Residential Location Impacts of Environmental Disamenity: The Case of Gravel Pit Operation and Landfills

Zhaohua Zhang, Ph.D. Student, Department of Agricultural Economics and Rural Sociology. Auburn University. zzz0025@auburn.edu

Diane Hite, Professor, Department of Agricultural Economics and Rural Sociology. Auburn University. *hitedia@auburn.edu*

Selected Paper prepared for presentation at the Southern Agricultural Economics Association's 2016 Annual Meeting, San Antonio, Texas, February, 6-9 2016

Abstract

In this paper, we analyze how environmental disamenity affects residential location choices using a horizontal sorting model. The environmental disamenity is measured by the distances between houses and the nearest landfill and gravel pit. The study area in this paper is the Franklin County of Ohio State and each of the housing units chosen by the households in the sample represents a housing type. The first stage estimation results show that rich white householder are more likely to select houses with longer distance from the gravel pits and landfills than rich black householder. After controlling for the price endogeneity, the second stage estimation supports the hypothesis that longer distance to the landfill increases the fixed utility of the house. Also, the direction for the effect of distance to the nearest gravel pit is as expected, which indicates that households prefer to select houses with longer distance to the gravel pit operation.

Key Words: Residential location choice, Sorting model, Gravel pit, Landfills

JEL Classification: R23, R32, Q51

Introduction

The value of property is affected by environmental factors to a large extent. People choose their residential location where they can get a high quality of life, and as a result, the quality of the neighborhood environment is largely responsible for the decisions made by the households on their residential location. The purpose of this paper is to conduct an empirical analysis on the impacts of landfills and gravel pit operation on households' residential location choice. The possible environmental damages associated with landfills are groundwater contamination, accumulation of methane gas, and increased traffic from transportation of waste. Pit operations include activities such as mechanical excavating, sorting, crushing, screening and washing of materials. Primary environmental issues relating to gravel pit operations are that it may release deleterious substances (sediment, sediment-laden waters) to a watercourse and air, and the use of heavy equipment and vehicles are to transport materials may make the neighborhood noisy. If these local disamenity generated by landfills and gravel pits operation are perceived by the residents, these perceptions can translate into discount of property values. Thus, the prices of nearby houses will be reduced to compensate the buyers for accepting such kind of disamenity.

In contrast to previous studies that employ the hedonic method to analyze the impact of environmental quality on house values, this research uses the sorting model to do the analysis. Sorting model was first proposed by Tiebout's (1956) who responded to Samuelson's paper, and after that the sorting model became one of the important tools to analyze the relationship between location choice and local public goods. The basic idea of Tiebout model is that people face a large number of communities offering different level of local public goods and sort to choose their most preferred community. Based on this idea, the impact that a landfill or gravel pit operation has on household residential location choice can be identified by estimating a two-stage sorting model, where in the first stage a multinomial Logit model for the personal choice is estimated and the second stage is an ordinary least square estimation on the community level. To employ the model, we choose Franklin County of Ohio State as the study area and a full year of 2010 real estate transaction data were collected and augmented with data from other sources. The demographic data for the households are obtained from 2010 census block and census block group micro data. Also, the distances from landfills and gravel pit for each household are created from maps and combined with data from other sources to account for environmental and neighborhood characteristics.

The next section of this paper lists some previous studies and compares these studies with ours. Section 3 develops the theoretical structure necessary for estimating the impacts of landfills and gravel pit operation on households' residential location choice. Housing price data and other data sources are described in Section 4. Section 5 reports results of this analysis, and the last part is conclusions.

Literature Review

There is a vast body of literatures analyzing the relationship between house value, environmental quality and household residential location choice. In this section I discuss some of the previous studies and make a comparison of these studies with ours.

