Do Superfund Sites Affect Local Property Values? Evidence from a Spatial Hedonic Approach

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Introduction

The hazardous waste sites of Love Canal and Valley of the Drums were catalysts for passage of the Comprehensive Environmental Response Compensation and Liability Act (CERCLA) in 1980. CERCLA, also called the Superfund program, is an environmental law imposing cleanup responsibilities for contaminated sites (Salzman and Thompson, 2003). The Environmental Protection Agency (EPA) defines Superfund sites as uncontrolled and abandoned locations with hazardous wastes.[1] The Superfund sites are placed on the National Priority List (NPL), created by the EPA, based on the Hazard Ranking System (HRS) score.[2]

The cleanup of Superfund sites is a non-market (i.e., environmental) good since its benefits are not purchased directly in a market. Therefore, valuing the benefits of the Superfund program (U.S. EPA, 2009) requires the application of non-market methods. The Hedonic Pricing Model (HPM) is a well-known revealed preference method to measure environmental amenities and dis-amenities. Many previous studies have used HPM to measure impacts of contaminated and hazardous sites on local property values.[3]

Although HPM is widely used, some criticisms and limitations remain. A commonly cited problem is omitted variable bias (Deaton and Hoehn, 2004, Abbott and Klaiber, 2011).[4] The absence of important data results in an endogeneity problem, making estimated coefficients

[1] http://www.epa.gov/superfund/sites/
[2] Based on the EPA, the Superfund sites are listed on the NPL if the hazardous ranking score is greater than 28.50.
[3] See examples of McClelland, et al. (1990), Michaels and Smith (1990), Kohlhase (1991), Thayer, et al. (1992), Kiel (1995), Kiel and Zabel (2001), Ihlandfeldt and Taylor (2004), Jenkins, et al. (2006), and Gamper-Rabindran and Timmins (2013).
[4] Abbott and Klaiber (2014) argue that use of spatial fixed effect is not an appropriate approach to control omitted variable bias in hedonic price models, because it does not take into account the proper scale of capitalization. They use the Hausman-Taylor (HT) estimator, which is a combination of fixed and random effect, to control endogeneity caused by omitted variables at multiple spatial scales. However, the HT estimator is useful only with panel data structure.

biased and inefficient. The repeat sales model is one method to control omitted variable bias in the HPM context (Sigman and Stafford, 2010) by incorporating changes in property value for the same property to control for unobservable time-invariant characteristics, such as neighborhood. Gayer, et al. (2002), Gayer and Viscusi (2002), Case, et al. (2006), and Gamper-Rabindran and Timmins (2013) use the repeat sales model to study Superfund sites.

Another approach used by Sigman and Stafford (2010) and U.S. EPA (2011) is the quasi-experimental method to avoid omitted variable bias and deal with unobserved heterogeneity. Generally used to evaluate the impacts of policy intervention by comparing random groups, there are three common quasi-experimental approaches described by Greenstone and Gallagher (2008) and Greenstone and Gayer (2009): Difference in differences (DD), Instrumental variables (IV), and Regression discontinuity (RD). Greenstone and Gallagher (2008) and Gamper-Rabindran, et al. (2011) use RD design to study Superfund sites.[5]

The issue of spatial dependence or autocorrelation has not yet been combined with these approaches. Housing values are commonly spatially correlated with neighbor locations (U.S. EPA, 2011). According to Dubin (1988) and Feng and Humphreys (2012), ignoring spatial dependence for the traditional HPM using Ordinary Least Squares (OLS) leads to inefficient and inconsistent estimations, biased standard errors, and inaccurate predicted values. Furthermore, Conley (1999 and 2008) addresses the problem of spatial dependence in cross-sectional data. The spatial dependence will result in misleading of the standard error.[6]

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[5] Greenstone and Gallagher (2008) also find that use of the quasi-experiment method in a hedonic framework improves not only estimates of local welfare impacts, but also valuation of environmental goods.

[6] Conley proposes a method to correct the standard error by allowing spatial dependence within a certain distance between agents. He uses a non-parametric approach of Generalized Method of Moment (GMM) estimator since it provides consistent estimates in dependent data.

Many previous studies examine the impact of the Superfund program on local property values by using HPM, but fail to explicitly address spatial dependence or autocorrelation.[7] In this study, Superfund sites in Jefferson County, Kentucky are examined using a spatial hedonic approach . The EPA categorizes Superfund sites according to four cleanup stages: proposed, listed, construction complete (i.e., final), and deleted.[8] Messer, et al. (2006), Kiel and Williams (2007), and Gamper-Rabindran and Timmins (2013) find that the impacts of the Superfund sites differ by cleanup stage. Herein, different impacts of the Superfund sites are considered for two statuses, final and deleted.[9] Finally, we analyze the impact of multiple nearby Superfund sites.

Literature Reviews

Previous research on the impact of Superfund sites on property values as well as those that consider and incorporate spatial dependence into HPM are especially germane to this study. Both areas are reviewed in turn.

Overview of Superfund Impacts

As mentioned above, Superfund cleanup proceeds through four stages: proposed, listed, final, and deleted. Proposed NPL sites tend to reduce housing prices due to perceived risk of exposure to toxic compounds (Gamper-Rabindran and Timmins, 2013). Hamilton and Viscusi

[7] See Michaels and Smith (1990), Kiel (1995), Ihlandfelt and Taylor (2004), Jenkins et al (2006), and Kiel and Williams (2007).

[8] The EPA conducts preliminary assessment or site inspection to evaluate whether the sites are considered a threat to human health. Then the EPA proposes the site based on the assessment. Listed status indicates the sites identified for long-term cleanup. Final status indicates that the cleanup process has been competed for necessary physical construction even though final cleanup levels have not yet been reached. Finally, deleted status indicates that all site cleanup activities and goals have been accomplished.

[9] The Superfund sites on NPL in Jefferson County, Kentucky are either final or deleted status. Therefore, only two statuses are considered in this study. All the Superfund sites considered in this study are reported with location, status, proposed date, listed date, completed construction date, and deleted date on NPL in Table 1A in appendix.

