)
$\mathit{invl3d}^{A}$	5,625.44	-81,383.98	35,021.45	-295.37	-5,691.31	-10,031.25
	(0.93)	(-1.48)	(1.16)	(-0.02)	(-0.58)	(-0.92)
$\mathit{invl3d}^{B}$	1,644.33	106,793.90	8,459.88	-8,938.38	9,373.88	-3,645.14
	(1.08)	(1.32)	(1.28)	(-0.40)	(1.03)	(-0.72)
N	916	230	730	1,433	208	711
R^2	0.368	0.661	0.477	0.638	0.747	0.357

Table 5.5. Difference Between Pre- and Post-listing Inverse Distance Coefficients for List1 Sites After Dropping Variables With t-statistics Less Than 0.50 from Base Models[a]

	Retail	Office	Industrial	Apartment/ Hotel/Motel	Auto-Related	Vacant
Post-listing ($invl1d^A$)	-10,597.61 (-2.03)	-856,675.20 (-2.60)	-33,189.59 (-2.30)	-11,565.63 (-0.23)	-46,735.51 (-2.85)	-9,045.60 (-0.73)
Pre-listing ($invl1d^B$)	-3,503.09 (-0.48)	-108,553.00 (-0.47)	-2,537.17 (-0.21)	-25,842.53 (-1.10)	-30,962.60 (-2.28)	-15,296.87 (-1.12)
Difference[b]	-7,094.52 (-0.88)	-779,144.30 (-2.46)	-30,652.42 (-1.81)	14,644.20 (0.30)	-15,772.90 (-1.21)	6,251.27 (-0.37)

[a] t-statistics in parentheses

[b] The coefficient is determined from a separate regressions in which $invl1d^A$ and $invl1d^B$ are combined to form $invl1d$ (defined as the inverse distance to nearest List1 site), where the regression models estimated include both $invl1d$ and $invl1d^A$. The coefficient reported is for the variable $invl1d^A$ from these models, which shows the difference between the coefficients for $invl1d^A$ and $invl1d^B$ and whether the difference is statistically significant.

Table 5.6. Results After Dropping Variables With t-statistics Less Than 1.0 from Base Models

	Retail	Office	Industrial	Apartment/ Hotel/Motel	Auto-Related	Vacant
$invl1d^A$	-4,806.75	-727,775.90	-35,956.76	-31,120.63	-40,481.46	-7,212.86
	(-1.01)	(-2.84)	(-2.47)	(-0.62)	(-2.79)	(-0.55)
$invl1d^B$	-4,828.26	-162,474.50	-6,561.41	-25,349.98	-34,598.90	-13,767.92
	(-0.60)	(-0.90)	(-0.53)	(-1.02)	(-2.44)	(-1.09)
$invl2d^A$	2,741.64	-30,619.81	2,485.79	-2,560.14	4,849.10	9,041.02
	(0.66)	(-0.18)	(0.24)	(-0.14)	(0.61)	(0.96)
$invl2d^D$	18,756.45	86,008.37	-9,944.60	-16,906.62	5,783.25	20,590.05
	(0.99)	(1.17)	(-0.98)	(-0.62)	(0.50)	(1.12)
$invl2d^B$	-2,179.22	-1,014,578.00	-53,886.20	-39,365.98	15,258.30	-34,388.30
	(-0.27)	(-1.46)	(-2.52)	(-1.26)	(1.49)	(-1.67)
$invl3d^A$	7,020.78	-61,737.46	25,349.03	-1,536.45	-6,633.90	-7,832.43
	(1.20)	(-1.22)	(0.93)	(-0.10)	(-0.65)	(-0.86)
$invl3d^B$	1,445.31	72,777.59	4,446.39	-9,201.72	7,901.19	-1,334.42
	(0.97)	(1.00)	(0.77)	(-0.42)	(0.93)	(-0.24)
N	916	230	730	1,433	208	711
R^2	0.358	0.640	0.451	0.632	0.726	0.318

Table 5.7. Difference Between Pre- and Post-listing Inverse Distance Coefficients for List1 Sites After Dropping Variables With t-statistics Less Than 1.0 from Base Models[a]

	Retail	Office	Industrial	Apartment/ Hotel/Motel	Auto-Related	Vacant
Post-listing	-4,806.75	-727,775.90	-35,956.76	-31,120.63	-40,481.46	-7,212.86
($invl1d^A$)	(-1.01)	(-2.84)	(-2.47)	(-0.62)	(-2.79)	(-0.55)
Pre-listing	-4,828.26	-162,474.50	-6,561.41	-25,349.98	-34,598.90	-13,767.92
($invl1d^B$)	(-0.60)	(-0.90)	(-0.53)	(-1.02)	(-2.44)	(-1.09)
Difference[b]	21.52	-565,301.50	-29,395.35	-5,770.66	-5,882.56	-6,555.06
	(0.00)	(-2.33)	(-1.72)	(-0.11)	(-0.52)	(-0.42)

[a] t-statistics in parentheses.

[b] The coefficient is determined from a separate regressions in which $invl1d^A$ and $invl1d^B$ are combined to form $invl1d$ (defined as the inverse distance to nearest List1 site), where the regression models estimated include both $invl1d$ and $invl1d^A$. The coefficient reported is for the variable $invl1d^A$ from these models, which shows the difference between the coefficients for $invl1d^A$ and $invl1d^B$ and whether the difference is statistically significant.

Table 5.8. Goodness-of-Fit Comparisons Using Full Set of Independent Variables

	Dependent Variable = Sale Price		Dependent Variable = Ln(Sale Price)	
	Inverse Distance	Log Distance	Inverse Distance	Log Distance
Retail	0.370	0.372	0.221	0.242
Office	0.666	0.611	0.597	0.594
Industrial	0.480	0.484	0.386	0.372
Apartment/Hotel/Motel	0.639	0.640	0.494	0.509
Auto-Related	0.759	0.765	0.790	0.801
Vacant	0.358	0.359	0.457	0.441

Table 5.9. Goodness-of-Fit Comparisons Using Reduced Set of Independent Variables

	Dependent Variable = Sale Price		Dependent Variable = Ln(Sale Price)	
	Inverse Distance	Log Distance	Inverse Distance	Log Distance
Retail	0.368	0.369	0.241	0.269
Office	0.661	0.654	0.383	0.382
Industrial	0.477	0.481	0.346	0.348
Apartment/Hotel/Motel	0.638	0.639	0.488	0.500
Auto-Related	0.747	0.748	0.791	0.787
Vacant	0.357	0.359	0.417	0.418

Table 5.10. Density of Contaminated Sites (Base Model Specification)

	Retail		Office		Industrial		Apartment/ Hotel/Motel		Auto-Related		Vacant	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
invl1d^{A}	-16,043.32	-1.86	-994,593.00	-1.72	-30,750.45	-1.96	-7,067.43	-0.15	-42,402.32	-2.27	397.00	0.03
invl1d^{B}	-47.27	-0.01	-321,722.50	-0.73	-4,039.43	-0.31	-23,636.44	-0.94	-31,944.30	-1.70	-13,644.54	-1.18
invl2d^{A}	-3,752.94	-0.65	103,284.30	0.38	13,479.33	1.32	-16,366.49	-0.79	13,866.32	0.90	3,297.55	0.32
invl2d^{D}	26,421.68	1.26	156,681.90	0.91	-4,240.02	-0.40	11,825.77	0.51	5,605.94	0.28	2,315.59	0.16
invl2d^{B}	-15,583.75	-1.54	-848,418.30	-0.84	-36,575.79	-1.47	-3,155.52	-0.11	-6,529.39	-0.21	-16,421.60	-0.71
invl3d^{A}	1,123.87	0.17	-98,511.82	-1.15	30,398.71	0.92	-9,156.53	-0.51	-6,842.35	-0.64	-13,933.61	-1.01
invl3d^{B}	682.03	0.34	90,603.99	0.88	6,534.78	0.89	9,990.27	0.47	4,174.46	0.56	-5,498.71	-0.95
l1den1hm^{A}	49,257.99	1.49			-39,809.51	-0.74	7,725.56	0.12			-21,849.66	-0.38
l1den1hm^{B}	-6,466.66	-0.29			-37,597.34	-0.70	-139,171.80	-2.15			-41,259.03	-0.92
l1den1qm^{A}			328,313.10	0.68					-43,038.45	-1.07		
l1den1qm^{B}			-373,904.70	-0.88					56,458.52	1.03		
l2den1hm^{A}	-9,504.74	-0.50			-46,475.25	-1.27	55,931.81	1.16			-27,517.58	-0.68
l2den1hm^{D}	-50,255.98	-2.03			-13,099.81	-0.45	34,471.80	0.58			-15,572.28	-0.36
l2den1hm^{B}	956.24	0.03			-43,408.81	-0.95	-20,858.28	-0.29			31,315.77	0.32
l2den1qm^{A}			-938,995.00	-1.99					-196.85	-0.01		
l2den1qm^{D}			-552,864.10	-1.56					12,839.86	0.51		
l2den1qm^{B}			-1,361,668.00	-1.30					41,992.47	0.57		
l3denhm^{A}	23,599.17	0.51	47,022.69	0.06	98,745.39	1.08	91,453.90	0.94	-14,825.83	-0.35	172,892.10	2.67
l3denhm^{B}	62,126.03	1.02	156,538.10	0.35	21,942.45	0.54	-180,965.40	-2.15	44,748.29	1.08	18,282.77	0.28

Table 5.11. Density of Contaminated Sites (Models Estimated Use Reduced Set of Independent Variables)

	Retail		Office		Industrial		Apartment/ Hotel/Motel		Auto-Related		Vacant	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
invl1d^A	-17,480.31	-2.04	-854,908.40	-2.47	-29,338.53	-1.91	-16,201.80	-0.32	-45,244.00	-2.71	-2,652.01	-0.23
invl1d^B	368.60	0.05	-68,176.37	-0.25	-3,274.34	-0.25	-20,640.40	-0.93	-36,416.82	-2.24	-10,124.79	-0.87
invl2d^A	-2,605.04	-0.45	70,648.88	0.42	12,506.48	1.13	-15,951.91	-0.77	11,584.84	1.04	6,743.14	0.60
invl2d^D	28,305.42	1.32	143,257.80	1.32	-6,877.88	-0.65	13,049.18	0.60	1,175.46	0.09	3,209.02	0.20
invl2d^B	-11,115.30	-1.27	-788,262.30	-0.98	-39,366.13	-1.92	-1,295.30	-0.04	-8,128.39	-0.46	-22,130.45	-1.11
invl3d^A	1,325.54	0.22	-92,762.47	-1.56	30,108.00	0.93	-13,415.06	-0.72	-4,800.60	-0.46	-13,985.39	-1.12
invl3d^B	946.46	0.46	93,124.87	1.03	7,012.94	0.99	10,293.74	0.50	6,065.20	0.70	-5,132.44	-0.92
l1den1hm^A	41,442.45	1.35			-31,448.70	-0.65	-1,877.50	-0.03			-18,119.15	-0.46
l1den1hm^B	226.60	0.01			-31,475.91	-0.62	-124,833.40	-2.19			-24,556.00	-0.59
l1den1qm^A			155,168.50	0.45					-12,309.05	-0.47		
l1den1qm^B			-181,972.50	-0.57					18,957.23	0.68		
l2den1hm^A	-6,132.81	-0.33			-34,567.93	-1.13	57,862.43	1.19			-29,049.47	-0.80
l2den1hm^D	-35,584.16	-1.68			-5,704.62	-0.22	46,410.93	0.80			-12,731.03	-0.38
l2den1hm^B	14,831.36	0.45			-41,470.10	-1.00	-21,905.72	-0.32			30,156.47	0.31
l2den1qm^A			-565,437.10	-1.82					-115.15	-0.01		
l2den1qm^D			-92,900.45	-0.45					3,482.63	0.23		
l2den1qm^B			-1,004,725.00	-1.27					37,941.82	0.88		
l3denhm^A	25,578.70	0.52	-103,575.10	-0.19	98,906.83	1.20	69,542.50	0.71	-9,034.19	-0.25	152,848.60	2.68
l3denhm^B	57,251.49	0.94	-48,968.12	-0.19	28,113.46	0.83	-183,212.40	-2.04	42,665.00	1.92	7,096.78	0.13

Table 5.12. Inverse Distance to Nearest Contaminated Site Interacted with Size of Contaminated Site (Base Model Specification)

	Retail		Office		Industrial		Apartment/ Hotel/Motel		Auto-Related		Vacant	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
$invl1d^A$	-17,687.75	-2.38	-1,032,929.00	-1.59	-40,869.25	-2.21	6,643.88	0.11	-40,465.73	-2.09	7,740.02	0.55
$invl1d^B$	-11,676.82	-1.25	-323,221.30	-0.69	-2,502.63	-0.14	-21,310.96	-0.79	-22,094.81	-1.17	-16,300.52	-1.17
$invl2d^A$	-2,941.77	-0.58	-103,404.20	-0.35	3,744.28	0.34	-1,551.87	-0.08	5,968.94	0.32	-140.41	-0.01
$invl2d^D$	11,585.15	0.66	86,969.58	0.49	-7,833.83	-0.66	6,266.90	0.34	9,819.20	0.53	-1,708.92	-0.16
$invl2d^B$	-14,544.58	-1.09	-792,045.10	-0.62	-414,195.40	-2.11	-9,938.12	-0.23	13,397.98	0.31	-58,609.76	-1.31
$invl3d^A$	4,075.79	0.70	-69,637.03	-0.91	313.89	0.01	-2,406.65	-0.13	-13,769.48	-0.80	-14,612.11	-1.09
$invl3d^B$	-884.65	-0.56	101,063.10	0.63	8,079.65	1.07	5,369.55	0.22	11,109.34	1.31	-3,265.66	-0.61
l1acre^A	-2,884.13	-1.54	-15,670.35	-0.25	-9,106.20	-1.16	1,013.94	0.07	-2,877.75	-0.47	9,381.47	1.10
l1acre^B	-1,162.27	-0.98	-196,788.80	-1.02	4,145.31	0.53	-10,839.93	-1.72	1,279.42	0.91	-1,293.86	-0.33
l2acre^A	-1,997.35	-1.05	18,133.38	0.17	-1,752.77	-0.30	-2,203.78	-0.32	-712.45	-0.29	-104.27	-0.03
l2acre^D	-3,356.68	-1.26	-5,506.97	-0.14	6,918.44	1.71	6,858.42	0.62	7,172.89	1.05	2,807.27	0.52
l2acre^B	75.84	0.01	12,188.31	0.03	-95,768.89	-0.89	10,682.48	0.17	-14,695.32	-1.38	-22,807.83	-1.12
l3acre^A	-2,657.72	-0.51	-100,797.90	-0.47	-33,057.31	-1.46	21,210.92	1.20	-516.45	-0.05	-18,219.26	-1.34
l3acre^B	-5,820.35	-1.31	-55,004.80	-0.47	1,463.50	0.15	28,699.57	1.27	7,900.67	1.03	11,797.49	1.33
invl1d^{A}acre	677.76	0.96	-5,500.26	-0.27	2,755.43	0.74	-3,820.14	-0.46	1,235.02	0.59	-5,388.43	-1.48
invl1d^{B}acre	61.58	0.10	88,994.66	0.96	-674.71	-0.28	3,418.56	1.21	-172.43	-0.29	-551.68	-0.30
invl2d^{A}acre	-169.68	-0.29	-15,091.36	-0.35	704.41	0.24	1,664.93	0.60	566.11	0.86	908.49	0.56
invl2d^{D}acre	1,374.63	0.85	-3,957.66	-0.10	-4,734.71	-1.98	-5,598.40	-0.97	-1,636.32	-0.88	35.32	0.01
invl2d^{B}acre	1,288.48	0.31	-24,385.16	-0.10	154,430.60	2.05	-14,427.34	-0.38	9,344.71	0.60	11,609.27	1.59
invl3d^{A}acre	-279.05	-0.12	-13,766.97	-0.28	13,203.66	1.31	3,500.42	0.33	1,651.70	0.61	4,529.10	1.42
invl3d^{B}acre	5,246.87	1.87	3,551.53	0.10	178.28	0.09	-5,998.55	-1.22	-2,636.96	-1.47	-1,011.21	-0.29

Table 5.13. Inverse Distance to Nearest Contaminated Site Interacted with Size (Model Using Reduced Set of Independent Variables)

	Retail		Office		Industrial		Apartment/ Hotel/Motel		Auto-Related		Vacant	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
invl1d^{A}	-15,652.99	-2.40	-966,014.30	-2.35	-38,172.83	-2.02	4,547.08	0.08	-49,795.28	-2.80	6,655.06	0.46
invl1d^{B}	-11,361.21	-1.26	-151,221.60	-0.55	-5,435.98	-0.31	-25,411.24	-1.04	-32,599.40	-2.02	-15,861.35	-1.06
invl2d^{A}	-2,523.50	-0.58	-87,437.73	-0.44	3,109.21	0.25	260.40	0.01	7,088.72	0.63	-1,056.56	-0.10
invl2d^{D}	10,381.80	0.61	85,338.47	0.69	-7,801.31	-0.66	4,974.10	0.28	14,385.53	1.12	-927.50	-0.10
invl2d^{B}	-19,340.71	-1.47	-1,226,593.00	-1.07	-374,326.00	-2.07	-10,597.73	-0.24	29,592.86	1.41	-57,466.20	-1.43
invl3d^{A}	6,333.76	1.17	-89,283.98	-1.55	2,483.91	0.06	-1,994.77	-0.12	-13,108.84	-0.96	-14,535.82	-1.36
invl3d^{B}	-631.77	-0.37	90,189.69	0.68	9,526.12	1.30	-283.87	-0.01	11,793.46	1.15	-3,332.30	-0.65
l1acre^{A}	-2,300.93	-1.20	-18,449.03	-0.44	-7,321.57	-1.05	774.18	0.06	-2,448.49	-0.60	9,013.72	1.14
l1acre^{B}	-943.76	-0.90	-72,160.82	-0.77	2,897.39	0.39	-10,148.04	-1.64	375.14	0.31	-1,706.39	-0.44
l2acre^{A}	-1,514.64	-0.78	25,666.46	0.45	-489.66	-0.09	-3,714.34	-0.61	-225.94	-0.12	-553.25	-0.23
l2acre^{D}	-2,834.09	-1.26	1,321.82	0.05	6,314.47	1.23	5,654.45	0.46	5,671.59	1.48	2,628.90	0.47
l2acre^{B}	-3,193.20	-0.48	-27,670.99	-0.11	-67,171.87	-0.81	8,554.36	0.14	-6,211.88	-0.85	-21,823.81	-1.09
l3acre^{A}	-2,672.38	-0.51	-83,914.41	-0.62	-29,907.63	-1.43	17,344.21	1.12	-4,169.90	-0.64	-17,492.16	-1.36
l3acre^{B}	-6,999.40	-1.59	-27,752.49	-0.34	4,356.92	0.48	25,133.35	1.28	4,246.24	0.66	11,604.90	1.54
invl1d^{A}acre	489.58	0.66	-2,957.76	-0.19	2,140.26	0.62	-3,450.98	-0.43	767.93	0.51	-5,312.62	-1.52
invl1d^{B}acre	10.12	0.02	26,650.14	0.56	-69.05	-0.03	3,332.81	1.18	48.82	0.09	-518.73	-0.29
invl2d^{A}acre	-275.04	-0.59	-13,853.99	-0.46	425.46	0.14	1,749.02	0.65	504.82	0.96	1,005.36	0.66
invl2d^{D}acre	1,301.48	0.79	-11,356.34	-0.34	-3,714.58	-1.51	-5,797.70	-0.97	-1,846.66	-1.41	112.87	0.02
invl2d^{B}acre	3,322.81	0.93	47,319.15	0.22	137,298.10	1.99	-14,027.95	-0.36	-3,920.72	-0.44	11,349.77	1.68
invl3d^{A}acre	-94.83	-0.04	9,834.76	0.28	12,516.06	1.31	4,847.54	0.46	2,158.35	1.23	4,109.12	1.41
invl3d^{B} acre	5,379.81	1.89	-2,983.32	-0.14	-365.15	-0.19	-5,221.85	-1.19	-2,261.69	-1.46	-1,047.82	-0.34