The hedonic technique has been widely used in previous studies to measure the effects of landfills on house value, however, different studies got different results. Bouvier et al. (2000) examines six landfills, which differ in size, operating status, and history of contamination. The effect of each landfill is estimated by the use of multiple regression and the results show that five of the landfills have no statistically significant effect on house values. In the remaining case, the result indicates that houses in close proximity to this landfill suffered an average loss of about six percent in value. Hite (2001) analyzed the impact of presence of landfills on nearby residential real estate prices using a hedonic price model. The author account for temporal effects by including housing transaction in areas with both open and closed landfills and control for information effects. The results suggest that closing landfills will not necessarily mitigate property-value impacts. Kinnaman (2009) used both a hedonic pricing model and a repeat-sales estimator to estimate how a landfill closure affects neighboring property values. Results of are used in the analysis. Housing data gathered before and after the closure of a solid waste landfill suggest property values increased by an estimated 10.8% with the closure of a solid waste landfill, but this estimate is not statistically significant. Also, property values continued to rise with distance from the open or closed landfill, suggesting a potential stigma effect associated with the old landfill site. Ready (2010) used a hedonic price function to estimate a region containing three landfills that differ in size and in their prominence in the landscape. The results show that the three landfills differ in their impact on nearby property values. While two of the three landfills have statistically significant negative impacts on nearby property values, the smallest, least prominent landfill does not. Though these previous studies got inconsistent conclusions, most of them find negative effects of landfills on house values. Thus, in this study we also assume that landfills may decrease the value of nearby houses and household would not like to live near landfills. By far, I have not found any studies analyze the effect of gravel pit operation on residential location choice using either hedonic price model or sorting model. In this study, including the effects of landfills we also estimate the effect of gravel pit operation, which is the innovation of this study.

Reviewing the previous, another technique used to estimate the impacts of environmental quality on household residential location choice is the sorting model. Sieg et al. (2004) uses a discrete continuous choice model measuring the general equilibrium willingness to pay for reductions in ozone concentrations in Los Angeles Metropolitan Area, which includes parts of five counties between 1990 and 1995. Bayer, Keohane and Timmins (2009) develops a discrete choice model by incorporating moving cost into the model and apply the method to the case of air quality. This paper focuses on metropolitan areas throughout the US for the year 1990 and2000. The model yields an estimated elasticity of willingness to pay with respect to air quality of 0.34-0.42, which imply that the median household would pay $149-$185 for a one-unit reduction in average ambient concentrations of particulate matter. Tra (2010) develops a discrete choice locational equilibrium model to evaluate the benefits of the air quality improvements that occurred in the Los Angeles area following the 1990 Clean Air Act Amendments. The results show that air quality improvement provided substantial general equilibrium benefits to households, and it also reveals the welfare impacts varied significantly across income groups. In this study, we also use the sorting model. From the above literatures, we can see that most of them focus on air quality, and there is no paper using the sorting model to estimate the effect of landfills and gravel pit operation on residential location choice. Therefore, this may be another innovation of our paper.

Empirical Methodology

Conceptual Model

Sorting model begins with a simple assumption that the amount and characteristics of housing and public goods varies across locations, and each household choose its preferred location to maximize their utility. The utility function specification is based on the random utility model, which includes choice-specific unobservable characteristics. The framework of this paper follows closely the sorting models developed by Bayer et al. (2007), which model the residential location decision of each household as a discrete choice of a single residence. We assume that each household choose the dwelling location h from a set of housing types H. Let X_h represent the observable characteristics of housing choice h, including characteristics of the house (e.g., size, age and type). Let N_j represents neighborhood attributes and ρ_h denote the price of housing choice h. Then, the explicit indirect utility function form is defined as:

$$(1) \qquad V_h^i = \alpha_X^i X_h + \alpha_N^i N_j - \alpha_\rho^i \rho_h + \xi_h + \varepsilon_h^i$$

where V_h^i represents the indirect utility of household i by choosing housing choice h , which is composed of the observed characteristics of the house X_h, neighborhood attributes N_j, housing price p_h, unobserved attributes of the housing type ξ_h and the idiosyncratic error termε_h^i. α_j^i ($j = X, N, \rho$) are parameters that need to be estimated.