(1999), Fischhoff (2001), Davis (2004), and Messer, et al. (2006) provide evidence of decreased housing values before sites are listed on the NPL. The U.S. EPA (2009)reports mixed results regarding listed sites from prior studies, with some studies suggesting decreased housing values and others suggesting increased values.[10] For the final and deleted status, housing values are likely to increase as immediate threats and health risks are addressed. For example, Gamper-Rabindran and Timmins (2013) find that owner-occupied housing values increased by 14.7% within three miles of the deleted sites investigated. However, Kiel and Williams (2007) evaluate 57 Superfund sites listed on NPL with HPM for houses within three miles of each site. They find statistically significant effects for 25 sites (18 positive effects and 7 negative) and no significant correlation for 32 sites.

While many recent studies measure impacts of the proximity to multiple Superfund sites, other studies such as McClelland, et al. (1990), Dale, et al. (1999), and Hurd (2002) focus on a single hazardous waste site. McClelland, et al. (1990) find that the values of 4,100 homes near the Operating Industries INC. (OII) Landfill in the Los Angeles, California declined by $40.2 million before closure and $19.7 million after closure. Later, Hurd (2002) re-examined the OII landfill by transforming the dependent variable with real price. He found that housing values declined during the initial listing period, but 80% of those losses were recovered after 10 years, towards the end of the cleanup process. Dale, et al. (1999) examined the RSR lead smelter site in Dallas County, Texas before, during, and after the closure. They find that property values decreased before and during the cleanup, and rebounded afterwards.

[10] U.S. EPA (2009) reviews many previous studies and suggests that most studies find that housing values are negatively affected when sites are proposed on the NPL. In addition, this review shows that many studies find that some housing values rebound after sites are listed on the NPL even though some studies find either no significant impacts or negative impacts on housing values near the sites.

Research therefore demonstrates that the Superfund effect varies by status. As the Superfund sites in Jefferson County are in either final or deleted status, model these separately. Most previous studies consider distance to the nearest Superfund site, even when there are multiple sites (Gayer, et al., 2000). In this study, however, we investigate the impacts of multiple sites located in close proximity within or near Jefferson County.

Reviews of Spatial Hedonic Model

Spatial effects in the hedonic house price model have been addressed by Dubin (1988) and Can (1990). They find that incorporating spatial effects shows more accurate results than the traditional hedonic model in the residential real estate market.

Anselin (2001) and Kim, et al. (2003) mention the importance of accounting for spatial effects, especially spatial dependence, on the efficiency and consistency of hedonic model estimates. Kim, et al. (2003) measured the marginal value of air quality improvement in Seoul, Korea by using a spatial lag model. They found that incorporating spatial effects into the hedonic model improves on the traditional hedonic model.

In addition to the spatial lag model, the spatial error model is used in some hedonic studies (Bell and Bockstael, 2000, Leggett and Bockstael, 2000, Feng and Humphreys, 2012). Leggett and Bockstael (2000) measure the impact of water quality on residential property values along the Chesapeake Bay by using the spatial error hedonic function. They find that property values are significantly and positively affected by improvements in water quality after correcting for spatial autocorrelation. A recent study by Feng and Humphreys (2012) examines the effect of proximity to a sports facility on residential property values. They use the census block group level data from the 1990 and 2000 and estimate the hedonic spatial error model with two different functional forms, which are linear and log-log. They find that proximity to a sports facility has positive impact on median housing values. Most previous studies in HPM related to Superfund sites do not explicitly address spatial dependence. Therefore, our findings comparing spatial HPM to traditional HPM will contribute to the literature on Superfund sites.

Conceptual Framework

Hedonic Pricing Model

Hedonic price techniques were initially introduced by Griliches (1961) and further developed by Rosen (1974), who applied HPM to find price for characteristics in differentiated products. According to Nesheim (2006), the main goal of hedonic analysis is to find the relationship between market equilibrium prices and structural characteristics. Consumer *x* maximizes utility by choosing bundle of attributes *z* given the hedonic prices *p(z)*. Here, the vector *x* represents a vector of consumer characteristics. Then, the consumer's problem can be written as

$$\underset{z}{Max}\{u(x,z,p(z))\} \tag{2}$$

By assuming that both utility and hedonic price are continuously differentiable and an interior solution exits, the first order condition can be written as

$$\frac{\partial u(x,z,p(z))}{\partial z}+\frac{\partial u(x,z,p(z))}{\partial p(z)}\frac{\partial p(z)}{\partial z}=0 \tag{3}$$

The equation can be rewritten in terms of hedonic price for the characteristic of *z*

$$\left(\frac{\partial u(x,z,p(z))}{\partial z} \Big/ \frac{\partial u(x,z,p(z))}{\partial p(z)} \right) = -\frac{\partial p(z)}{\partial z} \tag{4}$$

This equation indicates that the marginal rate of substitution equals the marginal price of *z*.

By solving for *z*, the hedonic demand function for consumer *x* can be derived.

Spatial Autocorrelation

Autocorrelation, also referred to the spatial dependence, can generally be found in times series and cross-sectional analysis. In cross-sectional analysis, autocorrelation is referred to as spatial autocorrelation when observed units such as houses are correlated by location. Based on Anselin and Bera (1998), the existence of spatial autocorrelation can be defined as following:

$$Cov(y_i, y_j) = E(y_i, y_j) - E(y_i) \cdot E(y_j) \neq 0 \text{ for } i \neq j \tag{5}$$

where y_i and y_j are observations of random variables at location *i* and *j*. Moran's *I* and Lagrangian Multiplier (LM) tests are generally used to test for the presence of spatial autocorrelation (U.S. EPA, 2011 and Anselin, 2001).

Data Description

The main source of data used in this study is the U.S. Census Bureau's American Community Survey (ACS) from 2010 to 2014. A block group is a statistical division containing between 600 and 3,000 people.[11] A main advantage of using block levels is to control and

[11] https://www.census.gov/geo/reference/gtc/gtc_bg.html

account for the spatial effects in that the block group covers a single contiguous area with demographic, housing, social, economic data, and geographical information. Shultz and King (2001) mention that housing data from Multiple Listing Services (MLS) or property-tax assessments are not spatially referenced and are generally expensive to use even though those data sets provide greater detail. Compared to census tract data, the census block data provides more robust hedonic price analysis (Goodman, 1977). In addition, Cao and Cory (1981) find a high level of heterogeneity when using aggregated land-use data at the tract level.