Table 5.14. Inverse Distance to Nearest List1 Site by Major Land-use of List1 Site (Base Model Specification)

	Retail		Office		Industrial		Apartment/ Hotel/Motel		Auto-Related		Vacant	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
invl1d^{A}ind	-12,276.79	-1.85	-330,746.50	-0.69	-36,912.17	-2.18	-39,234.94	-0.62	-54,192.58	-2.15	3,223.94	0.17
invl1d^{B}ind	-3,070.61	-0.35	-160,110.60	-0.49	-336.30	-0.03	-11,999.35	-0.27	-33,609.66	-1.58	-22,758.67	-1.68
invl1d^{A}oth	-8,953.44	-0.92	-1,836,105.00	-2.13	-22,579.44	-1.06	42,740.65	0.80	-35,474.82	-1.94	-22,657.76	-1.36
invl1d^{B}oth	-3,340.09	-0.38	-394,783.60	-0.63	-7,971.37	-0.31	-19,800.17	-0.73	-11,417.49	-0.43	1,590.38	0.07
invl2d^{A}	-2,555.00	-0.47	-172,896.50	-0.67	6,704.66	0.71	4,751.58	0.27	10,154.92	0.64	7,853.39	0.75
invl2d^{D}	17,924.31	0.88	85,599.55	0.53	-5,684.19	-0.49	-4,989.13	-0.18	12,276.93	0.70	5,355.29	0.34
invl2d^{B}	-11,036.59	-0.95	-1,265,080.00	-1.31	-34,067.72	-1.45	-22,557.43	-0.80	15,880.72	0.68	-23,957.30	-1.06
invl3d^{A}	3,964.45	0.61	-72,015.89	-1.01	34,901.46	1.12	-758.19	-0.04	-12,032.88	-1.12	-9,159.55	-0.70
invl3d^{B}	1,351.57	0.95	113,173.90	1.14	7,164.11	1.03	-5,236.18	-0.24	7,661.45	0.95	-3,635.67	-0.70

Table 5.15. Inverse Distance to Nearest List1 Site and Major Land-use of List1 Site (Model Using Reduced Set of Independent Variables)

	Retail		Office		Industrial		Apartment/ Hotel/Motel		Auto-Related		Vacant	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
invl1d^{A}ind	-13,194.35	-2.09	-402,328.20	-1.13	-36,069.82	-2.08	-31,288.69	-0.49	-58,721.42	-2.51	1,737.98	0.09
invl1d^{B}ind	-4,613.74	-0.50	-59,406.56	-0.27	1,231.42	0.10	-14,239.72	-0.34	-39,175.41	-1.99	-21,875.68	-1.55
invl1d^{A}oth	-4,138.30	-0.46	-1,554,191.00	-2.72	-23,278.37	-1.11	41,193.63	0.94	-38,981.08	-2.83	-22,762.57	-1.36
invl1d^{B}oth	-2,016.65	-0.25	-249,130.80	-0.69	-11,830.76	-0.48	-26,371.88	-1.06	-17,716.87	-0.86	1,446.14	0.06
invl2d^{A}	-1,515.72	-0.37	-173,221.00	-0.84	6,051.94	0.59	8,005.30	0.48	10,016.66	0.99	6,322.23	0.59
invl2d^{D}	18,859.73	0.94	66,067.85	0.56	-6,371.15	-0.58	-7,267.17	-0.27	12,891.03	1.02	6,377.84	0.38
invl2d^{B}	-9,892.33	-0.98	-1,205,790.00	-1.54	-34,982.54	-1.81	-22,964.72	-0.79	14,423.97	1.03	-23,395.78	-1.22
invl3d^{A}	5,432.97	0.90	-75,826.37	-1.37	35,197.84	1.15	572.70	0.04	-8,232.72	-0.82	-9,870.24	-0.89
invl3d^{B}	1,636.82	1.08	99,378.25	1.22	8,431.57	1.27	-9,603.84	-0.43	9,462.76	1.07	-3,631.10	-0.71

Table 5.16. Hedonic Models Corrected for Spatial Error Correlation

	Industrial				Auto-Related				Vacant			
Variable	Full	Full	Reduced	Reduced	Full	Full	Reduced	Reduced	Full	Full	Reduced	Reduced
invl1d^{A}	-26,182.6		-27,993.0		-36,721.7		-41,486.3		1,194.6		-2,064.2	
	(-1.48)		(-1.66)		(-3.05)		(-3.99)		(0.07)		(-0.12)	
invl1d^{B}	4,283.4		4,884.2		-22,559.8		-27,330.6		-13,593.4		-14,208.9	
	(0.30)		(0.36)		(-1.75)		(-2.40)		(-0.59)		(-0.63)	
invl1d^{A}ind		-29,700.6		-30,430.9		-37,375.3		-50,676.8		8,861.6		4,299.5
		(-1.53)		(-1.65)		(-2.38)		(-3.51)		(0.41)		(0.20)
invl1d^{B}ind		6,355.6		8,190.7		-27,108.6		-33,422.6		-20,680.6		-20,223.2
		(-0.39)		(0.53)		(-1.95)		(-2.76)		(-0.82)		(-0.81)
invl1d^{A}oth		-13,917.4		-19,406.4		-36,158.4		-35,357.3		-7,467.9		-8,703.4
		(-0.45)		(-0.63)		(-2.55)		(-3.01)		(-0.33)		(-0.39)
invl1d^{B}oth		-23.3		-2,600.7		-10,251.1		-15,512.7		4,711.6		1,790.9
		(0.00)		(-0.12)		(-0.53)		(-0.90)		(0.13)		(0.05)
invl2d^{A}	7,178.6	5,891.4	7,217.3	6,423.4	6,923.0	8,146.9	6,547.0	9,721.6	189.4	863.4	1,627.8	1,989.2
	(0.49)	(0.40)	(0.52)	(0.46)	(0.57)	(0.66)	(0.66)	(0.95)	(0.01)	(0.05)	(0.09)	(0.11)
invl2d^{D}	-16,502.9	-16,697.1	-14,324.6	-14,020.2	6,009.8	7,418.9	15,962.9	16,769.2	4,904.9	7,565.6	3,331.9	5,588.4
	(-1.10)	(-1.10)	(-0.99)	(-0.96)	(0.41)	(0.50)	(1.34)	(1.42)	(0.26)	(0.40)	(0.18)	(0.30)
invl2d^{B}	-27,342.6	-26,867.6	-33,035.0	-32,788.8	6,225.3	2,534.3	14,959.0	11,599.6	-26,829.3	-26,177.6	-26,143.3	-25,581.7
	(-0.91)	(-0.90)	(-1.18)	(-1.17)	(0.28)	(0.11)	(0.75)	(0.58)	(-0.84)	(-0.82)	(-0.83)	(-0.81)
invl3d^{A}	37,755.0	38,369.8	34,462.6	34,636.9	-19,297.5	-19,211.8	-10,715.8	-13,679.1	-9,774.4	-9,578.4	-8,861.5	-8,767.6
	(1.62)	(1.65)	(1.50)	(1.50)	(-1.72)	(-1.68)	(-0.97)	(-1.22)	(-0.92)	(-0.90)	(-0.85)	(-0.84)
invl3d^{B}	6,600.0	6,800.7	7,174.6	7,191.7	8,097.8	7,951.4	11,058.0	11,117.5	-5,766.9	-5,805.7	-5,853.5	-5,955.5
	(0.84)	(0.87)	(0.95)	(0.95)	(2.08)	(2.03)	(2.95)	(2.98)	(-1.15)	(-1.15)	(-1.17)	(-1.18)

CHAPTER 6

ESTIMATING THE EFFECTS OF PERCEIVED ENVIRONMENTALLY CONTAMINATED SITES ON COMMERCIAL AND INDUSTRIAL PROPERTY VALUES

Introduction

In this chapter, the extent to which properties that may be perceived as contaminated, but which do not necessarily have any documented record of a contaminant release, affect CI property markets is investigated. The results presented in Chapter 5 support previous findings that proximity to a known contaminated site negatively affects the value of nearby properties and these effects becomes less severe as distance to a contaminated site increases. Even though none of the contaminated sites in the analysis were on the Environmental Protection Agency's (EPA) National Priority List (NPL), the magnitude of the negative impacts were still quite significant.

However, many contaminated properties may never get discovered by state or federal authorities, but they may be perceived as such. If perceptions matter, then properties with no documented record of contamination may also be viewed as undesirable neighbors for nearby property owners in a way similar to properties listed on federal or state registries of contaminated sites. As a result, these properties could have substantial impacts when taken as a whole compared to the few "known contaminated sites," such as those on CERCLIS and HSI. Therefore, it is also important to understand if there are any negative externality effects associated with properties that are likely to be perceived as contaminated, but which do not have any documented record of contamination present.

The purpose of this chapter is to present the results of hedonic property value models estimated to examine the effects of CI properties that may be perceived as contaminated on neighboring property values. The set of properties perceived to be contaminated was generated by the probability of contamination model estimated in Chapter 4. The probability of contamination model was developed under the assumption that it adequately captured the important factors that signaled on-site contamination to CI property investors. If the model was successful in identifying such properties, then one may expect that properties perceived as contaminated could also negatively affect nearby CI property values. The coefficient estimates reported in this chapter will form the basis for the analysis in Chapter 7, which will discuss the economic importance of the results from the estimated hedonic models given in this chapter and Chapter 5 (i.e. comparisons are made between the hedonic models in Chapters 5 and 6, marginal impacts are estimated, and total impacts on CI property values are computed).

Properties Perceived to be Contaminated

The base ordered probit model from Chapter 4 was selected as the model to define the list of properties that may be perceived as contaminated (the base ordered probit model was referred to as the ordered probit full sample or OPFS model in Chapter 4).[62] In brief, the OPFS model defined CI properties as falling into on of three categories that describe the level of contamination on the property. CI properties on either the CERCLIS or HSI were classified as having a "high level" of contamination, properties on either the NFRAP or NonHSI were classified as having a "low level" of contamination, and properties not on any of these lists were classified as not having any publically known record of contamination present. After estimating the OPFS model and controlling for potential sample-selection bias, CI properties in the estimating sample and not in the estimating sample were then classified into one of three categories that describe the level of contamination present using the following decision rule:

$$\begin{aligned} \hat{c}_i &= 0 \quad \text{if} \quad \hat{P}_i^2 < k \ \text{ and } \ \hat{P}_i^1 < k \\ \hat{c}_i &= 1 \quad \text{if} \quad \hat{P}_i^1 \geq k \ \text{ and } \ \hat{P}_i^2 < k \\ \hat{c}_i &= 2 \quad \text{if} \quad \hat{P}_i^2 \geq k \,. \end{aligned} \tag{6.1}$$

The value for k represents a specified cut-off point, where CI properties with an estimated probability of "high" contamination ($\hat{p}_i^2$) greater than or equal to k are classified as "highly" contaminated ($\hat{c}_i = 2$), properties with an estimated probability of "low" contamination ($\hat{p}_i^1$) greater than or equal to k and with a probability of "high" contamination less than k are classified as having a "low" level of contamination ($\hat{c}_i = 1$), and properties with estimated probabilities for both "high" and "low" contamination less than k are classified as "not contaminated" ($\hat{c}_i = 0$).

For the analysis presented in Chapter 4, the three values chosen for k were 0.05,

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[62] Refer to Chapter 4 for a complete description of the OPFS model.

0.10, and 0.15. Table 6.1 provides the distribution of predicted outcomes generated by the OPFS model.[63] Out of 15,098 properties that have no documented record of a contaminant release, 633, 293 and 190 properties may be perceived to be highly contaminated when *k* equals 0.05, 0.10, and 0.15, respectively. The focus of the analysis in this chapter will be on these properties since this chapter is investigating the potential negative externality effects of properties that may be perceived as contaminated, but do not have any documented record of a contaminant release. Properties perceived to have a low level of contamination are not considered for this analysis since the results of Chapter 5 indicated that NFRAP and NonHSI sites do not negatively affect nearby CI property values. Therefore, it is reasonable to assume that properties perceived to have a low level of contamination also do not negatively affect nearby CI property values. Furthermore, it is reasonable to assume that NFRAP and NonHSI sites predicted to be highly contaminated by the OPFS model will not be perceived as such. Although these properties may share similar characteristics of highly contaminated sites (i.e. CERCLIS or HSI sites), CI property investors have publicly available information providing documentation that these properties have little or no contamination present. As such, it is assumed CI property investors do not form perceptions that these properties are highly contaminated because the public information about these sites states otherwise.

Hedonic Models Estimating the Effects of Sites Perceived to be Highly Contaminated

The negative externality effects of properties that may be perceived as highly

[63] Table 6.1 is identical to Table 4.5 from Chapter 4.

contaminated were measured in a way similar to List1 sites (i.e. CERCLIS/HSI sites). For the three cut-off values chosen for the probability of contamination model, the inverse distance to the nearest site predicted to be highly contaminated was computed. As such, it is assumed the price-distance relationship can be described by the reciprocal of distance to the nearest site predicted to be highly contaminated. A negative coefficient estimated for the distance variable indicates that price will increase with distance at a decreasing rate, nearing an asymptotically constant level. However, unlike List1 sites where the price-distance relationship is allowed to vary before and after listing of the site, the inverse distance for the predicted sites does not. This is due to the inability of the probability of contamination model to account for changes in perceptions over time that would enable one to predict the specific date a CI property may first be perceived as highly contaminated.

The general specification of the Base hedonic model given by Equation (5.1) in Chapter 5 that is modified to investigate the potential negative externality effects of sites that may be perceived as highly contaminated is expressed as follows:

$$\begin{aligned} P_{it} &= c + \sum_{t=1}^{T} \alpha_t \, YR_t + \sum_{j=1}^{J} \beta_j \, X_{ijt} + \delta_1 \, invl1d_i^A + \delta_2 \, invl1d_i^B + \gamma_1 \, invl2d_i^A \\ &+ \gamma_2 \, invl2d_i^D + \gamma_3 \, invl2d_i^B + \lambda_1 \, invl3d_i^A + \lambda_2 \, invl3d_i^B + \phi_1 invhxx_i + \epsilon_{it} \end{aligned} \tag{6.2}$$

where:

P_{it}	the sales price of CI property i at time t,
c	constant,
YR_t	dummy variables indicating the year the property was last sold,
X_{jit}	the j property characteristics that include location and neighborhood oriented variables for property i at time t,
$invl1d^A$	inverse distance of property i to nearest List1 site if sale occurred

	after the site was listed, 0 otherwise,
$invl1d^B$	inverse distance of property i to nearest List1 site if sale occurred before the site was listed, 0 otherwise,
$invl2d^A$	inverse distance of property i to nearest List2 site if sale occurred after the site was delisted (i.e. site was listed as NFRAP), 0 otherwise,
$invl2d^D$	inverse distance of property i to nearest List2 site if sale occurred after the site was listed on CERCLIS but before it was delisted, 0 otherwise,
$invl2d^B$	inverse distance of property i to nearest List2 site if sale occurred before the site was listed, 0 otherwise,
$invl3d^A$	inverse distance of property i to nearest List3 site if sale occurred after the site was listed, 0 otherwise,
$invl3d^B$	inverse distance of property i to nearest List3 site if sale occurred before the site was listed, 0 otherwise,
invh05	inverse distance of property i to nearest site predicted to be highly contaminated when k = 0.05
invh10	inverse distance of property i to nearest site predicted to be highly contaminated when k = 0.10
invh15	inverse distance of property i to nearest site predicted to be highly contaminated when k = 0.15
$\boldsymbol{\varepsilon}_{it}$	unobserved random error.

The results of the hedonic models estimated in Chapter 5 suggested that proximity to a List1 site has a negative effect on nearby property values and the magnitude of the effects may differ for List1 sites with industrial and non-industrial land-uses. As a result, the hedonic models estimated in this chapter will focus on the potential effects of proximity to a site that may be perceived as highly contaminated and the differences that may be apparent for sites with industrial and non-industrial land-uses. It should also be noted that the same set independent variables used to control for the property, location-oriented, and neighborhood-oriented characteristics in the Chapter 5 models are also used for the models presented in this chapter.