The heterogeneous preference of the households is allowed to vary with its own characteristics, z^i, which can be expressed by the interaction with observed characteristics of households. As a result, the parameter associated with housing and neighborhood characteristics and price α_j^i for $j \in \{X, N, \rho\}$, varies with household $i's$ own characteristics according to:

$$(2) \qquad \alpha_j^i = \alpha_{0j} + \sum_{k=1}^{K} \alpha_{kj} z_k^i$$

Equation (2) describes household $i's$ preference for choice characteristics j . Given the household's problem described in equations (1) and (2), household i chooses housing choice h which provides the maximum utility.

Econometric Implementation

The econometric model identifies the parameters defined in equation (1) and (2). Estimation of the model follows a two-step procedure, during which the first step estimates household preference parameters and the alternative-specific tastes while in the second step the mean taste parameters are recovered. Before proceeding to the two-step estimation strategy, we rewrite the indirect utility function as:

$$(3) \qquad V_h^i = \delta_h + \lambda_h^i + \varepsilon_h^i$$

where

$$(4) \qquad \delta_h = \alpha_{0X} X_h + \alpha_{0N} N_j - \alpha_{0\rho}\rho_h + \xi_h$$

and

$$(5) \qquad \lambda_h^i = \left(\sum_{k=1}^{K} \alpha_{kX} z_k^i\right) X_h + \left(\sum_{k=1}^{K} \alpha_{kN} z_k^i\right) N_j - \left(\sum_{k=1}^{K} \alpha_{k\rho} z_k^i\right) \rho_h$$

In equation (3), δ_h represents the utility provided by the housing choice h that is common to all households, and λ_h^i captures utility that is unique to households which arise from differences in the observed characteristics of household. z^i represents household characteristics and k indexes the kth characteristic. When the household characteristics included in the model are constructed to have mean zero, δ_h is the mean indirect utility provided by housing choice h. With this expression of the utility function, the first stage of the estimation procedure is a maximum likelihood estimation (MLE), which recovers the mean utility δ_h and the household-specific taste parameters in equation (5). For any combination of the heterogeneous parameters in equation (5) and the mean indirect utilities δ_h, the first stage predicts the probability that each household i chooses house h. We assume that the idiosyncratic error term ε_h^i is identically and independently distributed and has a Type Ⅰ Extreme Value distribution. Then the conditional logit probability of household i choosing housing type h is defined as:

$$(6) \qquad P_h^i = \frac{\exp(\delta_h + \lambda_h^i)}{\sum_k \exp(\delta_k + \lambda_k^i)}$$

The log-likelihood for the household choices is defined as:

$$(7) \qquad \ell = \sum_i \sum_h I_h^i \ln(P_h^i)$$

where I_h^i is a dummy variable that equals 1 if household i chooses housing type h.

To better understand the mechanics of the first stage of estimation, we take the derivative of the the log-likelihood equation (7) with respect to δ_h yields:

$$(8) \qquad \frac{\partial \ell}{\partial \delta_h} = \sum_{i=h} \frac{\partial \ln(P_h^i)}{\partial \delta_h} + \sum_{i \neq h} \frac{\partial \ln(P_h^i)}{\partial \delta_h} = S_h - \sum_i P_h^i = 0$$

From equation (8) we can see that in order to maximize the log-likelihood, the observed share of households choosing housing type h must perfectly match the sum of the household probabilities for choosing the same housing type.