The sample has 781 block groups. Even though Jefferson County is in the focus of this study, we incorporate adjacent counties: Oldham, Shelby, Spencer, Bullitt, and Hardin from Kentucky, and Harrison, Floyd, and Clark from Indiana. We measured distance from each block centroid in adjacent counties to the Jefferson County borderline, then we use block groups that are within 10-mile distance from the borderline for two reasons. First, housing value in Jefferson County is affected by housing values and characteristics in neighbor counties, and the block groups within 10 miles provide information for localized housing value. Second, many block groups beyond 10-mile distance result in “islands” that hinder the use of spatial analysis.[12] Our spatial hedonic framework uses rook-contiguity, based on shared borders between block groups. Therefore, inclusion of islands in spatial framework is not allowed.

The dependent variable is the median value of all owner-occupied housing units in each block group, and the average of the block group medians in the sample is $156,770. Figure 1 and 2 shows each block group of median owner-occupied housing values and population density with locations of deleted and final Superfund sites in the study area. Based on the figure 1 and 2,

[12] The islands are block groups that does not share borderline with neighbor block groups.

median housing values are higher on the east side of the county than the west side, and population density is relatively higher in the central area, which is Louisville. [13]

<Insert Figure 1 Here>

Feng and Humphreys (2012) point out that variable selection for HPM is paramount. Housing value is defined as a function of characteristics of housing structure, neighborhood, and environment. Table 1 shows summary statistics and description for the variables considered in this study.[14]

<Insert Table 1 Here>

Many previous studies use distance to the central business district (CBD) in HPM analysis to control for accessibility to employment opportunities and amenities. The housing values near the CBD are hypothesized to be higher than those further from the CBD.[15] The distance from the each centroid block groups to the centroid CBD is measured with Geographic Information System (GIS) software. [16]

Many previous studies use distance to the closest Superfund sites as an environmental attribute.[17] The distance from each census block group centroid to each Superfund site is measured by GIS software based on the longitude and the latitude provided from EPA and U.S

[13] Based on 2013 U.S. Census Bureau, the population density of Jefferson County is per 1,948 in square mile making it the most densely populated county in Kentucky.
[14] The housing structure characteristics are obtained based on owner-occupied housing units, and other control variables are selected based on previous hedonic studies that especially use aggregate level data even individual level data.
[15] See Graves, et al. (1988), Mahan, et al. (2000), Lutzenhiser and Netusil (2001), and Feng and Humphreys (2012).
[16] Since there are no specific points to represent the CBD, location of the County Government Office is used as the centroid of the CBD. The map for the CBD and a location of the County Government Office in Louisville, Kentucky is presented in Figure 2A in the appendix.
[17] See Gayer, et al. (2000), Kiel and Zabel (2001), Deaton and Hoehn (2004), and Kiel and Williams (2007)

Census Bureau. For the distance variable, we consider the minimum distance to the Superfund sites, following Gayer, et al. (2000).[18] Based on Noonan, et al. (2009), most distance effects are significant between one and three miles and are not statistically significant after six miles. To address different distance effects, this study assumes that proximity to Superfund sites has significant impacts only within 5 miles distance, and the impacts are negligible after 5 miles.[19] In addition, this study conducts robustness checks regarding distance. In the 5 miles distance framework, the distance is set equal to 5 if the distance from the site is greater than 5 miles, otherwise the distance is actual distance from the site.[20] Furthermore, more than one Superfund site might be located within 5 miles of a census block. To capture exposure effects from the multiple Superfund sites, we include a "Count" variable following Gamper-Rabindran and Timmins (2013). They measure the exposure of the block observations by using counts if sites are located within the same distance from the block centroid.

Model Specification

Selecting functional form is a key issue with HPM, since many different forms, such as linear, log-linear, linear-log, and log-log, have been used in previous studies. The Box-Cox

[18] For example, if distances to deleted Superfund sites are 2.3, 5, 7, and 10 miles respectively from a block group centroid, we use the minimum distance of 2.3 miles.
[19] The 5-mile threshold distance is based on previous studies suggesting that distance effects are significant between one and three miles, with no significant impacts after six miles. In this study, we could not apply a distance threshold less than 5 miles due to the limited number of observations. For example, only 32 observations are within 3-miles distance of deleted sites out of total 551 observations. In addition, only 2 observations are within 3-miles distance from final Superfund sites.
[20] This approach differs from other studies such as Kiel and Williams (2007), Greenstone and Gallagher (2008), and Gamper-Rabindran and Timmins (2013) that use only observations within a certain distance of the Superfund sites, thus ignoring other information about housing outside the threshold. We assume that ignoring those observations may omit relevant information.

(1964) transformation is one way to test the appropriate functional form. However, the Box-Cox test requires that a variable have positive values to be transformed (Haab and McConnell, 2002).[21] In this study, a log linear function form is used for two reasons: easy economic interpretation and outliers in linear dependent variable.[22]

This study begins with a standard hedonic regression of owner-occupied housing prices on the characteristics of the housing structure and the neighborhood.[23]

$$ln(\boldsymbol{P}) = \boldsymbol{N}\beta_1 + \boldsymbol{S}\beta_2 + \boldsymbol{E}\beta_3 + \varepsilon \tag{6}$$

where $\boldsymbol{P}$ is the vector of owner-occupied housing prices, $\boldsymbol{N}$ is a vector of neighborhood characteristics, $\boldsymbol{S}$ is a vector of housing structural characteristics, $\boldsymbol{E}$ is a vector of environmental variables (i.e., distance and count), and ε is a vector of independently and identically distributed (*i.i.d*) error terms.[24] The standard hedonic regression model is estimated by OLS.

The Spatial Autoregressive (SAR) lag and error models are well known models to account for spatial autocorrelation. Even though both SAR lag model and SAR error model are common approaches to control the spatial autocorrelation or dependence, the SAR error model is preferred for correcting the potential biasing influence of the spatial autocorrelation whereas the

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[21] Since some independent variables contain zero value, the Box-Cox test could not be conducted for independent variables. For the dependent variable, this study finds that no transformation is preferred.

[22] Results based on the box-and-whisker plots and the univariate kernel density estimation show the right-skewed linear dependent variable to have more outliers. Since more outliers indicate high variance, they cause more risk of heteroscedasticity. The results are reported in Figure 1A in the appendix.

[23] All the independent variables are tested by using Variance Inflation Factor (VIF) in order to check for multi-collinearity problems. Generally, there is severe multi-collinearity problem if VIF is greater than 10.

[24] The standard hedonic regression model is same for both the deleted and final sites. However, the distance variable is calculated differently for models with and without a 5-mile threshold. For example, the distance with no threshold framework is calculated by distance = min (site1, site2, site3). On the other hand, the distance with 5-mile threshold framework is measured by AdjDistance = min (distance, threshold). In addition, the count variable is only included in 5-mile threshold model. The count variable is calculated that count = 2 if there are two Superfund sites are located within 5-miles radius.