Proximity to Nearest Site Perceived to be Highly Contaminated

The general hedonic model given by Equation (6.2) is estimated separately for the three inverse distance variables used to control for the externality effects of sites perceived to be highly contaminated, or invh05, invh10, and invh15 (i.e. the inverse distance to the nearest site perceived to be highly contaminated when $k = 0.05$, 0.10, and 0.15, respectively). The increase in the value for k corresponds to a more strict definition for the list of sites that are predicted to be highly contaminated. The models from Chapter 5 replicated here were based on the models that used the full set of independent variables to control for property, location-oriented, and neighborhood-oriented characteristics (defined as the Base model in Chapter 5) and a variation of the Base model using a reduced set of independent variables (defined as the reduced Base model or RBM in Chapter 5 - the Base model where variables not associated with contaminated sites with t-statistics less than 0.50 were dropped).

The results of the Base model and the RBM that include the inverse distance to the nearest site perceived to be highly contaminated are given in Tables 6.2 and 6.3, respectively. In general, the overall results are unchanged regardless of the model specification chosen (i.e. model estimated using full set or reduced set of independent variables). For the six major land-use categories, approximately two-thirds of the estimated coefficients for invh05, invh10, and invh15 have negative signs. Only for the Industrial category was a statistically significant coefficient observed (invhp05), but it was positive. Although none of the inverse distance variables with negative signs were statistically significant, the coefficient estimates typically increased in magnitude as the cut-off value used to define the set of properties perceived to be highly contaminated increases (i.e. as k changes from 0.05, 0.10, to 0.15). This is consistent with expectations since it is reasonable to assume that the list of highly contaminated sites generated by a higher value for k may be more likely to generate negative externality effects for neighboring CI properties. Although the probability of contamination model predicts them to be highly contaminated, the list generated when $k = 0.05$ may include a large number of properties that have only minimal or no negative effects on neighboring CI property values. Using these properties when calculating the distance variables would result in incorrectly measuring proximity to the nearest site predicted to be highly contaminated. Therefore, the negative externality effects of sites predicted to be highly contaminated estimated by the hedonic models would be biased downward (i.e. the parameter value for the inverse distance variable would be less negative or positive).

The coefficients for the inverse distance to nearest List1 site listed at the time of sale ("post-listing distance" or $invl1d^A$) and not listed at the time of sale ("pre-listing distance" or $invl1d^B$) variables given in Tables 6.2 and 6.3 are similar in magnitude to the Base model and RBM estimated in Chapter 5 (see Tables 5.2 and 5.4). This indicates that the negative externality effects of List1 sites are robust across different specifications of the hedonic model, such that including proximity to a site perceived to be highly contaminated does not appear to bias the estimates for the List1 pre- and post-listing inverse distance coefficients.[64]

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[64] Hedonic models were also estimated where k = 0.33 was used to define the list of perceived highly contaminated properties. However, the level of significance and magnitude of the coefficient estimates across models were similar to the models when k = 0.15. As such, the overall results and conclusions drawn were unchanged.

As was done in Chapter 5, the hedonic models reported in this section were corrected for spatial error correlation. Although not reported, the overall results were consistent with what was observed for the non-spatially corrected models and that the externality effects of List1 sites are robust across model specifications.

Land-use of Nearest Site Perceived to be Highly Contaminated

Following the analysis completed for List1 sites in Chapter 5, it may be reasonable to assume that the externality effects of sites perceived to be highly contaminated may be different for industrial type properties and non-industrial properties. Industrial sites are likely to have aesthetic characteristics that may enhance the perceptions of nearby property owners regarding potential risks of contaminant migration or exposure to contamination for unexpected contaminant releases in the future (i.e. through air, water, or direct exposure through inadvertent crossing of property lines). Therefore, risk perceptions associated with industrial sites may be more apparent than for non-industrial sites.

To account for the major land-use type of the nearest site perceived to be highly contaminated, the inverse distance variables were modified as follows:

invh05ind	inverse distance of property i to nearest site predicted to be highly contaminated when k = 0.05 and if the site is an industrial site, 0 otherwise
invh05oth	inverse distance of property i to nearest site predicted to be highly contaminated when k = 0.05 and if the site is a non-industrial site, 0 otherwise
invh10ind	inverse distance of property i to nearest site predicted to be highly contaminated when k = 0.10 and if the site is an industrial site, 0 otherwise
invh10oth	inverse distance of property i to nearest site predicted to be highly

	contaminated when k = 0.10 and if the site is a non-industrial site, 0 otherwise
invh15ind	inverse distance of property i to nearest site predicted to be highly contaminated when k = 0.15 and if the site is an industrial site, 0 otherwise
invh15oth	inverse distance of property I to nearest site predicted to be highly contaminated when k = 0.15 and if the site is a non-industrial site, 0 otherwise

Using the above specification for the inverse distance variables, hedonic models were estimated with the full set of independent variables controlling for property, location-oriented, and neighborhood-oriented characteristics and a reduced set of independent variables.

The results of the Base model and the RBM that include the inverse distance to the nearest industrial and non-industrial site perceived to be highly contaminated are given in Tables 6.4 and 6.5, respectively. In general, the overall results are unchanged regardless of the model specification chosen (i.e. model estimated using full set or reduced set of independent variables). The results indicate that industrial sites perceived to be highly contaminated have a statistically negative effect on Retail property values (Table 6.4, refer to invh15ind for the Retail model), while non-industrial sites perceived to be highly contaminated may have a statistically significant negative effect on nearby Office and Vacant properties (Table 6.4, refer to invh10oth and invh15oth for the Office model and invh15oth for the Vacant model). Furthermore, the coefficient estimates for both the industrial and non-industrial inverse distance variables generally increased in magnitude as the cut-off value defining the set of properties perceived to be highly contaminated increased (i.e. as k changed from 0.05, 0.10, to 0.15).

The results observed for the Retail and Office categories were consistent with the hedonic models estimated in Chapter 5 where industrial sites (for Retail models) and non-industrial sites (for Office models) were found to have a greater negative impact on property values than non-industrial and industrial sites, respectively (see Tables 5.14 and 5.15 in Chapter 5). This suggests that Retail and Office investors may be sensitive to perceptions of nearby contamination and therefore, premiums (i.e. reduced prices) may be required to compensate for the risks of being located near a potentially contaminated site (risks include the potential for being held partially liable for clean up if contamination is discovered). These premiums may be higher for Office properties because the development or purchase of Office properties typically involve large investments. However, the negative and statistically significant estimate for invh15oth in the Vacant model was interesting since the List1 post-listing distance coefficients were not statistically significant, for the models estimated in this chapter and in Chapter 5. This suggests that Vacant property investors may only be sensitive to perceptions of contamination about nearby properties and not to properties with known contamination (i.e. List1 sites). Purchases of Vacant properties may be less likely to believe they will be held liable for clean up if there is a discovery of contamination on the property that is expected to be from a nearby site with known contamination present (i.e. List1 site).

The statistically insignificant coefficient estimates for the Industrial and Auto-Related models may not necessarily be surprising because these types of land-uses are more likely to be found on either CERCLIS or HSI (i.e. classified as a List1 site; see Table 3.10 in Chapter 3). Investors in these two categories may be more familiar with the threats (or lack of threats) posed by nearby properties and therefore, less likely to form negative perceptions that nearby properties may be contaminated. Therefore, investors are not likely to require premiums (i.e. reduced prices). As a result, properties values in these two categories may only be negatively affected after contamination has been discovered, which is indicated by the List1 post-listing distance coefficients (see Tables 6.2, 6.3, 6.4 and 6.5).

Including the inverse distance to industrial and non-industrial sites perceived to be highly contaminated had only minor effects on the magnitude of the post-listing distance coefficient for industrial List1 sites (invl1d^{A}ind) and the post-listing distance coefficient for non-industrial sites (invl1d^{A}oth) when compared to the results given in Tables 5.14 and 5.15 in Chapter 5. Only the post-listing distance coefficient for non-industrial sites (invl1d^{A}oth) in the Office model had a noticeable increase. Regarding the other major land-uses, the direction of the effect on the post-listing distance coefficients for industrial and non-industrial List1 sites varied across models. In general, the results for these models support those observed in the previous section where the negative externality effects of List1 sites are robust across different specifications of the hedonic model.[65]

Hedonic models that corrected for spatial error correlation were also estimated, but are not reported. Similar to the previous section, the overall results were consistent with what was observed for the non-spatially corrected models.

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[65] Hedonic models were also estimated where $k = 0.33$ was used to define the list of perceived highly contaminated properties. However, the level of significance and magnitude of the coefficient estimates across models were similar to the models when $k = 0.15$. As such, the overall results and conclusions drawn were unchanged.

Additional Hedonic Models Estimated

The risk perceptions of CI property investors may change over time from the acquisition of new information (e.g. access to publically available federal and states lists of contaminated sites). CI property investors that purchased a property in 1985 may have different perceptions of contamination than investors that purchased a property in 1995.[66] It is not known how perceptions of contamination for CI property investors changes over time. It can be argued that risk perceptions may have been strongest for a period of time after the advent of CERCLA in 1980. Since CERCLA provided one of the first publically available list contaminated sites, investors may have quickly formed negative perceptions of properties with land-uses similar to CERCLA sites. Therefore, perceived highly contaminated sites may have had a greater negative effect on property values for sales that occurred during the 1980's compared to sales that occurred later in the study period. However, one could also argue that perceptions of the negative effects of contamination became stronger over time as more information about contaminated sites became available. In addition to the information already provided by the CERCLA lists, the Georgia EPD started publishing their list of state priority contaminated sites call the Hazardous Site Inventory (HSI) in 1994. As such, the publishing of the HSI may strengthen the risk perceptions of properties with similar land-use as those that have known contamination present.[67]

To control for potential changes in perceptions over time and due to the inability

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[66] The study period is defined as 1980 to 2000.

[67] It should be noted that this may not necessarily apply to states other than Georgia, as other states may have instituted programs to remediate contaminated properties at different times. Furthermore, some states may not have any program that addresses the clean up of hazardous waste sites.

of the probability of contamination model to determine the date during the study period when a property may first be perceived as highly contaminated, hedonic models were estimated where distance to the nearest perceived highly contaminated site was interacted with a dummy variable indicating if the sale occurred between 1994 (corresponding to the first year the HSI was published) and 2000. These models would allow for potential differences in price gradients for properties with sales dates after 1994 compared to those prior to 1994, thereby providing some information about potential changes in risk perceptions that may have occurred over two distinct time periods.[68,69] Hedonic models were also estimated using a similar interaction variable while controlling for the potential differences in impacts for industrial and non-industrial sites.

Although not reported, the results of the models estimated with sale date interaction variable using the full set of independent variables (i.e. Base model specification) were consistent with what was observed for the hedonic models estimated without the interaction variable. Furthermore, the results were sensitive when using the reduced base model specification (i.e. RBM or models estimated with the reduced set of independent variables).[70] However, in all sets of models estimated, the inverse distance-sale date interaction variables were mostly never statistically significant suggesting that

[68] It was assumed that 1994 was a reasonable year to choose as the date to distinguish between the two time periods since the initial publishing of the HSI may have served as a signal to the public regarding the location of contaminated sites that may have previously been perceived as contaminated.

[69] Under this specification, a negative sign for both the inverse distance variable and the interaction variable would indicate that the impacts of the are greater for sales that occurred after 1994, while a positive sign for the interaction variable would indicate the impacts are greater for sales that occurred prior to 1994.

[70] This may be due to dropping some of the time dummy variables that are in the Base model specification.

the negative effects, if any, of perceived highly contaminated sites do not vary pre- and post-1994. As such, the results of these models do not necessarily provide any additional information on the potential impacts of perceived highly contaminated sites on nearby property values.

Hedonic models were also estimated where a distinction between the nearest List1 site and the nearest site perceived as contaminated was not made. In this instance, the distance measure was simply computed as distance to the nearest List1 site or perceived contaminated site. Furthermore, it may be reasonable to assume that potential negative impacts increase for List1 sites that are the nearest site after the site is listed on CERCLIS or HSI. According to this formulation, the inverse distance variables used in the empirical models were defined as follows:

invS1	inverse distance of property i to nearest site (List1 site or site predicted to be highly contaminated)
$invS1^A$	inverse distance of property i to nearest List1 site if sale occurred after site was listing, 0 otherwise

Specifying the distance measures in this manner assumes the market does not distinguish between sites perceived as contaminated (i.e. sites predicted to be highly contaminated) and List1 sites before the List1 sites are listed on CERCLIS or HSI. Alternatively stated, all sites (List1 and perceived contaminated) are homogeneously considered as potentially contaminated before listing. Only after a site has been investigated for contamination and placed on the publically accessible CERCLIS or HSI list does the market make a differentiation between potential threats of List1 sites and sites perceived as contaminated. This may be a reasonable assumption since CI property investors are unlikely to know which sites will eventually be placed on CERCLIS or HSI.

Hedonic models were estimated using the distance measures given above to control for proximity to a contaminated site for all six major land-use categories (Retail, Office, Industrial, Apartment/Hotel/Motel, Auto-Related, and Vacant). Models were estimated under the Base model specification (i.e. full set of independent variables) and the reduced base model specification (i.e. RBM or estimated with the reduced set of independent variables). Although not reported, the inverse distance to nearest contaminated site (invS1) was only statistically significant (0.10 level) and negative in the Office model. Except for Office properties, this suggests that property values are generally not negatively affected by proximity to contaminated site (perceived contaminated sites or List1 sites) prior to listing. Interestingly, the post-listing distance coefficient ($invS1^A$) was also only statistically significant (0.05 level) and negative in the Office model. Furthermore, the post-listing coefficient was greater in magnitude (absolute value) than the simple distance coefficient (invS1). The results of the Office model indicate that there are greater negative impacts on property values for List1 sites after they are listed. Similar results were observed for all land-use categories from the hedonic models estimated using the reduced set of independent variables (i.e. RBM).

When compared to the results given in Tables 6.2 and 6.3, these models suggest that CI investors may be able to differentiate List1 sites from sites that may only be perceived as contaminated. Therefore, it would be necessary to include separate distance measures for List1 sites and perceived contaminated sites in the empirical models. Not including separate distance variables may lead to a mis-measurement of the potential negative impacts caused by contaminated sites (List1 sites and sites perceived as contaminated). Overall, the results of these models do not necessarily provide additional evidence on the potential impacts of perceived contaminated sites on nearby property values.

Conclusion

This chapter focused on the estimation of hedonic property value models to investigate the negative effects properties that may be perceived to be highly contaminated have on nearby CI property values. First, the base hedonic model (Base) and a variation of the base model (i.e. RBM or reduced base model using a reduced set of independent variables) developed in Chapter 5 were replicated and included variables to control for the externality effects of sites that may be perceived as highly contaminated. Additional models were estimated to investigate to potential differences in impacts between industrial and non-industrial sites and to control for the presence of spatial error correlation in the models. The results indicate that proximity to a site that may be perceived as highly contaminated (defined by the probability of contamination model estimated in Chapter 4) may have a negative effect on nearby property values for properties in the Retail, Office, and Vacant land-use categories. These negative effects were observed for industrial sites in the Retail models, while non-industrial sites were found to have a negative effect on properties values in the Office and Vacant categories. Furthermore, any negative effects were primarily observed when the list of properties that may be perceived as highly contaminated was defined by the highest cut-off value (i.e. $k = 0.15$).

Utilizing the models estimated in Chapters 5 and 6, Chapter 7 will discuss the economic importance of these results in relation to CI property markets in Fulton County, Georgia. In Chapter 7, comparisons are made between the hedonic models from Chapters 5 and 6, marginal impacts are estimated, and total impacts on CI property values are computed.

Table 6.1. Predicted Outcomes for OPFS Model

	k=0.05			*k*=0.10			*k*=0.15		
	No (c = 0)	Low (c = 1)	High (c = 2)	No (c = 0)	Low (c = 1)	High (c = 2)	No (c = 0)	Low (c = 1)	High (c = 2)
No = 15,098 obs (98.3)[a]	11,797 (78.1)[b]	2,668 (17.7)	633 (4.2)	13,837 (91.6)	968 (6.4)	293 (1.9)	14,360 (95.1)	548 (3.6)	190 (1.3)
Low = 203 obs (1.3)[a]	45 (22.2)	79 (38.9)	79 (38.9)	91 (44.8)	60 (29.6)	52 (25.6)	118 (58.1)	57 (28.1)	28 (13.8)
High = 59 obs (0.4)[a]	8 (13.6)	23 (39.0)	28 (47.5)	21 (35.6)	17 (28.8)	21 (35.6)	30 (50.8)	13 (22.0)	16 (27.1)
Total = 15,360 obs	11,850 (77.2)	2,770 (18.0)	740 (4.8)	13,949 (90.8)	1,045 (6.8)	366 (2.4)	14,508 (94.5)	618 (4.0)	234 (1.5)

[a] Number in parentheses is the percentage of properties in the full sample which are classified as not contaminated, low level of contamination (on NFRAP/NonHSI lists), and high level of contamination (on CERCLIS/HSI list).

[b] Number is parentheses is the percentage of properties in the observed category that are predicted as not contaminated, low level of contamination, and high level of contamination.