As mentioned above, the purpose of the first stage estimation is to obtain the mean utility δ_h and the household-specific taste parameters. For any set of interaction parameters, contract mapping can be used to calculate the vector δ that satisfies the first order condition: $S_h = \sum_i P_h^i$. The mean indirect utility got from this method is consistent with the maximum likelihood and the equation for contraction mapping is shown as follows:

$$(9) \qquad \delta_h^{c+1} = \delta_h^c - \ln(\sum_i \frac{\widehat{Pr_{ih}}}{S_h})$$

where c indexes the iterations of the contraction mapping. Using this method, it is possible to estimate the full vector of indirect utility quickly even when there are a large number of elements, which reduces the computational burden.

When estimating equation (4), one important underlying assumption is that housing prices are uncorrelated with unobserved characteristics of residential locations. However, there is likely significant correlation between housing prices and unobserved housing/neighborhood attributes. To solve this endogeneity, following Bayer et al. (2007), this paper also introduce an instrument variable for price that is based on the exogenous attributes of distant. It is assumed that distant neighborhoods influence prices in local neighborhoods but the characteristics of those distant neighborhoods are unlikely to be correlated with local unobservable components of utility. There are two step to construct the instrumental variables.

The first step is to rearrange equation (4) by moving the price to the left hand side:

$$(10) \quad \delta_h + \alpha_{0\rho}\rho_h = \alpha_{0X}X_h + \alpha_{0N}N_j + \xi_h$$

Then, a plausible value for $\alpha_{0\rho}$ need to be guessed, which I denote it as $\widehat{\alpha_{0\rho}}$ and add additional regressors to the right hand side based on the observed neighborhoods attributes and neighborhood social demographics for all communities centroids within 1 and 2 mile ring from the current community centroid to form a new regression equation:

$$(11) \qquad \delta_h + \widehat{\alpha_{0\rho}}\,\rho_h = \alpha_{0X}X_h + \alpha_{0N}\widetilde{N}_h + \tilde{\xi}_h$$

where the tildes indicate the presence of additional control terms in the neighborhood variables vector. With these new variables, equation (10) is estimated using ordinary least square (OLS). By setting the OLS residual, $\tilde{\xi}_h$, equal to zero, the instrument for housing price is obtained as follows:

$$(12) \qquad \rho_h^{iv} = \frac{\delta_h - \widehat{\alpha_{0X}}X_h - \widehat{\alpha_{0N}}\widetilde{N}_h}{-\widehat{\alpha_{0\rho}}}$$

As mentioned above, the instrument price is dependent on the initial value of $\widehat{\alpha_{0\rho}}$. In order to eliminate this dependence, this paper will apply the method used by Allen Klaiber and Phaneuf (2010). The strategy is that after determining the initial price instrument and running IV, the estimated price coefficient is obtained and the entire process of determining the price instrument is re-run using the new price coefficient as the initial guess. By repeating this process several times, the price coefficient eventually stabilizes and the initial dependence on the conjecture for the price coefficient is removed.

Data Sources

Definition of Communities

One of the approaches used in previous papers to define the communities is to use census block groups or census tracts. One of the problems of using census block groups or census tracts as communities is that the size of the communities are different and the quality of public goods may be lower when averaged over a larger area than averaged over a smaller area, which may bias the result. Also, census tracts or census block groups are locally defined to create relatively homogenous entities, but such gerrymandering may also bias the estimation results. For these reasons, Banzhaf and Walsh (2008) use a different approach to define neighborhood, through which a set of half-mile-diameter circles evenly distributed across the study area are created as neighborhoods. In this paper, I use the same method and define the neighborhoods as a set of half-mile-diameter circles evenly distributed across the Franklin County of Ohio State. With the help of the ArcGIS software, demographic data from census blocks and housing characteristics variables can be attached to the new communities.