SAR lag model focuses on the calculation of existing spatial interactions (Anselin, 2001). Therefore, this study uses the SAR error model, with spatially correlated errors accounting for unobserved neighbor characteristics or omitted variables associated with location. The empirical hedonic spatial error model used here is:

$$ln(\boldsymbol{P}) = \boldsymbol{N}\beta_1 + \boldsymbol{S}\beta_2 + \boldsymbol{E}\beta_3 + \varepsilon$$

$$\varepsilon = \lambda\boldsymbol{W}\varepsilon + u \tag{7}$$

where ***P***, ***N***, ***S***, and ***E*** are the same as in equation (6), λ is the spatial autoregressive coefficient, ***W*** is the spatial weight matrix, and *u* is a vector of *i.i.d.* errors with variance σ^2. Based on Viton (2010), the spatial weights matrix is an $N \times N$ positive matrix and transformed from the spatial neighbor matrix ($\widetilde{\boldsymbol{W}}$) with "row-standardization" based on rook contiguity, which is the contiguity-based approach to specify the neighbor matrix (i.e., $\widetilde{w_{ij}}$).[25, 26] The spatial neighbor matrix is a square symmetric $N \times N$ matrix with $\widetilde{w_{ij}}$ elements, which is formally defined $\widetilde{w_{ij}} = 1$ if location *i* and *j* are neighbors, and $\widetilde{w_{ij}} = 0$ otherwise. Based on Kim, et al. (2003), the regression coefficients of the OLS estimators remain unbiased but inefficient in the spatial error model. Thus, the spatial error hedonic model is estimated by maximum likelihood.

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[25] To row-standardize, the weights need to sum to one in each row and each element in a row is divided by the sum of the elements in the row, then a spatial weights matrix *W* with element w_{ij} can be defined as

$$w_{ij} = \widetilde{w_{ij}} \Big/ \sum_j \widetilde{w_{ij}}$$

[26] The contiguity-based approach typically involves one of two different definitions, which are rook contiguity and queen contiguity. The rook contiguity is when locations share only a common border, whereas locations sharing common boundaries and vertices have queen contiguity. This study tested both queen and rook contiguities and found that results are not statistically different. In addition, the block group polygons used in this study primarily share borders but not vertices. For these reasons, this study uses rook contiguity rather than queen contiguity.

Results and Discussions

Estimation Results

This study estimates two different standard hedonic regressions for deleted and final sites. We also estimate each standard hedonic model with and without a 5-mile distance threshold. This allows us to test how impacts of Superfund sites vary by distance. Therefore, four different standard hedonic models are estimated: deleted Superfund sites with and without 5-mile threshold and final Superfund sites with and without 5-mile threshold. Table 2 shows the estimated coefficients for the standard hedonic model with robust standard errors, which is used to control heteroscedasticity.[27]

<Insert Table 2 Here>

The main reason to estimate the standard hedonic models is not only to compare with spatial models, but also to evaluate spatial dependence. Table 3 shows the results from the diagnostic tests for spatial dependence in both deleted and final Superfund sites with and without the 5-mile threshold. The diagnostic is conducted based on rook contiguity weights matrix. In table 3, the Moran's *I* and Lagrange Multiplier (LM) with p-values of 0.000 indicates evidence of spatial dependence for both deleted and final sites by rejecting the null hypothesis of the spatial randomness. Therefore, we need to use the spatial model instead of standard hedonic model.

<Insert Table 3 Here>

[27] Only significant variables are reported in table 2 because all insignificant variables are the same across all models

The estimated coefficients for the spatial error model with robust standard errors are presented in table 2. The variable of lambda in table 2 represents the spatial lag parameter, and the positive value of lambda with p-value at 1% significance level indicates that spatial dependence is important in this analysis. In both standard hedonic and spatial error models, the variables of median household income, average number of rooms, percentage of attached housing units, and percentage of households who have associate's and bachelor's diploma have positive impacts of the median housing value in owner-occupied housing units for all four models. On the other hand, the median housing values are negatively affected by the percentage of owner-occupied housing units, percentage of unemployment, and percentage of black (i.e., African American). These findings are consistent with hypothesized signs and most previous hedonic studies except for the percentage of owner occupied units. The negative sign of the percentage of owner occupied housing units contradicts our expectation. There are two potential reasons for this result. First, the variable might be correlated with other independent variables. Second, the higher housing values in block groups are mostly distributed with a low percentage of owner occupied units in our data set. The difference between the standard hedonic models and spatial error models occur with the number of vehicles and Hispanic variables, but their estimated signs are as expected.[28] Distance to CBD is statistically significant and positive in three of the four standard hedonic models.[29]

[28] We use number of vehicles as a proxy for the number of garage that is generally included in hedonic model to explain square feet of housing units.

[29] The positive sign in distance to CBD was not expected. Residents might not prefer to live near CBD (i.e., downtown Louisville) due to high traffic, complexity, and safety issues. Another possible reason is there might be strong correlation between distance to CBD and distance to Superfund sites. However, we find that inclusion of distance to the CBD does not lead to the multi-collinearity problem.

The key variable for the nearest distance to the final sites is only statistically significant in the standard hedonic model under no threshold framework at 5% significance level. It indicates that one mile close to the final Superfund sites will result, on average, the median housing values of owner-occupied housing units at block group increase by 0.4%. However, we find that the nearest distance to deleted sites is statistically significant under the spatial hedonic models with no threshold framework. It indicates that the median housing values decrease as one mile further from the deleted sites. In this study, we include a count variable to capture the effect of multiple Superfund sites located within 5 miles from the centroid of the block group. This study finds that the count variable is statistically insignificant across all models regardless of two different milestones of the Superfund cleanup process. In other words, it indicates that the housing values is not affected by additional number of Superfund sites if Superfund site is located within 5 miles from the centroid of the block group.