Table 6.2 Base Hedonic Model with Inverse Distance to Nearest Site Perceived to be Highly Contaminated

	Retail		Office		Industrial		Apartment/ Hotel/Motel		Auto-Related		Vacant	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
invl1d[A]	-10,805.49	-1.82	-949,588.70	-1.77	-33,466.77	-2.23	-16,214.25	-0.33	-42,091.05	-2.46	-15,401.64	-1.08
invl1d[B]	-2,705.11	-0.37	-162,332.30	-0.43	-4,304.48	-0.36	-20,648.30	-0.82	-27,540.48	-1.66	-18,956.69	-1.48
invh05	-2,284.05	-1.33	32,488.21	0.30	8,896.34	2.12	354.02	0.04	-2,307.97	-1.38	34,185.55	2.57
invl1d[A]	-11,082.85	-1.77	-970,589.20	-1.83	-30,266.50	-2.04	-18,196.86	-0.37	-43,274.48	-2.52	-7,968.48	-0.61
invl1d[B]	-2,753.80	-0.37	-87,658.18	-0.26	-3,076.83	-0.25	-20,315.60	-0.79	-26,222.79	-1.59	-15,855.57	-1.18
invh10	-8,276.76	-0.79	-124,991.40	-0.90	11,161.20	0.98	-2,156.22	-0.16	-9,009.42	-1.10	10,879.18	1.22
invl1d[A]	-12,219.34	-2.23	-1,001,575.00	-1.79	-29,434.21	-1.97	-19,717.97	-0.39	-18,974.40	-1.83	-9,112.57	-0.67
invl1d[B]	-4,955.27	-0.62	-59,691.39	-0.16	-2,521.26	-0.20	-17,406.84	-0.68	-2,667.74	-0.23	-17,080.02	-1.28
invh15	-4,018.43	-0.23	-180,112.00	-1.04	9,176.09	0.61	-1,313.17	-0.04	-8,921.05	-0.89	-16,828.06	-1.47

Table 6.3. RBM with Inverse Distance to Nearest Site Perceived to be Highly Contaminated

	Retail		Office		Industrial		Apartment/ Hotel/Motel		Auto-Related		Vacant	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
invl1d[A]	-9,698.14	-1.92	-883,437.20	-2.91	-34,171.90	-2.34	-10,408.09	-0.21	-45,703.95	-2.88	-16,981.11	-1.28
invl1d[B]	-2,625.88	-0.37	-102,393.50	-0.42	-4,765.95	-0.41	-26,207.48	-1.13	-31,630.81	-2.33	-14,693.20	-1.11
invh05	-2,333.22	-1.30	5,085.65	0.05	8,224.65	2.01	-211.89	-0.03	-1,722.02	-1.43	33,042.23	2.52
invl1d[A]	-9,853.49	-1.89	-889,264.20	-2.63	-33,756.50	-2.33	-12,056.76	-0.24	-46,552.94	-2.94	-8,762.71	-0.71
invl1d[B]	-2,711.32	-0.37	-75,899.47	-0.34	-4,251.13	-0.36	-25,794.95	-1.11	-31,553.77	-2.40	-14,650.30	-1.06
invh10	-7,163.20	-0.64	-79,853.97	-0.70	9,908.89	0.98	-685.21	-0.05	-5,172.25	-0.93	10,573.97	1.26
invl1d[A]	-10,109.28	-2.01	-936,537.70	-2.58	-29,712.90	-2.17	-13,730.01	-0.27	-19,586.03	-1.87	-10,185.93	-0.78
invl1d[B]	-4,397.53	-0.57	-68,760.03	-0.29	-4,207.81	-0.36	-22,477.66	-0.97	-10,746.48	-1.15	-18,237.73	-1.32
invh15	-2,243.43	-0.12	-127,111.70	-0.95	10,226.33	0.84	1,003.89	0.03	-3,697.85	-0.59	-16,115.78	-1.48

Table 6.4. Base Hedonic Model with Inverse Distance to Nearest Industrial and Non-Industrial Site Perceived to be Highly Contaminated

	Retail		Office		Industrial		Apartment/ Hotel/Motel		Auto-Related		Vacant	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
invl1d^{A}ind	-11,920.26	-1.83	-793,805.60	-1.18	-36,878.51	-2.15	-42,093.57	-0.65	-48,702.76	-2.16	11,985.12	0.60
invl1d^{B}ind	-963.04	-0.11	-339,746.20	-0.90	-2,146.02	-0.19	-18,391.69	-0.40	-32,550.84	-1.57	-18,291.55	-1.44
invl1d^{A}oth	-9,732.34	-1.04	-2,072,956.00	-2.20	-22,992.91	-1.06	36,046.03	0.65	-34,203.30	-1.89	-30,095.68	-1.99
invl1d^{B}oth	-4,186.27	-0.44	-643,102.90	-0.95	-11,008.49	-0.44	-21,791.15	-0.79	-14,378.22	-0.51	15,154.42	0.69
invh05ind	-2,094.72	-1.48	78,527.98	0.69	8,893.39	2.11	1,129.54	0.15	-2,275.85	-1.40	14,309.84	3.38
invh05oth	-4,559.97	-0.55	-304,102.00	-1.36	5,058.47	0.33	-16,169.68	-0.46	1,695.96	0.22	59,918.21	6.26
invl1d^{A}ind	-10,474.21	-1.67	-630,505.30	-1.21	-32,929.34	-1.93	-47,436.80	-0.74	-46,256.98	-2.04	3,548.28	0.18
invl1d^{B}ind	-14.05	0.00	-287,936.20	-0.82	1,934.03	0.16	-25,079.57	-0.53	-26,383.73	-1.33	-22,735.09	-1.67
invl1d^{A}oth	-8,607.29	-0.90	-2,270,512.00	-2.28	-15,537.64	-0.77	39,641.46	0.69	-33,849.93	-1.91	-23,008.65	-1.33
invl1d^{B}oth	-2,165.57	-0.23	-737,259.40	-1.03	-7,582.76	-0.30	-21,218.70	-0.72	-8,840.59	-0.29	290.10	0.01
invh10ind	-10,076.03	-1.59	-119,150.10	-0.92	10,428.09	0.94	1,224.64	0.12	-10,884.11	-1.33	11,009.09	1.38
invh10oth	-3,353.88	-0.13	-505,588.40	-1.68	38,407.47	1.25	-17,068.85	-0.43	861.94	0.08	5,572.36	0.11
invl1d^{A}ind	-9,765.42	-2.07	-647,225.50	-1.20	-33,226.99	-1.95	-47,714.35	-0.74	-20,523.74	-1.80	1,101.11	0.05
invl1d^{B}ind	1,155.03	0.12	-275,478.80	-0.76	252.09	0.02	-23,024.10	-0.51	-6,695.65	-0.65	-26,098.51	-1.85
invl1d^{A}oth	-8,978.09	-0.93	-2,362,234.00	-2.25	-16,202.75	-0.79	46,911.18	0.84	-16,048.02	-1.10	-27,001.52	-1.33
invl1d^{B}oth	-3,865.94	-0.39	-701,931.30	-0.89	-7,905.56	-0.33	-11,271.73	-0.43	14,170.47	0.58	-12,892.48	-0.56
invh15ind	-18,855.92	-1.66	-149,572.30	-0.97	8,557.58	0.53	2,733.26	0.08	-9,931.89	-1.05	-5,049.13	-0.44
invh15oth	14,296.89	0.44	-677,202.90	-2.02	12,197.20	0.59	-1,892.72	-0.04	-3,982.26	-0.33	-60,486.69	-2.79

Table 6.5. RBM with Inverse Distance to Nearest Industrial and Non-Industrial Site Perceived to be Highly Contaminated

	Retail		Office		Industrial		Apartment/ Hotel/Motel		Auto-Related		Vacant	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
invl1d^{A}ind	-12,800.01	-2.01	-706,288.30	-1.45	-37,192.33	-2.09	-35,213.32	-0.54	-56,473.16	-2.49	8,255.28	0.44
invl1d^{B}ind	-2,635.03	-0.29	-222,589.70	-0.79	-983.75	-0.08	-21,889.96	-0.51	-37,349.64	-1.97	-14,969.23	-1.15
invl1d^{A}oth	-3,933.55	-0.43	-1,636,667.00	-2.81	-24,247.17	-1.14	34,194.04	0.74	-37,533.77	-2.78	-30,581.85	-1.94
invl1d^{B}oth	-2,545.81	-0.29	-393,462.20	-0.95	-14,550.57	-0.60	-28,571.51	-1.12	-20,692.91	-0.90	22,062.69	0.96
invh05ind	-2,059.82	-1.43	75,251.52	0.87	8,271.81	2.01	723.43	0.11	-1,594.35	-1.45	14,053.97	3.44
invh05oth	-4,458.97	-0.55	-275,493.20	-1.25	7,306.86	0.55	-17,764.64	-0.54	1,254.53	0.19	57,013.12	5.94
invl1d^{A}ind	-10,950.51	-1.86	-548,793.30	-1.43	-36,409.92	-2.10	-41,771.15	-0.64	-54,981.48	-2.43	1,958.75	0.11
invl1d^{B}ind	-1,154.05	-0.13	-203,918.30	-0.77	1,614.63	0.13	-26,899.35	-0.60	-33,880.11	-1.84	-21,720.58	-1.56
invl1d^{A}oth	-1,643.44	-0.18	-1,736,206.00	-2.74	-17,616.76	-0.90	42,158.95	0.87	-36,628.73	-2.76	-23,174.65	-1.34
invl1d^{B}oth	-258.13	-0.03	-505,067.00	-1.28	-9,021.67	-0.37	-29,840.08	-1.15	-16,799.31	-0.71	1,360.71	0.05
invh10ind	-9,601.59	-1.33	-54,899.88	-0.54	8,915.26	0.91	3,888.89	0.32	-6,565.73	-1.20	10,795.96	1.42
invh10oth	-81.16	0.00	-363,125.80	-1.67	38,148.91	1.42	-18,340.43	-0.50	2,400.28	0.26	5,956.56	0.12
invl1d^{A}ind	-9,580.19	-2.18	-651,131.80	-1.60	-33,239.21	-2.04	-42,314.95	-0.64	-29,259.02	-2.28	-508.66	-0.03
invl1d^{B}ind	408.68	0.04	-261,870.80	-0.95	-364.85	-0.03	-23,914.34	-0.56	-17,450.64	-1.44	-28,024.84	-1.88
invl1d^{A}oth	-133.14	-0.01	-1,869,438.00	-2.74	-16,809.06	-0.86	49,757.67	1.05	-11,390.69	-1.12	-26,783.37	-1.36
invl1d^{B}oth	-2,359.56	-0.26	-569,753.20	-1.34	-10,210.00	-0.44	-18,846.07	-0.79	9,257.59	0.48	-14,264.35	-0.62
invh15ind	-16,329.11	-1.26	-82,620.72	-0.69	8,805.11	0.66	8,644.02	0.23	-3,861.01	-0.67	-5,610.08	-0.48
invh15oth	16,717.25	0.54	-516,990.30	-2.17	17,116.76	0.91	-2,499.06	-0.06	3,112.84	0.41	-56,201.99	-2.90

CHAPTER 7

CONCLUSION

Introduction

The objective of this dissertation was to investigate the extent to which perceptions of environmental contamination may affect commercial and industrial (CI) property markets. A theoretical model of CI property values was developed to demonstrate that contaminated sites or perceived sites could reduce nearby property values due to potential risks of contaminant migration to surrounding properties, fouling of nearby air quality, hazards to those who inadvertently cross property boundaries, and exposure to contaminants from future releases at sites without any known contamination.[71] Gaining a better understanding of the role of perceived contamination, when combined with an analysis of known contamination, results in a more complete characterization of the negative effects that environmentally contaminated sites (both known and perceived) have on CI property markets.

To empirically implement the model, a framework was developed to estimate the set of sites that may be perceived as contaminated. In this framework, a CI property's

[71] Determining the differences in impacts associated with the mechanism by which the externality effect of contamination affects nearby property values is beyond the scope of this research.

land-use was assumed to be an important signal. Next, hedonic property value models were estimated for six major land-use categories (Retail, Office, Industrial, Apartment/Hotel/Motel, Auto-Related, and Vacant) to determine the extent that known contaminated sites affect nearby CI property values. These hedonic models incorporated characteristics of the nearest site (i.e. size and land-use type), density of sites nearby, and tests for spatial error correlation. Preferred models were selected and then re-estimated to include controls for proximity to sites that may be perceived as contaminated. The results of the estimated hedonic models suggest that perceptions of contamination may negatively affect properties in the Retail, Office, and Vacant land-use categories, while sites known to be contaminated were found to negatively affect Retail, Office, Industrial, and Auto-Related properties.

In this chapter, the results of the hedonic property models estimated in Chapters 5 and 6 are used to compute the total property value losses from sites with known contamination and sites perceived to be contaminated for CI properties in Fulton County, Georgia. The impacts of sites with known contamination are discussed first, followed by the impacts of sites perceived to be contaminated. Attention will be payed to the spatial distribution of the impacts since both sites with known contamination and perceived contamination are typically located in lower-income, minority neighborhoods. The chapter concludes with a discussion of caveats and future research.

Property Value Impacts of Known Contaminated Sites

The results of the hedonic models estimated in Chapter 5 indicate that proximity to a List1 site has a negative effect on nearby property values for properties in the Retail, Office, Industrial, and Auto-Related land-use categories. Furthermore, the results suggest that the magnitude of the effects may vary between List1 sites with industrial and non-industrial land-uses. The general specification of the hedonic model estimated to investigate the impacts of List1 sites is given by the following:

$$P_{it} = c + + \sum_{j=1}^{J} \beta_j X_{ijt} + \delta_1 \, invl1d_i^A + \delta_2 \, invl1d_i^B \tag{7.1}$$

where X_{ijt} represents all variables other than proximity to a contaminated site in the original equation expressed in Chapter 5 (including the distance measures for List2 and List3 sites). Equation 7.1 assumes the price-distance relationship can be described by the reciprocal of distance to the nearest List1 site, where the price-distance relationship is also allowed to vary before and after site listing. Negative coefficients estimated for the inverse distance variables indicate that price will increase with distance at a decreasing rate, while nearing an asymptotically constant level.

The functional form given by Equation 7.1 was chosen as the Base model because it is consistent with the assumed nature of the negative externality effects of contaminated sites. Risks of contaminated sites to nearby property owners include potential contaminant migration to surrounding properties, fouling of nearby air quality, and potential hazards to those who inadvertently cross property boundaries (Ihlanfeldt and Taylor, 2004). It is expected that the size of these negative effects will continuously decline as distance from a contaminated site increases, and these effects are expected to disappear beyond some point. This implies that the price of CI properties will increase at a decreasing rate as distance to a contaminated site increases, but price will not be affected after some distance, suggesting the function should have an asymptote. The reciprocal relationship is the only functional form that specifically demonstrates a relationship between price and distance that is consistent with the assumed nature of the externality effects of contaminated sites. In addition, goodness-of-fit comparisons to other functional forms indicated Equation 7.1 was an appropriate functional form.

As stated earlier, the hedonic models estimated in Chapter 5 indicate that proximity to a List1 site has a negative effect on nearby property values for properties in the Retail, Office, Industrial, and Auto-Related land-use categories, while List2 and List3 do not have a negative impact on neighboring property values. Table 7.1 provides the coefficient estimates for the List1, List2, and List3 inverse distance measures from the Base model specification (i.e. model based on Equation 7.1).[72] As may be expected, the List1 post-listing distance coefficient ($invl1d^A$) was observed to be the largest in magnitude for Office. Office investors may face potentially higher risks from List1 sites due to the large investment made when purchasing an Office property.[73] To compensate for the higher risks, Office investors may require larger premiums (i.e. reduced market prices) to purchase a property in close proximity to a List1 site as compared to other major land-uses. Although the List1 post-listing distance coefficients were significantly smaller in magnitude for the Retail, Industrial, and Auto-Related models, they indicate that investors in these categories also require premiums to compensate for the risks of being located in close proximity to a List1 site.

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[72] Coefficient estimates are from Table 5.2 in Chapter 5.

[73] Office had the highest average sale price among the six major land-uses.

The results observed for List1 sites in the Apartment/Hotel/Motel and Vacant models were surprising. One could expect List1 sites to have a negative impact on Apartment/Hotel/Motel properties since it may be reasonable to assume that landlords could charge higher rents for properties located further away from a List1 site due to improved quality (holding everything else constant). The higher rents suggest that property values should also increase as distance to a List1 site increases. As such, it is not clear why results contrary to expectations were observed for Apartment/Hotel/Motel. For Vacant properties, investors may not face risks from being located in close proximity to a List1 site because they are not likely to be held liable for the clean up of contamination if discovered. Since the property has yet to be developed (i.e. structural improvements have not been constructed), it is probable that the discovery of contamination may be linked to a known contaminated site nearby (i.e. List1 site).

For List2 sites, none of the inverse distance measures are statistically significant and many are not even of expected sign (i.e. negative). It is interesting to observe that List2 sites are treated differently in the market than List1 sites, since List2 sites are temporarily classified as CERCLIS sites. However, this may be explained by differences in perceived risks between List2 and List1 sites. As Ihlanfeldt and Taylor (2004) indicate, List2 sites do appear on CERCLIS after initial discovery, but the EPA records generally show that most of the sites were delisted quickly after a site assessment had taken place (sites are initially listed on CERCLIS prior to the site assessment that determines the severity of contamination present). Ihlanfeldt and Taylor (2004) suggest that CI property investors may place a low probability on a site's potential for future risks until the assessment has been completed. Different from List2 sites (i.e. NFRAP sites), the List1 sites that continue to remain on CERCLIS after site assessments may provide a signal to the market that these sites have significant contamination present. This is also evident for the List1 sites found on the HSI since the Georgia EPD only places a site on the HSI if they determine there has been a significant release of contaminants. As such, CI property investors may not perceive the long term risks associated with being located in close proximity to a List1 site in a similar way for List2 sites.

Similar to List2 sites, none of the List3 inverse distance measures are statistically significant. It is reasonable to expect that distance to the nearest List3 site would not have any negative effect on CI properties. It is likely that the market does not necessarily perceive these sites to be very dangerous because they represent sites that were tested by the Georgia EPD, but were not found to be contaminated enough to be placed on Georgia's HSI list. Typically, these sites are characterized by a small release of contaminants (e.g. cleaning agents used by a dry cleaner) where there are not expected to be any long term impacts or risks to nearby property owners. Furthermore, these sites are not on any list publically published by the Georgia EPD. Therefore, any information or knowledge about any these sites can only be acquired by reviewing records kept on file at the Georgia EPD's offices. Based on the results of the hedonic models estimated, only the property value impacts of List1 sites are investigated further.

The implicit price of proximity to a List1 site is the change in price associated with a change in distance, and is computed as the derivative of the hedonic model with respect to distance. According the functional form given by Equation 7.1, the implicit price of distance to a List1 site prior to listing is:

$$\frac{\partial P}{\partial\, l1d} = -\hat{\delta}_1 \frac{1}{l1d^2}, \tag{7.2}$$

and the implicit price of distance to a List1 site after listing is:

$$\frac{\partial P}{\partial\, l1d} = -\hat{\delta}_2 \frac{1}{l1d^2}, \tag{7.3}$$

where $\hat{\delta}_1$ is the coefficient estimate for invl1d^B, $\hat{\delta}_2$ is the coefficient estimate for invl1d^A, and l1d is distance to the nearest List1 site.