The study area in this paper is the Franklin County of Ohio State. The communities are constructed by placing an equidistant grid across the study area. Both the width and height of the grid are half miles. After the grids have been constructed, a 0.25-mile buffer is placed inside each grid, creating a set of circles that are evenly distributed across the study area. This process creates 2171 communities and figure 2 shows the distribution of the new communities across the study area. The demographic data are assigned to communities based on the percentage of the block's geographic area lying within each community.[1] The number of blocks ranges from a low of 1 block per circle to 118 blocks per circle and the fiftieth percentile is 13 blocks per circle. Table 1 shows the descriptive statistics of the demographic variables for all the communities. The average population for all the communities is 419 and white people account for 70% of the population. The percentage of population under the poverty line is about 17%.

Household and Housing Characteristics

The housing data used in this paper are real transaction data of residential one family dwelling of Franklin County in 2010, which can be downloaded from the Franklin County Auditor's office website. The data provide transaction records for residential properties located in Franklin County. Each record includes the property's address, transaction price and the structure characteristics. Though the data provide detail information about the house, there is no information about the households who are occupying the houses. To deal with this problem, I approximate household level characteristics using block level data from 2010 census, which is the smallest level of spatial resolution that is publicly available. The household level variables which are approximated at census block level include household size and householder's race. Since household income is only available at the block group level, we assign the median household income of each block group to households located within this group. Based on previous papers, observations used in this paper only include houses within 3.25 miles from the

[1] For block group-level data, the values were distributed to the blocks based on population shares, then distributed to the communities as for the block-level data.

nearest gravel pit or houses within 3.25 miles from the nearest landfill. After cleaning the data, there are 1592 single family dwellings transactions. Table 1 provides the summary statistics of housing characteristics. The mean values of structure characteristics of all houses.

The purpose of this paper is to estimate the impact of gravel pit operation and landfill on household residential location choice. In the study area, there are three landfills and one of these landfills accepts municipal solid waste from Franklin County while two of these landfills are licensed to accept demolition material. Figure 1 shows a picture of one of the landfills. We draw four points of the landfill (northwest, northeast, southwest and southeast) and calculate the distances to the nearest point to measure the environmental disamenity. There are 12 gravel pit sites in the study area. To account for effects of gravel pit operation on residential location choice, distances from each property to the nearest gravel pit site are measured and included in the data set.

Determining the Choice Set of Households

After cleaning the data, there are 1592 single family dwelling transactions in our data set. Following Tra (2013), this paper assumes that each of the 1592 housing units chosen by the households in the sample represents a housing type. Though some papers (Tra 2010,Allen Klaiber and Phaneuf 2010) use discrete housing types rather than housing units to reduce the number of alternatives, Tra (2007) has shown that alternatives characterization of the product space using a smaller versus a larger number of housing types yields very similar parameter estimates. Therefore, the households' relevant choice set of alternatives are the 1592 housing types in the sample. However, the large choice set will make the estimation computationally infeasible. To solve this problem, following McFadden (1978) we construct the choice set by sampling a few alternatives from the full set of available alternatives, which includes the household's chosen residential location and a random sample of several nonchosen alternatives. This estimation strategy results in consistent estimates, but does reduce the precision of the first stage estimates.