Robustness Tests

We conduct tests to check whether estimated coefficients are robust to different functional forms and different threshold distances. Even though the Box-Cox test suggests not to transform the dependent variable, we test four different functional forms: linear-linear, log-linear, Box-Cox linear, and Box-Cox quadratic. A recent paper by Kuminoff, et al. (2010) discuss the benefits of linear Box-Cox and quadratic Box-Cox for empirical hedonic research.[30] For the linear Box-Cox and quadratic Box-Cox, the dependent variable and variable of interest,

[30] Kuminoff, at al. (2010) argue that the more flexible specifications such as the quadratic Box-Cox model outperform the simple linear, log-linear, and log-log models. The performance of quadratic Box-Cox is poorer in cross-sectional data than panel data.

which is distance to sites, are transformed by estimated lambda from the Box-Cox test. This transformation is based on equation developed by Box and Cox (1964).[31]

$$y^{\lambda} = \frac{y^{\lambda}-1}{\lambda} \tag{8}$$

Table 4 shows the marginal effects of distance to Superfund sites on housing value with different functional forms under the spatial error models.[32] Table 4 also shows the estimated lambda based on a model assuming both dependent and distance variables are transformed with same functional form.[33] In table 4, the estimated coefficient of the distance variable in the benchmark functional form (i.e., log-linear) is robust with other functional forms across most spatial error models. The benchmark functional form of log-linear is consistent only with Box-Cox linear functional form.

<Insert Table 4 Here>

For further robustness testing, we examine three different functional forms for the distance variable: linear, log, and inverse distance. Table 5 shows the results with different functional forms of distance. We find that the results are generally robust across different forms of the distance variable, with the sign reversing as expected for inverse distance.

<Insert Table 5 Here>

[31] Box and Cox (1964) mention that the transformation will result that the residuals are less heteroskedastic and more likely normal.

[32] This table reports the estimated coefficient for the distance variable since it is the main variable of interest. The marginal effect from the linear and quadratic box-cox transformation is calculated as following: First, calculate the predicted value of transformed outcome. Second, increment distance variable by one unit, and transform and repeat for second predicted outcome. Finally, take the difference between second predicted outcome and first predicted outcome.

[33] The theta model assumes both variables are transformed with different functional form, but this study assume two variables are transformed with same functional form. For the result of the null hypothesis test in the box-cox test is presented in Table 2A in appendix. Based on table 4, the results show the null hypothesis of lambda = -1, 0, 1 are rejected with p-values of 0.000. It indicates that all the possible specifications for reciprocal, log, and linear respectively for dependent and distance variables are rejected.

Finally, we examine different threshold distances by using 3-, 4-, and 6-mile threshold models compared to benchmark of 5 miles. Table 6 shows estimates from different threshold distances under the spatial error models. We find that results are strongly similar across the different threshold distances, including for the distance and count variables, suggesting that the benchmark specification (5-mile threshold) is robust.

<Insert Table 6 Here>

Conclusion

This paper employs the spatial error hedonic price model to evaluate the impacts of the Superfund sites in Jefferson County, Kentucky utilizing census block group data. We find that the standard hedonic pricing model ignoring spatial dependence or autocorrelation provides incorrect results. This finding further contributes to existing literature by suggesting that spatial dependence needs to be considered in hedonic models measuring the impact of Superfund sites on the local property values.

We also investigate the different impacts of Superfund sites at two different milestones of the cleanup process. We find no significant impact from deleted sites in 5-mile threshold distance framework. This lack of impact might be explained by the fact that most deleted Superfund sites were removed from the NPL over 10 plus years ago, and the direct impacts have dissipated over time. These estimates of impacts from deleted Superfund sites on the local property values contribute to policy makers or regional planning committees' understanding of housing values in Jefferson County. Last but not least, we address the implications of multiple Superfund sites. We find that housing values are not significantly affected as additional

Superfund sites are located within 5 miles from the housing units. This finding is novel to the literature on Superfund sites.

We face several limitations with this study. First, we use aggregated data especially from the 2010-2014 ACS 5 year estimates at block group level. The ACS 5 year estimates are updated on a yearly basis and the ACS was fully implemented in 2005, thus fully implemented data sets are not available before 2005. In addition, we cannot use data for the 2005-2009, 2006-2010, 2007-2011, and 2008-2012 periods due to the facts that all observations are overlapped, and a key variable (housing value in this study) is not available from previous ACS 5 year estimates data. Second, we can provide only average effects instead of individual effects since the block group is aggregated level data. In other words, median or average values from the block group may not reflect the actual distributions of property values in the individual data. Finally, we might have other potential endogeneity problems even though we control correlated error terms from unobserved neighbor characteristics.

This study compares between the traditional hedonic price model by using OLS and the spatial error model. However, many recent hedonic price analyses take advantage of panel or pooled cross-sectional data for considering quasi-experimental research designs into the hedonic theory. It is due to the fact that simple hedonic analysis by using OLS specification with a cross-section is arguably inadequate. Therefore, further study needs to compare the spatial error model with a cross-section of data with the quasi-experimental designs method. Difference in Difference (DD) approach could be used as one of the quasi-experimental designs to estimate the impacts of Superfund sites by comparing status of Superfund sites over time. In DD approach, treatment group will be sites that changes in status from final to deleted sites, and control group will be the sites that do not change in status from final. Therefore, this study could be improved by using richer data set that include median sale price data from different years.