Table 7.2 provides the expected change in sales price for properties in the Retail, Office, Industrial, and Auto-Related categories after the site has been listed (i.e. implicit price was calculated using Equation 7.3) in one-tenth mile increments from 0.5 miles to 2.0 miles. Apartment/Hotel/Motel and Vacant are not included since the hedonic models estimated indicated that List1 sites do not negatively affect property values in these two major land-use categories. The estimated price changes were calculated using the results of the Base model specification and the RBM specification (i.e. variables other than contaminated site variables in the Base model with t-statistics less than 0.50 were dropped). The price changes can be quite large for properties located in very close proximity to a List1 site. For example, an Office property located 0.5 miles from a List1 site is expected to sell for around \$357,609 less (Base model) than if it were located one-tenth of a mile further away (i.e. 0.6 miles from a List1 site). At 0.5 miles, this represents 18.4 percent of average sales price of Office properties. The impacts are less severe for Retail, Industrial, and Auto-Related where a property in these categories located 0.5 miles from a List1 site would be expected to sell for \$4,570, \$13,464, and \$17,655 less, respectively. This corresponds to 1.5, 1.7, and 7.4 percent of the average sales price for

Retail, Industrial, and Auto-Related properties, respectively. It should be noted that the distance measures were calculated using centroid coordinates of the properties. As such, the distance between a property and a List1 site would be lower if distances were measured between property boundary lines. Regardless, the price changes decline quickly as distance to a List1 site increases. At one mile, the price impacts are less than $4,500 for properties in the Retail, Industrial, and Auto-Related categories and just under $89,500 for an Office property. Beyond one mile, the price changes generally become insignificant in magnitude. Similar changes in price were observed when using the results of the RBM.

The negative price impacts presented in Table 7.2 are consistent with expectations about the externality effects of List1 sites. Although the properties located in very close proximity to a List1 site are shown to sell for significantly less, these negative impacts dissipate quite quickly. This is not surprising since the negative externality effects of List1 sites are expected to be highly localized since they do not represent properties with as severe contamination as sites found on EPA's National Priorities List (NPL).

To determine the size of the total impacts on CI property markets in Fulton County, Georgia, the reduction in property value associated with being located in close proximity to a List1 site is computed. Losses are calculated by comparing the value of the property prior to listing of a List1 site to the value of the property after listing. According to the functional form expressed by Equation 7.1, which uses the pre- and post-listing inverse distance to the nearest List1 site, the difference in property before and after listing can be given as:

$$\Delta \hat{P}_{ij} = \hat{P}_{ij}^{B} - \hat{P}_{ij}^{A} = (\hat{\delta}_{1j} - \hat{\delta}_{2j}) \frac{1}{l1d_i} \ . \tag{7.4}$$

Equation 7.4 states that the change in value of property *i* in land-use *j* associated with proximity to a List1 site equals the difference in the predicted price of property *i* in land-use *j* before and after the site is listed. Alternatively stated, the difference in the price of property *i* in land-use *j* is equal to the difference in the coefficient estimates for invl1d^{A} and invl1d^{B} weighted by the distance to the nearest List1 site. Note, the coefficients estimated for invl1d^{A} and invl1d^{B} are specific to each major land-use category. This method allows for the possibility that List1 sites may also have a negative (or even positive) effect on nearby property values prior to discovery of contamination.

An alternate method to compute changes in property values can be given by:

$$\Delta \hat{P}_{ij}^{alt} = - \hat{\delta}_{2j} \frac{1}{l1d_i} \ . \tag{7.5}$$

This method simply states the change in price is the reduction in property value associated with a particular distance to a List1 site after the site has been listed. The method given by Equation 7.5 ignores any impacts of List1 sites prior to site listing because it assumes the price impacts of a List1 site prior to listing are zero. Furthermore, it will be a less conservative measure of the price impacts if the pre-listing coefficient estimate (invl1d^{B}) is negative, which would indicate that List1 sites have a negative effect on property values pre- and post-listing (assuming the post-listing coefficient is also negative).

To account for differences in price effects for industrial and non-industrial List1 sites, Equation 7.4 can be restated as:

$$\Delta \hat{P}_{ij} = (\hat{\delta}_{1j} - \hat{\delta}_{2j}) \frac{1}{lldind_i} \quad \textit{if nearest List1 site is industrial}$$

$$\Delta \hat{P}_{ij} = (\hat{\delta}_{3j} - \hat{\delta}_{4j}) \frac{1}{lldoth_i} \quad \textit{if nearest List1 site is other than industrial.} \tag{7.6}$$

Based on the alternate method given by Equation 7.5, changes in property values for industrial and non-industrial List1 sites are computed as:

$$\Delta \hat{P}_{ij}^{alt} = - \hat{\delta}_{2j} \frac{1}{lldind_i} \quad \textit{if nearest List1 site is industrial}$$

$$\Delta \hat{P}_{ij}^{alt} = - \hat{\delta}_{4j} \frac{1}{lldoth_i} \quad \textit{if nearest List1 site is other than industrial.} \tag{7.7}$$

Total property value impacts are only computed for List1 sites since the results of the hedonic models estimated in Chapter 5 indicated that List2 and List3 do not have negative effects on neighboring CI property values.

Similar to calculating implicit prices, total losses in property value are only calculated for Retail, Office, Industrial, and Auto-Related. Total impacts are not computed for properties in Apartment/Hotel/Motel and Vacant since the hedonic models indicated that proximity to a List1 site does not have a negative effect on the value of properties in these two categories. The property value losses are computed for every property in the Retail, Office, Industrial, and Auto-Related categories that are within either 1.25 or 1.50 miles of a List1 site, regardless of whether or not the property actually sold. The distance cut-off chosen for each major land-use category is based on the distance cut-off used in estimating the hedonic models. Therefore, property value losses are computed for all Retail and Industrial properties within 1.50 miles of a List1 site and for all Office and Auto-Related properties within 1.25 miles.

As Ihlanfeldt and Taylor (2004) state, this method to compute losses reflects the realized capital loss of all CI properties near a List1 site. However, it should not necessarily be expected to represent the total potential gain in property value that could result if all List1 sites were remediated. Remediating all List1 sites would likely affect the entire real estate market and cause the equilibrium hedonic price schedule to shift, and thus it would be indeterminate how CI property values would respond ex-post to remediation of all List1 sites (Ihlanfeldt and Taylor, 2004). Property values may also not fully recover after remediation due to stigma effects. Patchin (1991) provides some evidence that remediation of known contaminated commercial and industrial properties does not always lead a full recovery of the property's own value. Furthermore, studies on the effects of contaminated sites on residential property markets do not provide clear evidence of residential property values completely recovering after the nearest site has been remediated (Kiel, 1995, Kohlhase, 1991, McCluskey and Rausser, 2003). As such, the estimates of total loss in CI property values due to List1 sites would be an over-estimate of the potential gains from their clean up.

The total property value loss associated with proximity to a List1 sites is computed using the results from four specifications of hedonic models estimated. The four models include the Base model (BM), Reduced Base Model (RBM), Land-use Base model (LBM), and Land-use Reduced Base model (LRBM). The BM is described by Equation 7.1 and is specified with the full set of independent variables controlling for property, location-oriented, and neighborhood-oriented characteristics. The RBM is similar to the BM, but is described as using a reduced set of independent variables (i.e.

variables in the BM other than the contaminated site variables with t-statistics less than 0.50 were dropped). The LBM and LRBM are the same as the BM and RBM except that the pre- and post-listing inverse distance variables for the nearest List1 site are defined separately for industrial and non-industrial sites. The pre- and post-listing inverse distance coefficients for the BM, RBM, LBM, and LRBM used to compute the changes in property values are given in Tables 5.2, 5.4, 5.12, and 5.13 of Chapter 5, respectively. Total losses for each major land-use are determined by summing the individual value losses estimated for properties within the particular land-use.

Tables 7.3 and 7.4 provide the total estimated loss in property value associated with List1 sites in Fulton County, Georgia for properties in the Retail, Office, Industrial, and Auto-Related land-use categories. The losses computed in Table 7.3 were calculated using Equations 7.4 or 7.6 (now referred to as Method 1), while the losses computed in Table 7.4 were calculated using Equations 7.5 or 7.6 (now referred to as Method 2). The estimates provided in Table 7.4 (i.e. losses computed using Method 2) also include ninety percent confidence intervals of the total losses. Confidence intervals were not computed for the losses calculated in Table 7.3 (i.e. Method 1) since there was not a statistically significant difference between the pre- and post-listing distance coefficients. As discussed in Chapter 5, this was primarily due to the large standard errors for the pre-listing coefficients. Furthermore, for brevity, the total loss estimates provided in Table 7.4 were only calculated using the results of the BM and LBM.

The total losses estimated are quite substantial, equaling close to \$1.07 billion regardless of the specific model used to compute the total (based on Method 1 - see Table

7.3), and the BM and RBM produced the maximum and minimum total loss estimates of $1.07 billion and $1.04 billion. Using Method 2 and the BM results, total losses were estimated to be $1.26 billion with a ninety percent confidence interval of $2.42 billion to $135.90 million. When accounting for differences in price impacts for industrial and non-industrial List1 sites, total losses in Table 7.3 (i.e. Method 1) were estimated to be $988.13 million (LBM) and $1.02 billion (LRBM). Assuming the pre-listing impacts of industrial and non-industrial List1 sites are zero (i.e. Method 2), total losses given in Table 7.4 were $1.33 billion (ninety percent confidence interval of $2.75 billion - $234.18 million). When removing the value losses associated with non-industrial List1 sites for Retail and Industrial properties, and the value losses associated with industrial List1 sites for Office properties, the total estimated loss in property value across all land-uses is $844.24 million for the LBM and $783.94 million for the LRBM (see Table 7.3). Even when using the less conservative method (i.e. Method 2), total losses were still estimated at $1.06 billion (ninety percent confidence interval of $1.89 billion - $234.18). This scenario was considered since the post-listing distance coefficient for non-industrial List1 sites (indl1d^{A}oth) was not statistically significant in the Retail and Industrial models and the post-listing distance coefficient for industrial List1 sites (indl1d^{A}ind) was not statistically significant in the Office models, while both post-listing distance coefficients were statistically significant in the Auto-Related models. Removing losses from non-industrial List1 sites for Retail and Industrial and losses for industrial List1 site for Office did not have a large impact on total losses because they did not represent a large portion of the total losses estimated in these three land-use categories. This demonstrates that the magnitude of property value losses are still sizeable even when distinguishing between industrial and non-industrial List1 sites.

Among major land-uses, losses associated with the Office category represent nearly three-quarters of the estimated losses for all land-use categories combined (Table 7.3 - Office totals ranged from $735.26 million (LBM) to $813.55 million (BM)). Furthermore, when distinguishing between the impacts of industrial and non-industrial List1 sites, nearly seventy-five percent of the Office total estimated is a result of impacts from non-industrial sites. Similar observations are made when losses are computed using Method 2. In this instance, total Office losses are $952.00 million (BM in Table 7.4) and range from $1.85 billion to $54.21 million (ninety percent confidence interval). Using the LBM results and only considering losses due to non-industrial List1 sites, total Office losses were $799.61 million ranging from $1.42 billion to $176.99 million (ninety percent confidence interval).[74] The large loss estimates for the Office category is not surprising since it had the steepest gradient of all major land-uses, as indicated by the implicit price impacts given in Table 7.2. Furthermore, of the 557 total Office properties used to compute the total losses, 56.9 percent are within 0.75 miles of a List1 site. As a result, a large percentage of properties are estimated to have significant negative price changes after a List1 site is listed.

Industrial properties also had sizeable price impacts, ranging from $187.22 million (BM) to $184.62 million (RBM) across model specifications when computing losses using Method 1. Unlike Office, the bulk of the Industrial losses were associated

[74] Losses due to industrial List1 sites were not included here since the coefficient estimate for the post-listing distance variable for industrial sites was not statistically significant.

with industrial List1 sites ($160.45 of $184.35 million total and $163.63 of $182.36 million total for the LBM and LRBM, respectively). If the pre-listing impacts of List1 sites were not included, total industrial losses were $202.74 million (ninety percent confidence interval of $350.83 million - $54.65 million) using the BM coefficient estimates and were $161.92 million (ninety percent confidence interval of $284.25 million to $39.60 million) using the LBM estimates.[75] Although the Industrial price gradient is not as steep as Office (see Table 7.2), 79.5 percent of the Industrial properties used to compute the total losses are within 0.75 miles of a List1 site. When combined, the Office and Industrial categories comprise around ninety-three percent of the total losses estimated across the models used to generate the estimates in Tables 7.3 and 7.4.

Property value losses for Retail and Auto-Related were only a small fraction of the estimated totals, varying from $22.24 million (LRBM)[76] to $38.16 million (BM) for Retail and $23.19 million (RBM) to $32.24 million (LBM) for Auto-Related using Method 1 (see Table 7.3). The implicit prices given in Table 7.2 show that Retail has the least steep price gradient, where price impacts were computed to be less than one thousand dollars beyond one mile. Although there are over two thousand properties used to compute the Retail total, the small price impacts results in modest losses in total property value. The steeper price gradient for Auto-Related is offset by the lower number of properties used to compute total property value losses. As such, total property value losses are also modest when compared to Office and Industrial.

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[75] These estimates do not include losses for non-industrial List1 sites.

[76] Estimates does not include losses for non-industrial List1 sites.

To further put the total losses into context, they are compared with the total value of all Retail and Industrial properties within 1.50 miles of a List1 site and all Office and Auto-Related properties within 1.25 miles of a site. The distance cut-off for each major land-use category was chosen to be consistent with the distance cut-off used when estimating the hedonic models. The total value of all properties in each land-use, regardless of whether or not the property actually sold, is based on the 2000 tax assessed value of each property. Since tax assessed values generally underestimate actual property values, the size of total losses relative to total value will be overstated.

Table 7.5 presents the ratio of total losses to total value. As the table indicates, losses as a percent of total value is quite substantial for Office (42 percent), but are more modest for Retail, Industrial, Auto-Related (4 percent, 10 percent, and 12 percent, respectively). Again, the very high percentage loss for Office is primarily due to the steep price gradient (see Table 7.2) and because 56.9 percent of the 557 Office properties used to compute the total losses are within 0.75 miles of a List1 site. Overall, total losses for these four land-uses combined are 22.0 percent of the total assessed value of all properties within close proximity to a List1 site and 8.0 percent of the total assessed value of Retail, Office, Industrial, and Auto-Related properties in Fulton County, Georgia. Excluding Office, the total losses of $253.3 million represent 9.0 percent of the total assessed value of Retail, Industrial, and Auto-Related properties within close proximity of a List1 site and 2.0 percent of the assessed value for these categories in Fulton County.[77]

To describe the spatial distribution of the total property value impacts of List1

[77] This scenario was presented due to the large losses associated with the Office category.

sites, total property value losses were calculated by census tract. Figure 7.1 summarizes the CI property value losses by census tract.[78] The figure indicates that there is substantial spatial variation in the losses. Five census tracts had impacts over $50 million, where the largest impacts ($90.7 million) were in a census tract located slightly north of the Atlanta Central Business District (cbd) and west of the split between Interstate 75 and Interstate 85.[79] Census tracts with higher losses are typically concentrated in the central/south-central portions of Fulton County and follow the major highways within the county. There are forty-two census tracts with no losses associated with List1 sites, where most of these tracts are located in northern Fulton County. Overall, the average loss per census tract is $7.3 million.

Total losses in CI property values were also summed by List1 site and are presented in Figure 7.2. As expected, Figure 7.2 shows that total losses by List1 site follow a similar spatial pattern as losses by census tract.[80] The sites with the largest impact are found in the central portion of Fulton County. This is not surprising since most Office properties are typically located close to the CBD and the Office category displayed the steepest price gradient among all major land-use categories. Five List1 sites had impacts over $50 million, where the largest was $131.4 million. The site with the largest impact was located in the central portion of Fulton County near the CBD where

[78] Estimates of total losses by census tract are based on the coefficient estimates from the Base Model.

[79] Interstate 75 and 85 join south of the Atlanta CBD and then separate north of the CBD. After the split, I-75 continues in a northwest direction and I-85 continues in a northeast direction.

[80] Estimates of total losses by List1 site are based on the coefficient estimates from the Base Model.

sixty-six Office properties were within 1.25 miles, and combined with the steep price gradient for the Office category leads to the large total. Five List1 sites had impacts between $25 and $50 million, thirty-two sites had impacts between $5 and $25 million, and eleven sites had impacts less than $5 million. On average, the loss per List1 site was $20.1 million.

The impacts on CI property values are also in mostly poor areas with higher concentrations of minority populations. The relationship between the proportion of minority population in a census tract and median census tract income to the estimated property value losses by List1 sites are given in Figures 7.3 and 7.4, respectively. As indicated in Figure 7.3, sites with the greatest impact are located in or near census tracts with minority populations greater than fifty percent. It is also interesting to see the close spatial resemblance between losses by List1 site and the median income levels. Figure 7.4 shows that sites with higher impacts are located primarily in poor areas with median incomes less than $25 thousand.

The results presented in this section suggest that List1 sites have a large negative impact on CI property values and that these impacts are primarily in poorer neighborhoods with high concentrations of minority populations that are located near the central portion of Fulton County. As discussed earlier, the total estimated losses should not necessarily be expected to represent the total potential gain in property value that could result if all List1 sites were remediated. However, the magnitude of the total losses suggest that significant gains can still be achieved if property values respond by only a fraction of the estimated total losses.

Property Value Impacts of Sites Perceived to be Contaminated

To account for proximity to a perceived highly contaminated site, the general specification of the hedonic model estimated to investigate the impacts of List1 sites (given by Equation 7.1) was modified as follows:

$$P_{it} = c + + \sum_{j=1}^{J} \beta_j X_{ijt} + \delta_1 \, invl1d_i^A + \delta_2 \, invl1d_i^B + \delta_3 \, invphd_i \qquad (7.8)$$

where X_{ijt} represents all other variables (including the distance measures for List2 and List3 sites) and $invphd_i$ is the inverse distance to the nearest perceived contaminated site. As with List1 sites, it is assumed that the price-distance relationship can be described by the reciprocal of distance to the nearest site perceived to be highly contaminated. However, unlike List1 sites, the price-distance relationship does not vary before and after site is "listed" since the probability of contaminated model is unable to determine a specific date a property may first be perceived as contaminated. Negative coefficients estimated for the inverse distance variable indicate that price will increase with distance at a decreasing rate, while nearing an asymptotically constant level.

The results reported for the hedonic models estimated in Chapter 6 suggest that proximity to a site that may be perceived as highly contaminated may a negative effect on nearby property values for properties in the Retail, Office, and Vacant land-use categories. Specifically, these negative impacts were due to proximity to industrial sites for Retail properties and non-industrial sites for Office and Vacant properties.