Appendix

Table 1A. List of Superfund Sites on the NPL with Status

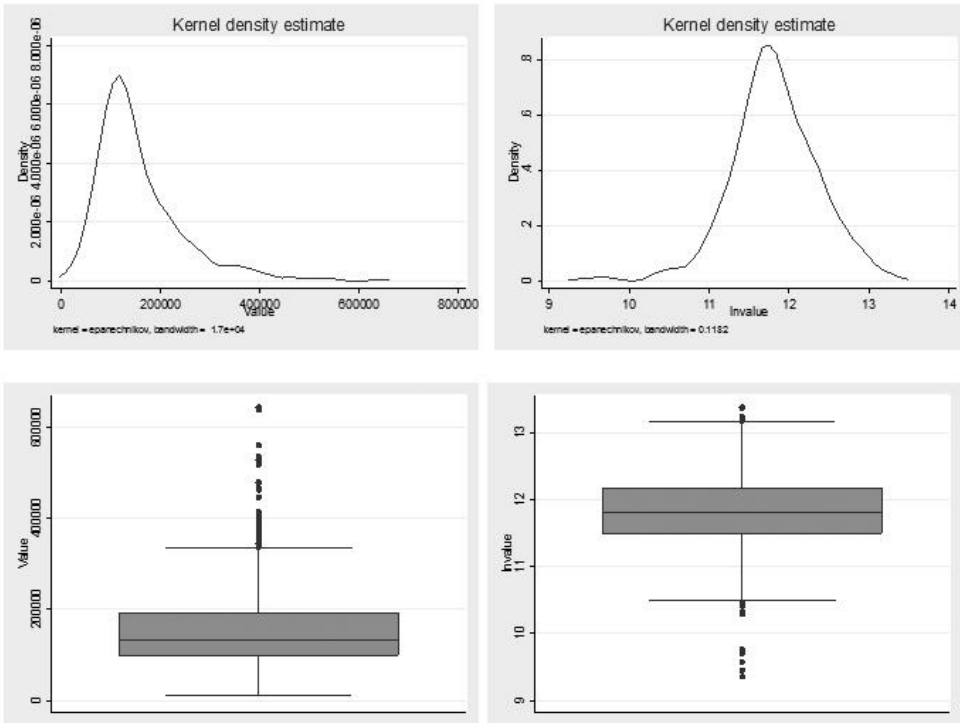
Site Name	County	Proposed	Listed	Final	Deleted	Status
A.L Taylor	Bullitt	12/30/1982	9/8/1983	8/10/1990	5/17/1996	Deleted
Lee's Lane Landfill	Jefferson	12/30/1982	8/8/1983	3/18/1988	4/25/1996	Deleted
Red Penn Sanitation	Oldham	6/24/1988	3/31/1989	9/22/2000	9/14/2001	Deleted
Smith's Farm	Bullitt	10/15/1984	6/10/1986	9/23/1998		Final
Tri-City Disposal	Bullitt	6/24/1988	3/31/1989	3/29/1996		Final
Distler Brickyard	Hardin	12/30/1982	9/8/1983	1/11/1995		Final
Distler Farm	Jefferson	12/30/1982	9/8/1983	7/9/1992		Final

Table 2A. Results from Box-Cox Test

	Deleted Sites		Final Sites	
	No Threshold	Threshold	No Threshold	Threshold
lambda	0.346*** (0.031)	0.347*** (0.031)	0.349*** (0.031)	0.344*** (0.031)
Test H0:	P-value	P-value	P-value	P-value
lambda = -1	0.000	0.000	0.000	0.000
lambda = 0	0.000	0.000	0.000	0.000
lambda = 1	0.000	0.000	0.000	0.000
Log likelihood	-9227.489	-9226.951	-9227.003	-9226.138

***, **, * Significant at p=0.01, 0.05, and 0.10 respectively

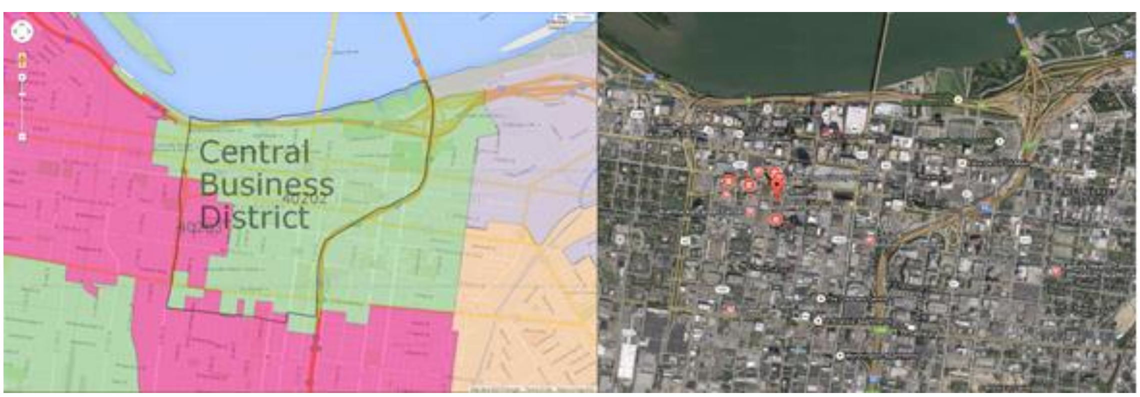
Notes: Parenthesis represents standard error



Linear Housing Value

Log Housing Value

Figure 1A. Results from the box-and-whisker plots and the univariate kernel density estimation



Source: Zipmap[34] and Google Map

Figure 2A. Central Business District (CBD) in Louisville, Kentucky

[34] http://www.zipmap.net/Kentucky/Jefferson_County/Z_Central_Business_District.htm

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Table 1. Descriptive Statistics for the Variables (N=781)

Vector	Variable	Description	Mean	Std. Dev.
P	Housing Value	Median housing value for owner-occupied housing units	156,770.00	89,940.31
E	Distance (Deleted)	Nearest distance to the deleted Superfund sites (in miles)	7.63	3.14
	Distance (Final)	Nearest distance to the final Superfund sites (in miles)	13.97	5.98
	Count (Deleted)	Number of deleted Superfund sites within 5 miles from block centroid	0.20	0.40
	Count (Final)	Number of final Superfund sites within 5 miles from block centroid	0.08	0.35
S	Bedrooms	Average number of bedroom in owner-occupied housing units	3.04	0.41
	Complete kitchen	Percentage of complete kitchen facility in owner-occupied housing units	99.65	1.54
	Rooms	Average number of rooms in owner-occupied housing units	6.41	0.82
	Year built	Median year structure built in owner-occupied housing units	1968.20	19.27
	Heating	Percentage of utility gas for heating in owner-occupied housing units	64.24	22.09
	Attached units	Percentage of attached housing units in owner-occupied housing units	8.02	15.32
	Vehicles	Average number of vehicles in owner-occupied housing units	1.92	0.37
N	Median Income	Median household income in the past 12 months (in thousands)	54.06	27.45
	Population Density	Population density in each block group (in m2)	0.001	0.001
	Occupied units	Percentage of owner-occupied housing units	66.28	24.20
	High school	Percentage of regular high school diploma	24.15	10.39
	College	Percentage of associate's degree and bachelor's degree	23.39	11.92
	Unemployment	Percentage of unemployment	10.02	8.32
	Hispanic	Percentage of population who are Hispanic	4.22	7.23
	Black	Percentage of population who are black	17.53	25.52
	Distance to CBD	Distance from each block group centroid to the CBD (in miles)	8.65	5.52

Note: The Count variables for both deleted and final sites are only included in 5-mile threshold framework

Table 2. Estimates from OLS and Spatial Error Model for Deleted Sites (N=781)

	OLS (Deleted)		Spatial Error (Deleted)		OLS (Final)		Spatial Error (Final)	
Variable	No Threshold	Threshold	No Threshold	Threshold	No Threshold	Threshold	No Threshold	Threshold
Distance to sites	0.004	0.037	0.009**	0.039	-0.004**	0.027	-0.002	0.016
	(0.003)	(0.033)	(0.004)	(0.031)	(0.002)	(0.039)	(0.002)	(0.036)
Count	–	0.031	–	0.009	–	-0.046	–	-0.078
	–	(0.030)	–	(0.029)	–	(0.056)	–	(0.059)
Distance to CBD	0.004*	0.005	0.001	0.002	0.005**	0.006*	0.003	0.003
	(0.003)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Median income	0.005***	0.005***	0.005***	0.005***	0.006***	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Occupied units	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002**	-0.002**	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Rooms	0.287***	0.287***	0.293***	0.291***	0.296***	0.287***	0.298***	0.293***
	(0.037)	(0.030)	(0.028)	(0.029)	(0.027)	(0.030)	(0.030)	(0.029)
Attach	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Vehicle	0.098**	0.094*	0.088*	0.086	0.093**	0.096*	0.084	0.083
	(0.039)	(0.055)	(0.053)	(0.053)	(0.039)	(0.054)	(0.054)	(0.051)
College	0.006***	0.006***	0.005***	0.005***	0.007***	0.006***	0.006***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Unemployment	-0.005***	-0.005***	-0.005**	-0.005**	-0.005***	-0.005**	-0.005**	-0.005**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Black	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Hispanic	-0.005***	-0.005	-0.006	-0.006*	-0.005***	-0.005	-0.005	-0.006*
	(0.001)	(0.003)	(0.003)	(0.003)	(0.001)	(0.004)	(0.003)	(0.003)
Lambda	–	–	0.288***	0.255***	–	–	0.229***	0.271***
	–	–	(0.068)	(0.066)	–	–	(0.071)	(0.065)
R-squared	0.772	0.772			0.773	0.800		
Log likelihood			-52.102	-53.974			-55.025	-50.126

***, **, * Significant at p = 0.01, 0.05, and 0.10 respectively

Table 3. Diagnostic Tests for Spatial Dependence

	Deleted Sites					
	No Threshold Distance			Threshold Distance		
Test	Statistic	df	P-Value	Statistic	df	P-Value
Moran's *I*	4.756	1	0.000	4.374	1	0.000
Lagrangian Multiplier	21.084	1	0.000	17.84	1	0.000
	Final Sites					
	No Threshold Distance			Threshold Distance		
Test	Statistic	df	P-Value	Statistic	df	P-Value
Moran's *I*	3.86	1	0.000	4.753	1	0.000
Lagrangian Multiplier	13.622	1	0.000	21.15	1	0.000

Table 4. Robustness Check for Distance Effect with Different Functional Forms

Functional forms	Deleted Sites		Final Sites	
	No Threshold	Threshold	No Threshold	Threshold
Linear-Linear	426.169	3129.018	-351.319	-265.390
	(572.206)	(2989.878)	(283.114)	(4351.463)
Log-Linear (Base)	0.009**	0.039	-0.002	0.016
	(0.004)	(0.031)	(0.002)	(0.036)
Box-Cox Linear	1042.252**	3375.208	-101.746	599.712
	(461.252)	(1148.309)	(41.028)	(194.690)
Box-Cox Quadratic	1026.964	1888.695	-254.519	4418.553
	(520.166)	(1047.948)	(1547.382)	(1513.158)
lambda	0.346***	0.347***	0.349***	0.344***
	(0.031)	(0.031)	(0.031)	(0.031)

***, **, * Significant at p=0.01, 0.05, and 0.10 respectively
Notes: Parenthesis represents standard error

Table 5. Robustness Check for Different Functional Forms of Distance

	Deleted Sites		Final Sites	
	No Threshold	Threshold	No Threshold	Threshold
Functional Forms	Coef	Coef	Coef	Coef
Linear distance	0.009**	0.039	-0.002	0.016
	(0.004)	(0.031)	(0.002)	(0.036)
Log distance	0.061**	0.101	0.011	0.002
	(0.025)	(0.086)	(0.033)	(0.079)
Inverse distance	-0.172	-0.156	-0.148	0.040
	(0.113)	(0.160)	(0.109)	(0.123)

***, **, * Significant at p=0.01, 0.05, and 0.10 respectively
Notes: Parenthesis represents robust standard error

Table 6. Different Threshold Distance for both Deleted and Final Sites

Variable	Deleted Sites				Final Sites			
	3 Miles	4 Miles	5 Miles	6 Miles	3 Miles	4 Miles	5 Miles	6 Miles
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
Distance to Sites	0.050	0.035	0.039	0.006	-0.217	-0.058	0.016	0.020
	(0.112)	(0.044)	(0.032)	(0.016)	(0.253)	(0.126)	(0.036)	(0.035)
Count	-0.016	0.001	0.009	-0.022	-0.327	-0.195	-0.078	-0.052
	(0.100)	(0.053)	(0.029)	(0.035)	(0.291)	(0.163)	(0.059)	(0.040)
Median Income	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Occupied Units	-0.003***	-0.002**	-0.002***	-0.002***	-0.002**	-0.002**	-0.002**	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Rooms	0.292***	0.291***	0.291***	0.292***	0.299***	0.297***	0.293***	0.287***
	(0.028)	(0.029)	(0.028)	(0.029)	(0.028)	(0.028)	(0.029)	(0.029)
Attached	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
College	0.006***	0.005***	0.006***	0.006***	0.006***	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Unemployment	-0.005**	-0.005**	-0.005**	-0.005**	-0.005**	-0.005**	-0.006**	-0.006**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Black	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Hispanic	-0.006*	-0.006*	-0.006*	-0.006*	-0.006*	-0.006*	-0.006*	-0.006*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Spatial lag	0.254***	0.257***	0.255***	0.264***	0.638***	0.267***	0.271***	0.274***
	(0.065)	(0.065)	(0.066)	(0.065)	(0.144)	(0.064)	(0.065)	(0.064)
Log Likelihood	-54.136	-54.016	-53.974	-54.364	-51.393	-49.043	-50.126	-49.862
Variance ratio	0.744	0.743	0.744	0.742	0.746	0.745	0.744	0.744