Table 7.6 provides the estimated coefficients from the Land-use Base Model

(LBM)[81] for the List1 site and perceived contaminated site distance measures.[82] The results observed for the Retail and Office categories were consistent with the hedonic models estimated in Chapter 5 where industrial sites (for Retail models) and non-industrial sites (for Office models) were also found to have a greater negative impact on property values than non-industrial and industrial sites, respectively (see Tables 5.14 and 5.15 in Chapter 5). Retail and Office investors may be sensitive to perceptions of nearby contamination and therefore, premiums (i.e. reduced prices) may be required to compensate for the risks of being located near a potentially contaminated site (risks include the potential for being held partially liable for clean up if contamination is discovered). Again, these premiums are likely to be higher for Office properties because the development or purchase of Office properties typically involve large investments.

The negative and statistically significant estimate for invh15oth in the Vacant model was interesting since the List1 post-listing distance coefficients were never statistically significant in any of the hedonic models estimated. This suggests that Vacant property investors may only be sensitive to perceptions of contamination about nearby properties and not to properties with known contamination (i.e. List1 sites). As discussed earlier, purchasers of Vacant properties may be less likely to believe they will be held liable for clean up upon the discovery of contamination that can be linked to a nearby site with known contamination (i.e. List1 site). However, they may believe they could be

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[81] The LBM allowed the impacts of the nearest site (perceived and List1) to vary for industrial and non-industrial sites.

[82] Coefficient estimates are from Table 6.4 in Chapter 6. However, only the estimates for the models where the list of perceived contaminated sites was defined by the highest cut-off value are reported (i.e. k = 0.15).

held liable for remediation costs if contamination is discovered when there is greater uncertainty about the potential source of the contamination.

The statistically insignificant coefficient estimates for the Industrial and Auto-Related models may not necessarily be surprising because these types of land-uses are more likely to be found on either CERCLIS or HSI (i.e. classified as a List1 site; see Table 3.10 in Chapter 3). Investors in these two categories may be more familiar with the threats (or lack of threats) posed by nearby properties and therefore, less likely to form negative perceptions that nearby properties may be contaminated. Therefore, investors are not likely to require premiums (i.e. reduced prices). As a result, properties values in these two categories may only be negatively affected after contamination has been discovered, which is indicated by the List1 post-listing distance coefficients (see Tables 6.2, 6.3, 6.4 and 6.5 in Chapter 6). The results observed for the Apartment/Hotel/Motel models were consistent with the hedonic models that did not included proximity to nearest perceived contaminated site, suggesting that perceived or known contaminated sites do not negatively affect nearby property values. Based on the hedonic models estimated, the property value impacts of perceived contaminated sites on Retail, Office, and Vacant properties are investigated further.

The implicit price of proximity to a perceived highly contaminated site is the change in price associated with a change in distance, computed as the derivative of the hedonic model with respect to distance to the perceived contaminated site. This implicit price can be given as:

$$\frac{\partial P}{\partial phd} = - \hat{\delta}_3 \frac{1}{phd^2} , \tag{7.9}$$

where $\hat{\delta}_3$ is the coefficient estimate for invphd and phd is distance to the nearest perceived contaminated site.

The hedonic models estimated in Chapter 6 indicated that proximity to industrial perceived contaminated sites negatively affected property values in the Retail category, while non-industrial sites negatively affected property values in the Office and Vacant categories. Table 7.7 provides the expected change price for properties in the Retail, Office, and Vacant categories due to proximity to a perceived contaminated site in one-tenth mile increments, from 0.5 miles to 2.0 miles. The price changes are computed using the coefficient estimates reported in Table 6.4 in Chapter 6 when the cut-off value used to generate the list of sites equaled 0.15 (i.e. k = 0.15). The results of the hedonic models estimated when the list of sites perceived to be contaminated were defined by a lower cut-off values (i.e. k = 0.10 and 0.05) suggest that sites identified in this manner do not have any negative effect on neighboring CI property values. Industrial, Apartment/Hotel/Motel, and Auto-Related were not computed since the models estimated indicated that proximity to a perceived contaminated site did not have a negative effect on nearby property values in these three categories. Table 7.7 also provides the expected change in sales price for properties in the Retail, Office, Industrial, and Auto-Related categories associated with proximity to a List1 site after the site has been listed. For consistency, these implicit prices were calculated using the results of the coefficient estimates for List1 sites reported in Table 6.4 in Chapter 6. Furthermore, depending of the category, the price impacts of proximity to a perceived contaminated site and a List1 site were either based on proximity to an industrial site or non-industrial site. As such, the price impacts calculated using Equations 7.3 and 7.9 for Retail, Industrial, and Auto-Related are based on proximity to industrial sites, while the price impacts for Office and Vacant are based on proximity to non-industrial sites.

Table 7.7 indicates that the price changes can be quite large for properties located in very close proximity to a perceived contaminated site. Similar to List1 sites, the changes in price were largest for Office. For example, an Office property located 0.5 miles from a perceived contaminate site (non-industrial) is expected to sell for around \$270,881 less than if it were located one-tenth of a mile further away (i.e. 0.6 miles from a site). The impacts are less severe for Retail and Vacant where a property in these categories located 0.5 miles from a perceived contaminated site (industrial for Retail and non-industrial for Vacant) would be expected to sell for \$7,542 and \$24,195 less, respectively. These negative price impacts do decline quickly as distance to a perceived contaminate site increases. At one mile, the change in price is less than \$68,000, \$6,100, and \$1,900 for properties in the Office, Vacant, and Retail categories, respectively. And similar to List1 sites, the changes in price associated with proximity to a perceived contaminated site generally becomes insignificant in magnitude beyond one mile.

Some interesting observations are made regarding the implicit prices of proximity to List1 sites for Retail and Office. Compared to the results reported in Table 7.2, the price impacts of List1 sites more than double for Office when proximity to a perceived contaminated site is included in the estimated model. However, it should be noted that the price impacts reported in Table 7.7 for Office properties are based on proximity to a non-industrial List1 site. The hedonic models estimated in Chapter 5 that distinguished between industrial and non-industrial List1 sites, but did not include proximity to a perceived contaminated site demonstrated a similar change in the magnitude of the coefficient estimates used to compute the implicit prices. Furthermore, the price impacts would be significantly lower if the pre-listing coefficient estimate were considered in the calculations. It is also interesting that for Retail, the price impacts for industrial perceived contaminated sites are greater than for industrial List1 sites. This suggests that Retail investors may be more concerned about locating near properties without a documented record of contamination compared to sites that they know have contamination present (i.e. List1 sites). However, in both instances, the price impacts dissipate quickly as distance to the nearest site increases.

As was done for List1 sites, the reduction in property value associated with being located in close proximity to a site perceived to be highly contaminated is computed to estimate the total impacts of these sites. According to the functional form estimated that accounted for differences in industrial and non-industrial site perceived to be contaminated, the loss in property value can be given as:

$$\begin{aligned} \Delta \hat{P}_{ij} &= -\hat{\delta}_{3j} \frac{1}{dPHind_i} \quad \textit{if nearest perceived site is industrial} \\ \Delta \hat{P}_{ij} &= -\hat{\delta}_{4j} \frac{1}{dPHoth_i} \quad \textit{if nearest perceived site is other than industrial.} \end{aligned} \tag{7.10}$$

Since the inverse distance variables for sites perceived to be highly contaminated does not vary according to a pre-/post-listing distinction, losses are simply computed to be equal to the coefficient estimate for $invdPHind_i$ or $invdPHoth_i$ weighted by the distance to the nearest site perceived to be highly contaminated. The coefficient estimates for

$invdPHind_i$ and $invdPHoth_i$ are specific to Retail, Office, and Vacant land-use categories. Total property value impacts were non computed for Industrial, Apartment/Hotel/Motel, and Auto-Related since the models estimated indicated that proximity to a perceived contaminated site did not have a negative effect on nearby property values in these three categories.

Total property value impacts are computed for sites perceived as highly contaminated when the cut-off value used to generate the list of sites equaled 0.15 (i.e. k = 0.15). The results of the hedonic models when the list of sites perceived to be highly contaminated were defined by a lower cut-off values (i.e. k = 0.10 and 0.05) suggest that sites identified in this manner do not have any negative effect on neighboring CI property values. In addition, property value losses are computed for every property in the Retail, Office, and Vacant land-use categories that are within either 1.25 or 1.50 miles of a site perceived to be contaminated, regardless of whether or not the property actually sold. Similar to List1 sites, the distance cut-off chosen for each major land-use category is based on the distance cut-off used in estimating the hedonic models. Therefore, property value losses are computed for all Office and properties with 1.25 miles of a site and for all Retail and Vacant properties within 1.50 miles. Finally, losses associated with proximity to a site perceived to be contaminated are computed using the results reported in Table 6.4 in Chapter 6. As such, Equation 7.10 is used to compute losses from industrial sites for Retail and losses from non-industrial sites for Office and Vacant.

Table 7.8 provides the total estimated loss in property value associated with sites that may be perceived to be contaminated in Fulton County, Georgia for properties in the

Retail, Office, and Vacant land-use categories. For consistency, Table 7.8 also provides losses in property value due to proximity to List1 sites for Retail, Office, Industrial, and Auto-Related using the List1 coefficient estimates reported in Table 6.4 in Chapter 6. Combining the loss estimates for perceived contaminated sites and List1 sites provides an aggregate estimate of loss in property value due to environmentally contaminated sites (i.e. perceived contamination and known contamination). Total losses in property value from perceived contaminated sites are discussed first followed by the aggregate total from perceived and List1 sites.

The total losses in property value due perceived contaminated sites are quite substantial ($663.09 million) considering they are based on sites that do not have any documented record of a contaminant release. Losses to Office properties from non-industrial sites comprise 65.7 percent of the overall total, where the range of losses estimated are $793.46 million to $78.08 million (ninety percent confidence interval). This is not surprising since the price gradient for Office is very steep compared to Retail and Vacant (see Table 7.7). Additionally, these observations are consistent with the loss in property values from List1 sites discussed in the previous section. Total losses for Vacant ($175.20 million with ninety percent confidence interval of $278.72 million to $71.69 million) are less than half of Office losses and are 26.4 percent of the overall total. The remaining 7.9 percent of total losses from perceived contaminated sites is for Retail ($52.12 million with ninety percent confidence interval of $103.82 million to $0.41 million).

Together, total loss in property values due to List1 sites and perceived contaminated sites is estimated at $1.88 billion (ninety percent confidence interval of $3.33 billion to $450.86 million), where losses due to perceived contaminated sites are 35.2 percent of the overall total. Similar to the impacts of just List1 sites discussed in the previous section, Office is the category with largest combined losses ($1.46 billion). This is primarily a result of Office having the steepest price gradient for both List1 sites and perceived contaminated sites. Losses for Auto-Related were modest ($18.50 million), where these losses were only due to List1 sites. For Retail, Industrial, and Vacant, total combined losses were $77.43 million (List1 and perceived sites), $145.76 million (List1 sites only), and $175.20 million (perceived sites only).

To put the total losses into context, Table 7.9 compares total losses with the total assessed value of properties near a List1 site and perceived contaminated site. The table indicates that losses due to perceived contaminated sites as a percent of total assessed value is largest for Vacant (18 percent), but are more modest for Retail and Office (three percent and seven percent, respectively). Overall, total losses for these three land-uses combined are seven percent of the total value of all properties within close proximity to a perceived contaminated site and five percent of the total value of Retail, Office, Industrial, Auto-Related, and Vacant properties in Fulton County, Georgia. The combined losses for Office were highest at twenty-five percent of the assessed value of properties in close proximity to a List1 or perceived contaminated site, followed by Vacant at eighteen percent. Retail was lowest where total combined losses were only three percent of the total value of properties. Combined, losses due to List1 sites and perceived contaminated sites are fifteen percent of the total assessed value of Retail, Office, Industrial, Auto-Related, and Vacant properties in close proximity, and thirteen percent of the total assessed value for these categories in Fulton County.

To describe the spatial distribution of the total property value impacts due to perceived contaminated sites, losses in property value were calculated by census tract. First, Figure 7.5 shows the spatial distribution of the perceived contaminated sites throughout Fulton County, Georgia, while Figure 7.6 summarizes the CI property value losses from 190 perceived contaminated sites by census tract. As Figure 7.5 indicates, most perceived contaminated sites are located in the central portion of the county and Figure 7.6 shows that most tracts with losses greater than $5 million are located in this same area. The census tract with the largest impacts ($69.82 million) is located slightly north of the Atlanta CBD. However, there are also areas in the northern portion of the county with losses greater than $10 million. It is interesting to observe in Figure 7.5 that several perceived contaminated sites are located in these same areas. Unlike the spatial distribution of losses from List1 sites in Figure 7.1, there are only nine census with zero losses. Twenty-three census tracts had losses greater than $10 million, while sixty-five tracts had losses under $1 million. Overall, the average loss per census tract is $4.5 million.

The total losses from List1 sites by census tract were also computed and are given in Figure 7.7. The spatial distribution of losses from List1 sites given in Figure 7.7 closely resembles the spatial distribution of losses from List1 sites presented in Figure 7.1, even though two different hedonic models were used to compute the estimates. As such, the areas found to have higher property value losses from List1 sites are still observed to be primarily located in the central/south-central portions of Fulton County.

Figure 7.8 presents the spatial distribution of the combined property value losses due to List1 sites and perceived contaminated sites. As the figure indicates, most of the areas with the greatest impacts are located in the central and south-central southern portions of Fulton County. The census tract with the highest loss in property value ($305.5 million)[83] is located near the Atlanta cbd. This is not surprising as there are several Office properties in this area and Office was estimated to have the steepest price gradient for List1 sites and perceived contaminated sites. Twenty-one tracts have estimated losses greater than $25 million. Although most of the these areas are located in the central/south-central portion of Fulton County, there are three tracts in northern Fulton County with combined impacts greater than $25 million. For one these tracts, the $29.8 million in property value losses are entirely due to perceived contaminated sites. Overall, average loss per census tract was $12.9 million, where only eight tracts have estimated losses equal to zero. The similar spatial pattern of the combined impacts of List1 sites and perceived contaminated sites and the impacts of List1 sites only indicates that primarily poorer areas with higher concentrations of minority populations are being most affected.

The results presented in this section suggest that the combined negative impacts on CI property values of List1 sites and sites that be perceived as contaminated are substantial. The impacts of perceived contaminated sites further supports the expectation that the total estimated losses from List1 sites are not likely to equal the gains from the

[83] It should be note that this figure would be substantially lower if the pre-listing distance coefficient for List1 sites was used to compute property value losses.

remediation of all List1. For example, property owners may still perceive there to be risks associated with being located in close proximity to a List1 site after it has been remediated. It is reasonable to believe that property values will recover, but maybe only to the level for which perceptions of contamination still negatively affects an investor's valuation of a property. Therefore, the losses estimated from known contaminated sites (i.e. List1 sites) would be an over-estimate of the potential gains from their clean up.

Discussion

This dissertation investigated the extent to which perceptions of environmental contamination may affect commercial and industrial (CI) property markets, in additional to the impacts of known environmental contamination. The negative property value impacts of sites that may be perceived as contaminated were estimated at $663.09 million, while impacts from known contaminated sites were estimated at slightly over $1 billion. Although the property value impacts are substantial, they are not equivalent to the expected gains that may result from the remediation of all List1 sites due to potential stigma effects and the unknown level of response in the CI property market. However, the magnitude of the total losses estimated suggests that significant gains can still be achieved if property values respond by only a fraction.

Although the magnitude of the impacts from sites that may be perceived as contaminated are substantial, it is not clear if perceptions of contamination are being captured accurately. This is primarily due to the inability of the probability of contamination model that was estimated in Chapter 4 to determine the point in time during the study period a property may first be perceived as contaminated. The results of the estimated hedonic models show that there is a difference in price impacts for known contaminated sites (i.e. List1 sites) after the site has been listed. This indicates that there is a "signaling" effect for sites once they are listed. As such, there may be a similar response by CI property investors for sites that may be perceived as contaminated, where this "signaling" effect occurs when investors first perceive a site to be contaminated.

To appropriately address this issue, future research would involve collecting the necessary CI property data and developing an empirical model that would enable one to determine the point in time a property may first be perceived as contaminated. Hedonic property value models can then be estimated to determine the impacts of sites that may be perceived as contaminated, while being able to control the "signaling" effect in a similar way to listed sites (i.e. List1 or CERCLIS and HSI sites).

The significant property value impacts of known contaminated sites suggest that large potential gains could still be realized even if property values recover only a fraction of the estimated losses. This research could provide information to use for the prioritization of site remediation for sites located in Fulton County. Factors that can be considered in this process include total impacts caused by a site and total impacts relative to a site's location with respect to income and population types. For example, site remediation could be targeted to benefit minority and/or economically depressed areas to help spur economic development. These local areas could benefit from an increase in the tax base, resulting in greater property tax revenues for the provision of public services for the community. In addition, the economic development could provide access to new jobs for local residents.

This research would also benefit by extending the analysis to other counties within the greater Atlanta Metropolitan area, of which Fulton County is only small fraction of the total, and from an analysis of residential property markets. Although impacts on CI property values alone were substantial, extending to residential property markets allows for a complete characterization the total impacts of contaminated sites. This would provide further information towards the potential gains that may be realized from their remediation. In addition, extending the analysis to other counties outside of Fulton County would enable a complete characterization of the region wide impacts of contaminated sites. This information would be valuable to regional policy makers in helping to combat urban sprawl, an important concern in the Atlanta Metropolitan area.