***, **, * Significant at p = 0.01, 0.05, and 0.10 respectively

Notes: Parenthesis represents robust standard error

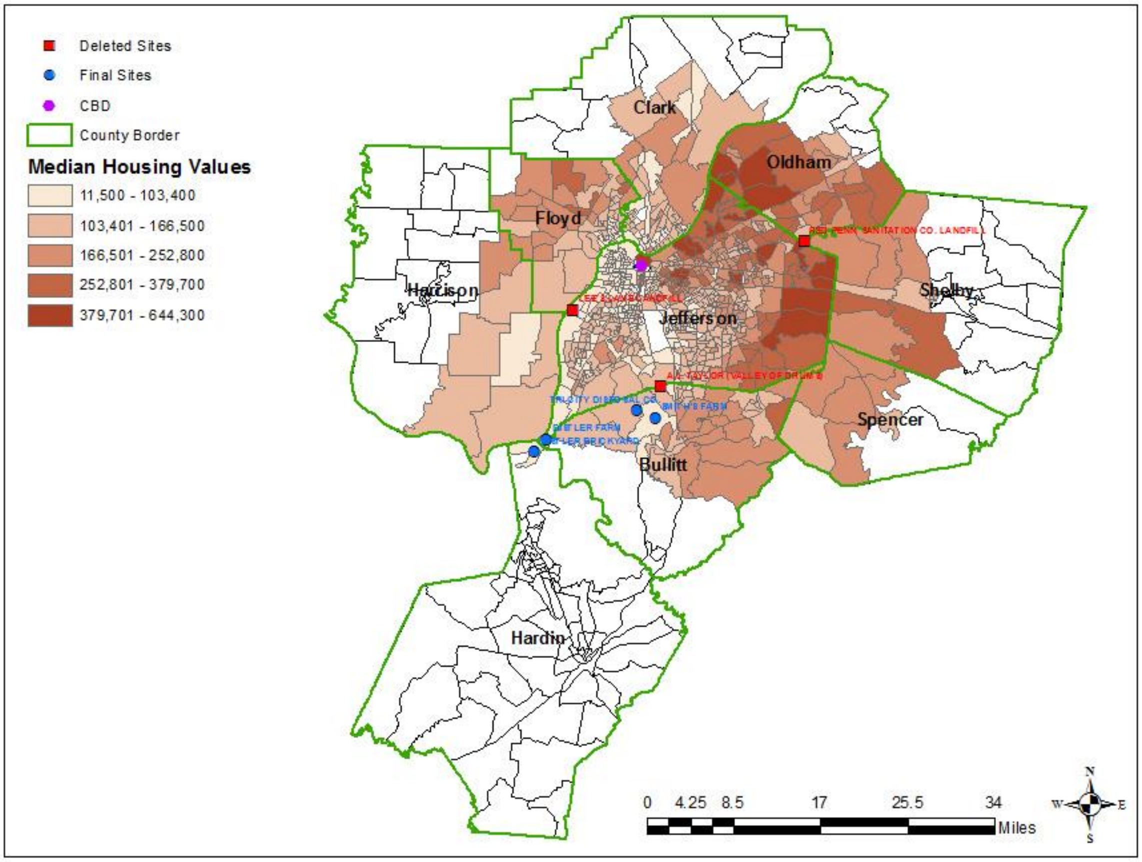

Figure 1. Median value of owner occupied housing units and location of the Superfund sites in Jefferson County, Kentucky

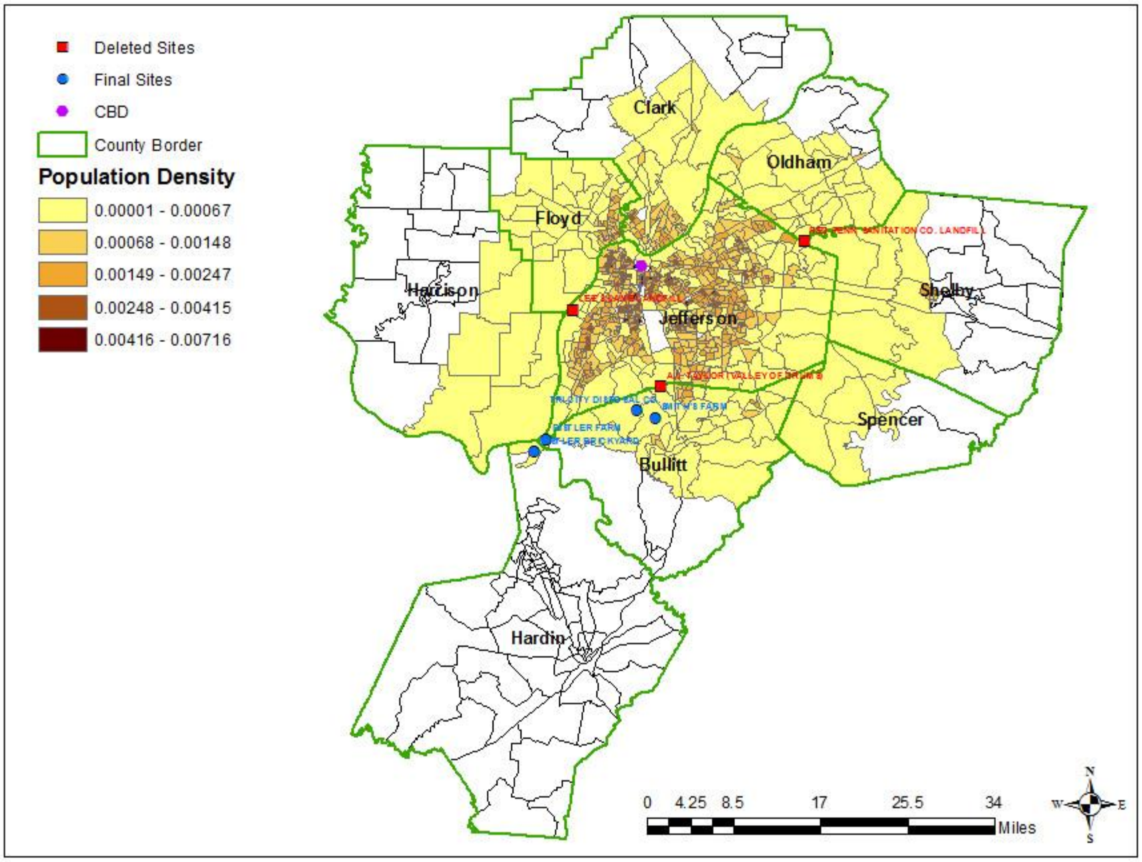

Figure 2. Population density and location of the Superfund sites in Jefferson County, Kentucky