Table 7.1. Coefficient Estimates for List1, List2, and List3 Sites from Base Hedonic Model

	Retail	Office	Industrial	Apartment/ Hotel/Motel	Auto-Related	Vacant
Variable	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
invl1d^A	-11,424.04 **	-894,023.20 **	-33,661.13 *	-17,167.13	-44,137.37 *	-8,353.59
invl1d^B	-3,477.60	-130,800.80	-2,577.02	-20,751.47	-25,204.34	-16,089.66
invl2d^A	-2,567.62	-81,903.82	7,914.31	2,117.59	7,722.25	6,532.66
invl2d^D	18,059.43	103,668.00	-5,911.73	-3,996.63	12,435.69	2,546.71
invl2d^B	-10,985.64	-1,198,286.00	-34,534.77	-26,329.34	18,451.26	-24,053.93
invl3d^A	4,012.95	-81,176.58	34,372.07	-2,035.00	-10,326.89	-9,455.78
invl3d^B	1,343.17	119,446.70	7,009.28	-4,880.32	7,408.19	-3,736.43

* Significant at 5 percent level
** Significant at 10 percent level

Table 7.2. Price Impacts of Proximity to a List1 Site After Site Listing

	Retail		Office		Industrial		Auto-Related	
Mean Sale Price[a]	$295,390		$1,940,444		$806,138		$237,752	
Distance to List1 Site	Base	RBM	Base	RBM	Base	RBM	Base	RBM
0.50 miles	-4,570	-4,239	-357,609	-342,670	-13,464	-13,276	-17,655	-18,694
0.60 miles	-3,173	-2,944	-248,340	-237,965	-9,350	-9,219	-12,260	-12,982
0.70 miles	-2,331	-2,163	-182,454	-174,832	-6,870	-6,773	-9,008	-9,538
0.80 miles	-1,785	-1,656	-139,691	-133,856	-5,260	-5,186	-6,896	-7,302
0.90 miles	-1,410	-1,308	-110,373	-105,762	-4,156	-4,097	-5,449	-5,770
1.00 miles	-1,142	-1,060	-89,402	-85,668	-3,366	-3,319	-4,414	-4,674
1.10 miles	-944	-876	-73,886	-70,800	-2,782	-2,743	-3,648	-3,862
1.20 miles	-793	-736	-62,085	-59,491	-2,338	-2,305	-3,065	-3,246
1.30 miles	-676	-627	-52,901	-50,691	-1,992	-1,964	-2,612	-2,765
1.40 miles	-583	-541	-45,613	-43,708	-1,717	-1,693	-2,252	-2,384
1.50 miles	-508	-471	-39,734	-38,074	-1,496	-1,475	-1,962	-2,077
1.60 miles	-446	-414	-34,923	-33,464	-1,315	-1,296	-1,724	-1,826
1.70 miles	-395	-367	-30,935	-29,643	-1,165	-1,148	-1,527	-1,617
1.80 miles	-353	-327	-27,593	-26,441	-1,039	-1,024	-1,362	-1,442
1.90 miles	-316	-294	-24,765	-23,731	-932	-919	-1,223	-1,295
2.00 miles	-286	-265	-22,351	-21,417	-842	-830	-1,103	-1,168

[a] Calculated as mean sale price of estimating sample for Base model.

Table 7.3. Total Property Value Losses due to List1 Sites in Fulton County, Georgia (Method 1)

	Retail	Office	Industrial	Auto-Related	Total
Number of Properties	2,100	557	1,801	521	4,979
Value Loss ($ millions)					
Base Model (BM)					
Total	38.16	813.55	187.22	27.84	1,066.77
Reduced Base Model (RBM)					
Total	34.07	797.45	184.62	23.19	1,039.34
Land-use Base Model (LBM)[a]					
Nearest List1 Site is Industrial	23.86	107.58	160.45	18.55	310.44
Nearest List1 Site is Non-Industrial	12.41	627.68	23.90	13.69	677.68
Total	36.27	735.26	184.35	32.24	988.13
Land-use Reduced Base Model (LRBM)[a]					
Nearest List1 Site is Industrial	22.24	216.19	163.63	17.62	419.68
Nearest List1 Site is Non-Industrial	4.69	568.34	18.73	12.10	603.86
Total	26.93	784.54	182.36	29.72	1,023.55

[a] Although the coefficient for the post-listing distance variable was not significant for non-industrial sites in the Retail and Industrial models and for industrial sites in the Office models, total losses were computed for illustrative purposes.

Table 7.4. Total Property Value Losses due to List1 Sites in Fulton County, Georgia (Method 2)[a]

	Retail	Office	Industrial	Auto-Related	Total
Number of Properties	2,100	557	1,801	521	4,979
Value Loss ($ millions)					
Base Model (BM)	54.86	952.00	202.74	64.90	1,275.48
	(101.58 - 8.15)	(1,851.74 - 54.21)	(350.83 - 54.65)	(110.91 - 18.89)	(2,415.06 - 135.90)
Land-use Base Model (LBM)[b, c]					
Nearest List1 Site is Industrial	31.82	208.52	161.92	48.85	451.12
	(60.16 - 3.49)	(710.22 - 0.00)	(284.25 - 39.60)	(86.53 - 11.17)	(1,141.16 - 54.25)
Nearest List1 Site is Non-Industrial	19.79	799.61	36.94	20.19	876.53
	(55.28 - 0.00)	(1,422.23 - 176.99)	(94.39 - 0.00)	(37.44 - 2.94)	(1,609.33 - 179.93)
Total	51.61	1,008.13	198.87	69.04	1,327.65
	(115.44 - 3.49)	(2,132.45 - 176.99)	(378.64 - 39.60)	(123.97 - 14.11)	(2,750.49 - 234.18)

[a] 90 percent confidence interval in parentheses

[b] Although the coefficient for the post-listing distance variable was not significant for non-industrial sites in the Retail and Industrial models and for industrial sites in the Office models, total losses were computed for illustrative purposes.

[c] The post-listing coefficient was set to zero to compute losses when the lower-bound coefficient estimate was positive when calculating the ninety percent confidence interval.

Table 7.5. Total Losses in Property Value due to List1 Sites as a Percent of Total Assessed Value

	Retail[b]	Office[c]	Industrial[b]	Auto-Related[c]	Total
Value Loss ($ millions)[a]	38.16	813.55	187.22	27.84	1,066.77
Total Assessed Value (Near List1 Site)	945.87	1,926.87	1,798.12	225.96	4,896.81
Value Loss as Percent of Assessed Value	0.04	0.42	0.10	0.12	0.22
Total Assessed Value (Fulton County)	2,972.42	7,077.35	2,816.06	534.03	13,399.86
Value Loss as Percent of Assessed Value	0.01	0.11	0.07	0.05	0.08

[a] Losses computed using coefficient estimates from Base model.

[b] Total losses and total assessed value computed for properties within 1.50 miles of a List1 site.

[c] Total losses and total assessed value computed for properties within 1.25 miles of a List1 site.

Table 7.6. Coefficient Estimates for List1 and Perceived Contaminated Sites from Land-use Base Model (LBM)

	Retail		Office		Industrial		Apartment/ Hotel/Motel	Auto-Related		Vacant	
Variable	Coefficient		Coefficient		Coefficient		Coefficient	Coefficient		Coefficient	
invl1d^{A}ind	-9,765.42	*	-647,225.50		-33,226.99	**	-47,714.35	-20,523.74	**	1,101.11	
invl1d^{B}ind	1,155.03		-275,478.80		252.09		-23,024.10	-6,695.65		-26,098.51	**
invl1d^{A}oth	-8,978.09		-2,362,234.00	*	-16,202.75		46,911.18	-16,048.02		-27,001.52	
invl1d^{B}oth	-3,865.94		-701,931.30		-7,905.56		-11,271.73	14,170.47		-12,892.48	
invh15ind	-18,855.92	**	-149,572.30		8,557.58		2,733.26	-9,931.89		-5,049.13	
invh15oth	14,296.89		-677,202.90	*	12,197.20		-1,892.72	-3,982.26		-60,486.69	*

* Significant at 5 percent level
** Significant at 10 percent level

Table 7.7. Price Impacts of Proximity to a List1 Site After Site Listing and Proximity to a Perceived Contaminated Site

	Retail		Office		Industrial	Auto-Related	Vacant
Mean Sale Price	$291,385		$2,120,508		$799,413	$191,102	$426,821
Distance to Site	List1	Predicted	List1	Predicted	List1	List1	Predicted
0.50 miles	-3,906	-7,542	-944,894	-270,881	-13,291	-8,209	-24,195
0.60 miles	-2,713	-5,238	-656,176	-188,112	-9,230	-5,701	-16,802
0.70 miles	-1,993	-3,848	-482,089	-138,205	-6,781	-4,189	-12,344
0.80 miles	-1,526	-2,946	-369,099	-105,813	-5,192	-3,207	-9,451
0.90 miles	-1,206	-2,328	-291,634	-83,605	-4,102	-2,534	-7,467
1.00 miles	-977	-1,886	-236,223	-67,720	-3,323	-2,052	-6,049
1.10 miles	-807	-1,558	-195,226	-55,967	-2,746	-1,696	-4,999
1.20 miles	-678	-1,309	-164,044	-47,028	-2,307	-1,425	-4,200
1.30 miles	-578	-1,116	-139,777	-40,071	-1,966	-1,214	-3,579
1.40 miles	-498	-962	-120,522	-34,551	-1,695	-1,047	-3,086
1.50 miles	-434	-838	-104,988	-30,098	-1,477	-912	-2,688
1.60 miles	-381	-737	-92,275	-26,453	-1,298	-802	-2,363
1.70 miles	-338	-652	-81,738	-23,433	-1,150	-710	-2,093
1.80 miles	-301	-582	-72,908	-20,901	-1,026	-633	-1,867
1.90 miles	-271	-522	-65,436	-18,759	-920	-569	-1,676
2.00 miles	-244	-471	-59,056	-16,930	-831	-513	-1,512

[a] Calculated as mean sale price of estimating sample for LBM (Land-use Base model).

Table 7.8. Total Value Losses due to List1 Sites and Perceived Contaminated Sites

	Retail	Office	Industrial	Auto-Related	Vacant	Total
Value Loss due to List1 Sites ($ millions)						
Number of Properties	2,100	557	1,801	521	-	4,979
Nearest Site is Industrial	25.31	-	145.76	18.50	-	189.57
	(45.44 - 5.19)	-	(269.17 - 22.34)	(35.58 - 1.42)	-	(350.18 - 28.96)
Nearest Site is Non-Industrial	-	1,028.74	-	-	-	1,028.74
	-	(1,785.75 - 271.72)	-	-	-	(1,785.75 - 271.72)
Total	25.31	1,028.74	145.76	18.50	-	1,218.31
	(45.44 - 5.19)	(1785.75 - 271.72)	(269.17 - 22.34)	(35.58 - 1.42)	-	(2,135.93 - 300.68)
Value Loss due to Perceived Contaminated Sites ($ millions)						
Number of Properties	1,807	1,096	-	-	1,539	4,442
Nearest Site is Industrial	52.12	-	-	-		52.12
	(103.82 - 0.41)	-	-	-		(103.82 - 0.41)
Nearest Site is Non-Industrial	-	435.77	-	-	175.20	610.97
	-	(793.46 - 78.08)	-	-	(278.72 - 71.69)	(1072.18 - 149.77)
Total	52.12	435.77	-	-	175.20	663.09
	(103.82 - 0.41)	(793.46 - 78.08)	-	-	(278.72 - 71.69)	(1,175.99 - 150.18)
Total Value Loss (List1 and Perceived Sites)	77.43	1,464.50	145.76	18.50	175.20	1,881.40
	(149.25 - 5.6)	(2,579.21 - 349.80)	(269.17 - 22.34)	(35.58 - 1.42)	(278.72 - 71.69	(3,311.93 - 450.86)

Table 7.9. Total Value Losses due to List1 Sites and Perceived Contaminated Sites as a Percent of Total Assessed Value

	Retail	Office	Industrial	Auto-Related	Vacant	Total
Proximity to List1 Sites						
Value Loss ($ millions)	25.31	1,028.74	145.76	18.50	-	1,218.31
Assessed Value[a]	945.87	1,926.87	1,798.12	225.96	-	4,896.81
Value Loss as Percent of Assessed Value	0.03	0.53	0.08	0.08	-	
Proximity to Perceived Contaminated Sites						
Value Loss ($ millions)	52.12	435.77	-	-	175.20	663.09
Assessed Value[b]	2571.59	5,822.56	-	-	952.64	9,346.80
Value Loss as Percent of Assessed Value	0.02	0.07	-	-	0.18	0.07
List1 and Perceived Contaminated Sites						
Total Value Loss	77.43	1,464.50	145.76	18.50	175.20	1,881.40
Total Assessed Value[c]	2,659.76	5,836.18	2,620.27	471.75	981.89	12,569.84
Value Loss as Percent of Assessed Value	0.03	0.25	0.06	0.04	0.18	0.15
Total Assessed Value in Fulton County	2,972.42	7,077.35	2,818.06	534.03	1,298.15	14,700.01
Value Loss as Percent of Assessed Value	0.03	0.21	0.05	0.03	0.13	0.13

[a] Total assessed value is based on a property's proximity to a List1 site.

[b] Total assessed value is based on a property's proximity to a perceived contaminated site.

[c] Total assessed value is based on a property's proximity to a List1 or perceived contaminated site.

Figure 7.1. Total Losses in Commercial and Industrial Property Value by Census Tract

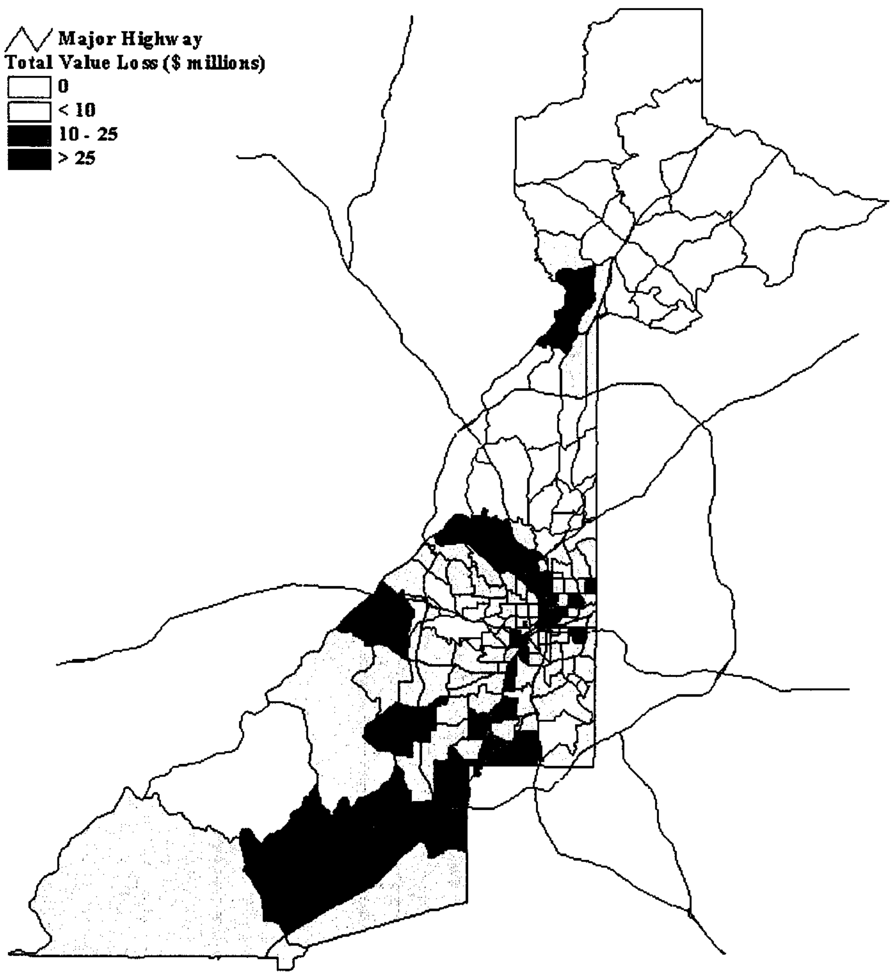


Figure 7.2. Total Losses in Commercial and Industrial Property Value by List1 Site

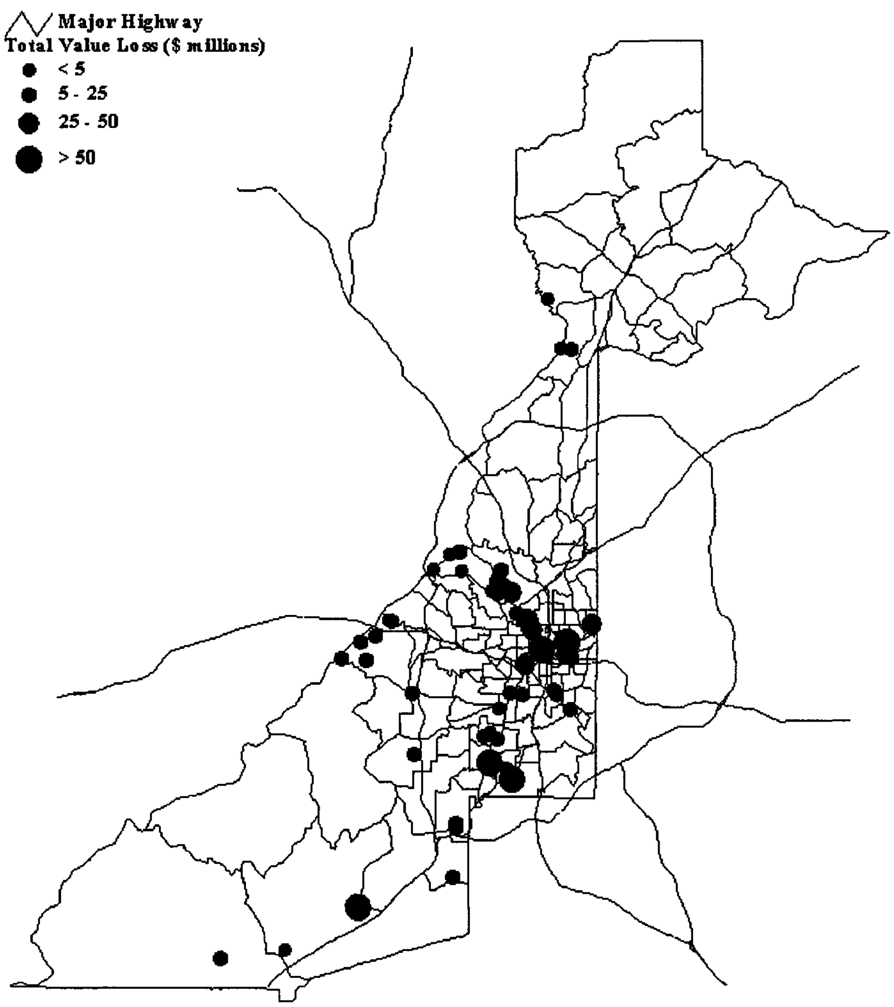


Figure 7.3. Total Losses in Commercial and Industrial Property Value by List1 Site and Census Tract Racial Composition

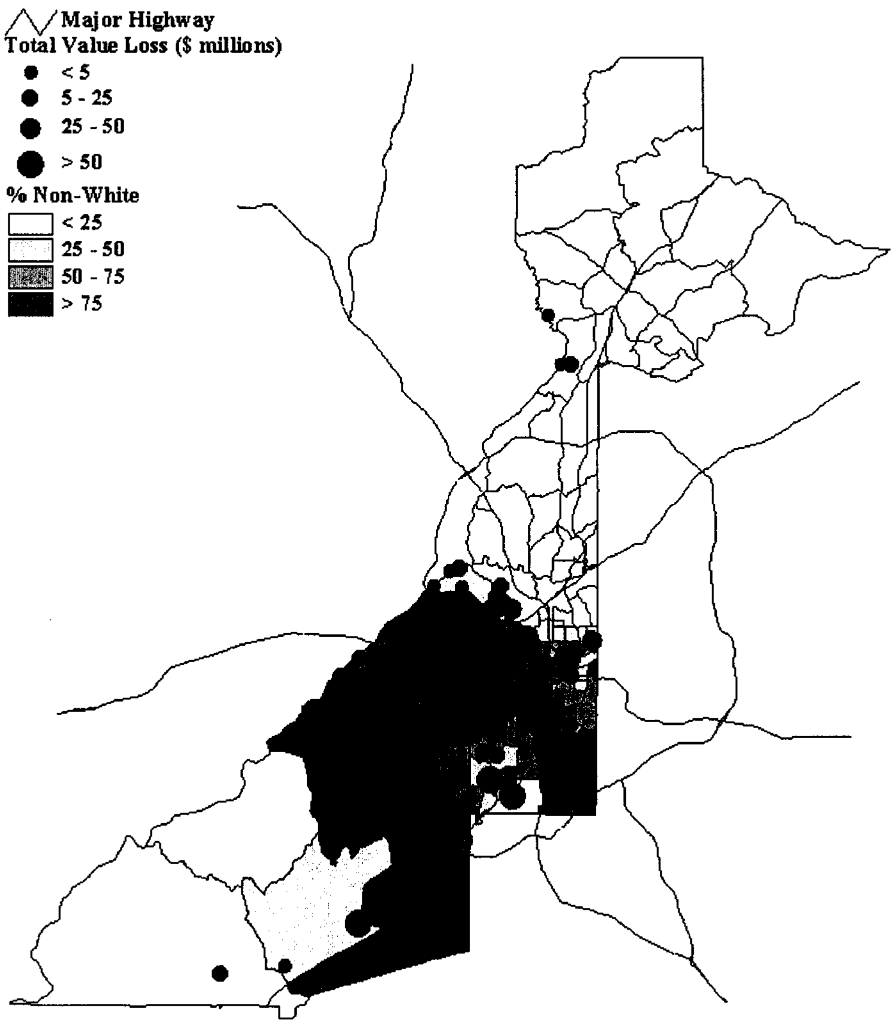


Figure 7.4. Total Losses in Commercial and Industrial Property Value by List1 Site and Census Tract Median Income

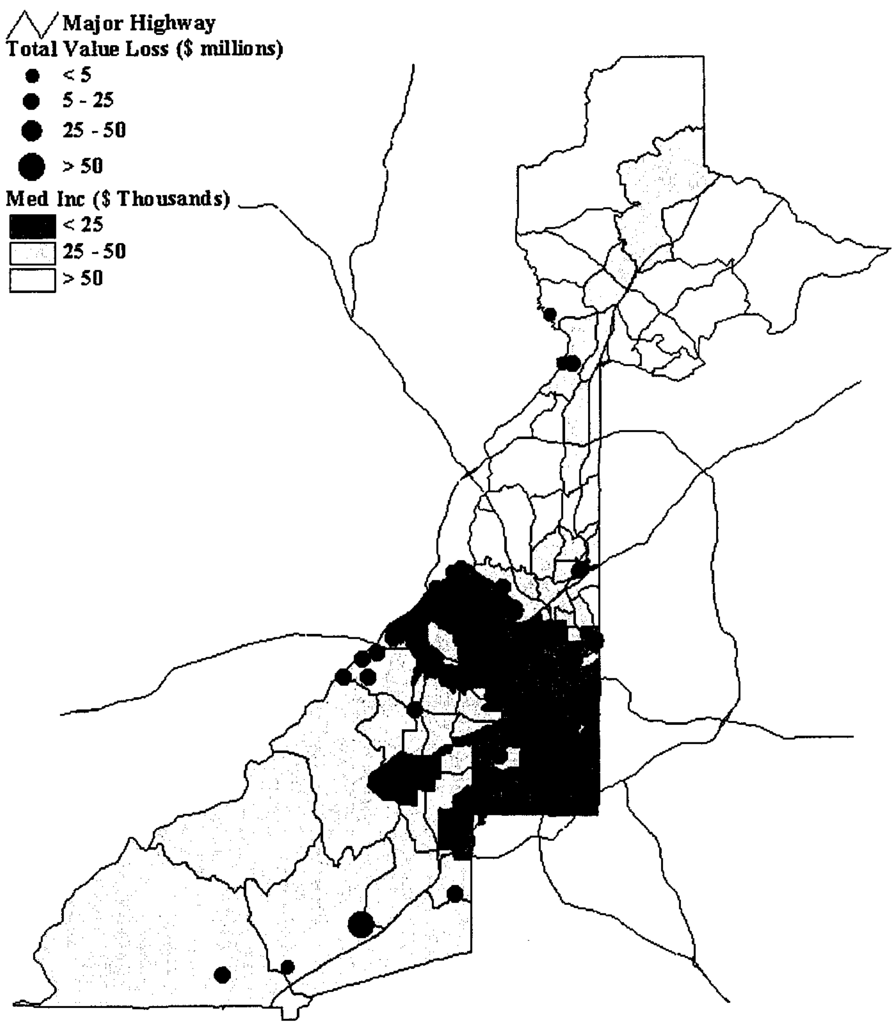


Figure 7.5. Spatial Distribution of Perceived Contaminated Sites

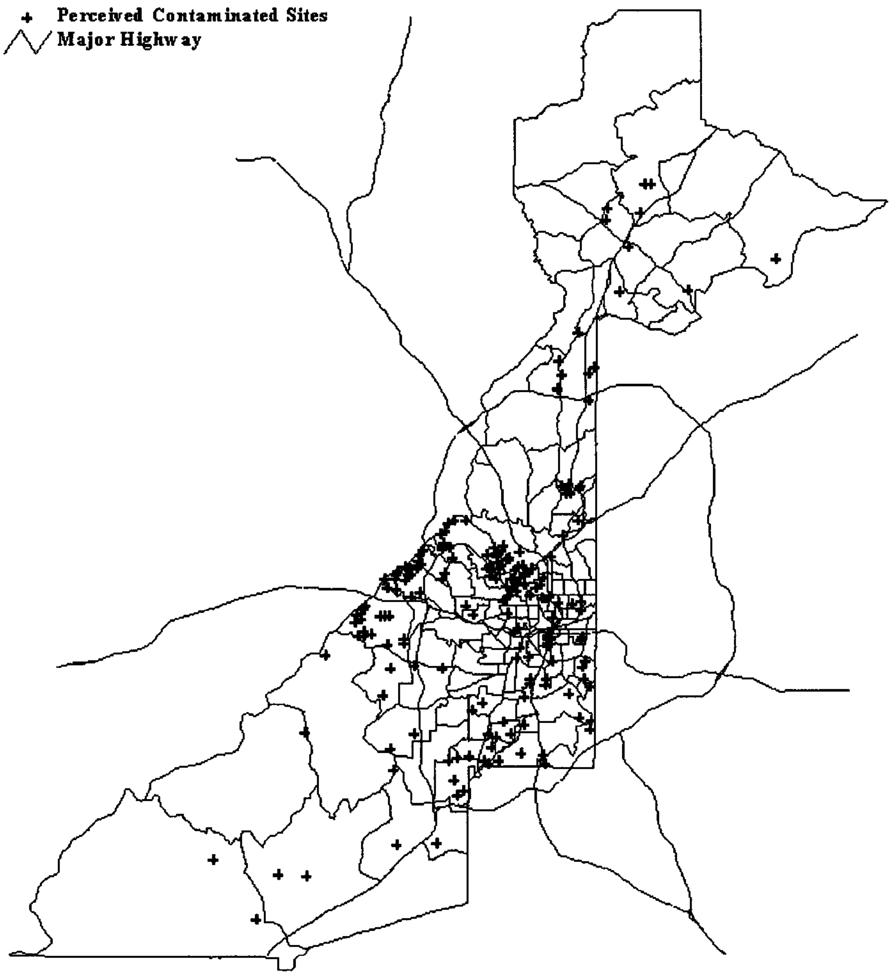


Figure 7.6. Total Losses in Commercial and Industrial Property Value from Perceived Contaminated Sites by Census Tract

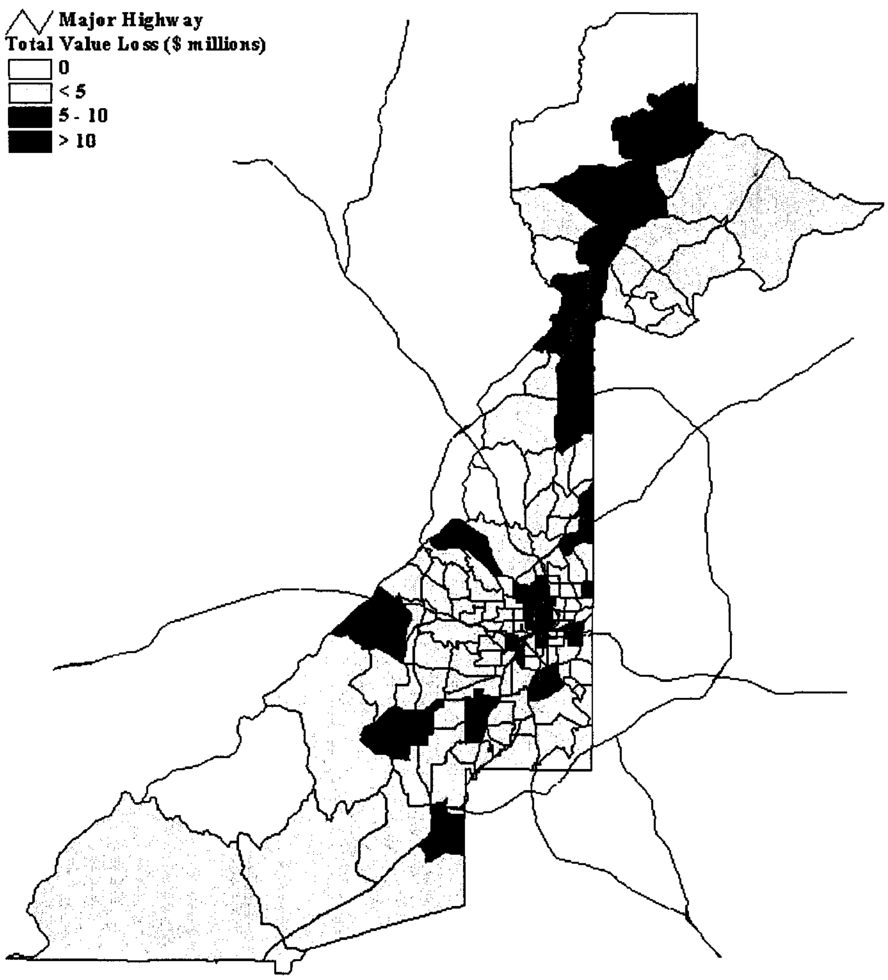


Figure 7.7. Total Losses in Commercial and Industrial Property Value due to Listl Sites by Census Tract

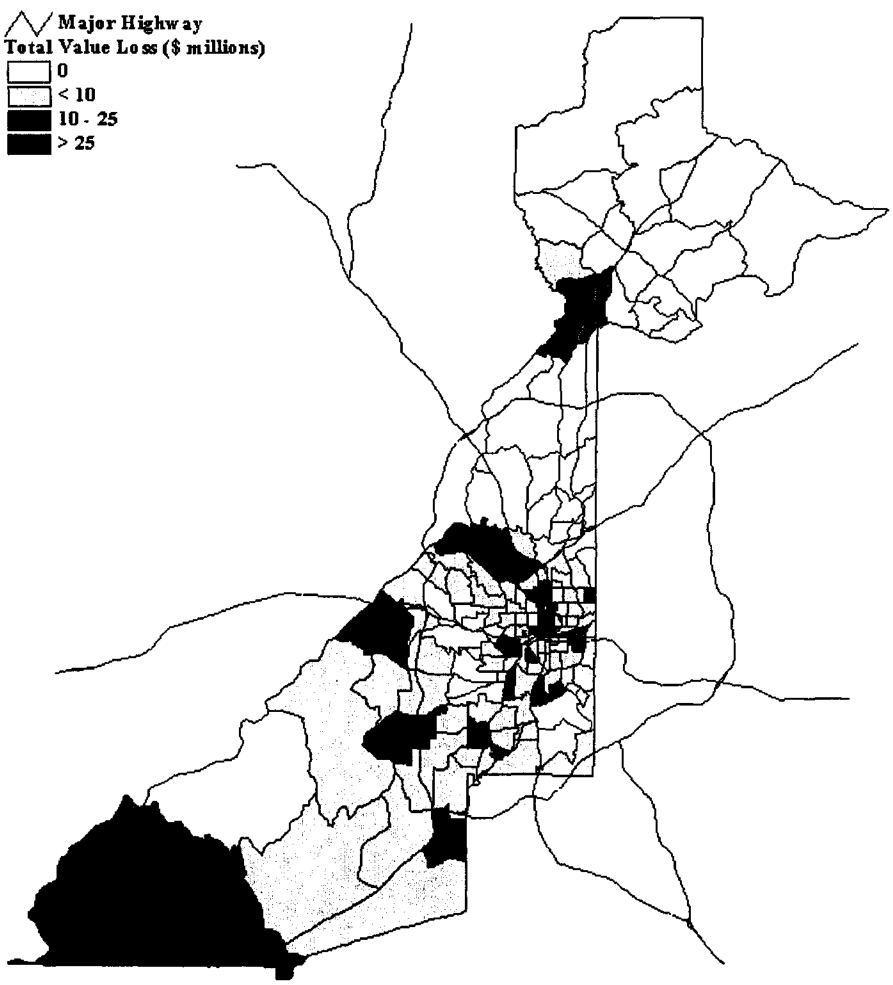
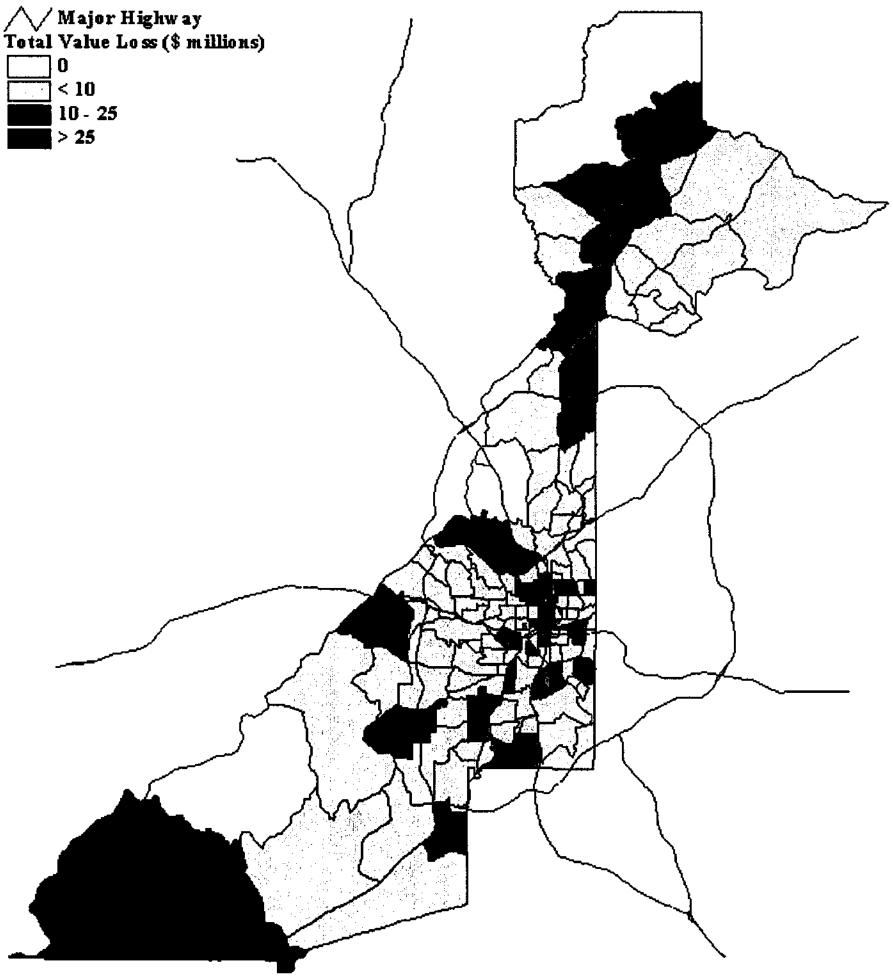


Figure 7.8. Total Losses in Commercial and Industrial Property Value due to Listl Sites and Perceived Contaminated Sites by Census Tract



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VITA

Peter Edward Grigelis was born in Montreal, Canada on July 5, 1974. At the age of three, his family moved to Pompano Beach, Florida. He attended Ithaca College from 1992 to 1996 and received a Bachelor's of Arts degree in Mathematics/Economics, along with minors in General Business and Financial Institutions. After graduating from Ithaca College, he was employed as a mortgage broker for Charter Mortgage Corporation in Fort Lauderdale, Florida.

In 1997, Peter joined the Andrew Young School of Policy Studies at Georgia State University to pursue a doctorate degree in economics. While attending Georgia State University, he worked as a graduate research assistant and as a teaching assistant in the Department of Economics. His research assistantship work was primarily related to issues in environmental economics. In 2002, Peter became a U.S. citizen.

Peter moved from Atlanta to the Washington, DC metro area in 2003 to work as an economist with the Damage Assessment Center in the Office of Response and Restoration of the National Oceanic and Atmospheric Administration. His work focused on providing economic analysis for natural resource damage assessment cases. In May of 2005, Peter accepted a position with the Division of Economics at the U.S. Fish and Wildlife Service.