Estimation Results

First Stage Estimation Results

The model is estimated at the level of house types, which are defined by housing units in this paper. To characterize a choice alternative, all structural and neighborhood variables used in the model are created at the house type level. The purpose of the first stage is to recover the interaction parameters as well as a vector of mean indirect utilities for each housing type. In specifying the model, we include a limited set of interactions between household characteristics and the neighborhood attributes. By reducing the number of interactions according to the reasonable intuition, the degree of freedom for the estimation could be conserved and the potential problem of linearity could also be limited. Since most of households with white householders around the gravel pits and landfills are poor, I divide these households into poor white households and rich white households. Poor white households are defined as households with white householders and lower income than the median household income of the community in which the households are located, while rich white households are defined as households with white householder and higher income than the median household income of the community. The interactions estimated in the first stage include interactions of householder characteristics with distance to the nearest landfill and distance to the nearest gravel pit. The interaction of household size with the number of bathrooms and the interaction of household income and the poverty level of the communities are also included in the first stage estimation. Regarding the poverty level, we use the percentage of people under the poverty line for each community. Table 2 shows the first stage estimation of the household-specific taste parameters. The results show that the interactions between rich black householder and distances to the nearest landfill and the nearest gravel pit are not statistically significant. Rather than the magnitude of the coefficients, we are more interested in the signs of the coefficients for the interactions. The interaction between distance to the nearest landfill and rich-white is positive, which indicates that households with higher income and white householder prefer to live far away from the landfill and gravel pit. The same result is also get for the gravel pit, which is also as expected for the reason that this is in accordance with the hypothesis that households with white householder and higher income prefer to live far away from the landfill and gravel pit. However, the coefficient of the interactions of household size with the number of bathrooms is negative and statistically significant. This indicates that household of bigger size prefers to live in houses with fewer bathrooms, which is not consistent with the hypothesis. This may because we just keep observations within 3.25 miles from the gravel pit or within 3.25 miles from the landfill, and most of the large households we kept in our estimation choose to live in houses with fewer bathrooms. Generally, the first stage estimation shows that there is heterogeneity in preferences for distance to the nearest landfill and gravel pit.

Second Stage Estimation Results

As mentioned before, when the choice set is large, it is computationally restrictive to estimate the fixed utility for each choice. To solve this problem, this paper follows McFadden (1978) and construct the choice set by sampling a few alternatives from the full set of available alternatives, which includes the household’s chosen residential location and a random sample of several nonchosen alternatives. The method of contract mapping is used to do the estimation. Based on the estimation results of the mean taste parameters from the first stage estimation, the second stage estimation can be implemented. Since the landfills and the gravel pit operation could only affect nearby house value, the observations used in the estimation are houses located within 3.25 miles away from the landfills or 3.25 miles away from the gravel pit site. When estimating equation (4), one important underlying assumption is that housing prices are uncorrelated with unobserved characteristics of residential locations. However, there is likely significant correlation between housing prices and unobserved housing/neighborhood attributes. To address the price endogeneity, and instrument is created by adding a variety of neighborhood variables to equation (11) to account for observable determinants of housing prices. These variables include all the second stage regressors as well as all the community characteristics for the cumulative 1 and 2 mile rings around each community centroid. After the instrument variable for price is creates, the IV estimation of equation (4) is run and results are shown in table 3. The particular interest of this paper is the distance to the nearest landfill and gravel pit. The result for the distance to the nearest landfill support the hypothesis that longer distance to the landfill increases the fixed utility of the house. Also, the direction for the effect of distance to the nearest gravel pit is as expected, which indicates that households prefer to select houses with longer distance to the gravel pit operation. After controlling for the price endogeneity we find that house price has negative effect on fixed utility and the effect is statistically significant. We also include other variables in the regression. However, the results show that the house age, the percentage of people in poverty and whether a house has air conditioner and fireplace has no significant effect on fixed utility. The number of bedrooms and bathrooms has positive effect on the fixed utility.

Conclusion

This paper uses a sorting model to analyze the impact of environmental disamenity (distance to the nearest landfill and gravel pit) on household residential location choice. Since the size of neighborhood may affect the accuracy of the estimation results, this paper creates half mile diameter circles randomly across the Franklin County of Ohio State as communities. To assign neighborhood characteristics to each community, the percentage of the block's geographic area lying within each circle is calculated and the demographic data are assigned to communities based on this percentage. To solve price endogeneity, this paper introduces an instrument variable for price that is based on the exogenous attributes of distant neighborhood in the second stage estimation. During the analysis we just keep observations within 3.25 miles from the gravel pit or within 3.25 miles from the landfill. The first stage estimation results show that rich white householder are more likely to select houses with longer distance from the gravel pits and landfills than rich black householder. After controlling for the price endogeneity, the second stage estimation supports the hypothesis that longer distance to the landfill increases the fixed utility of the house. Also, the direction for the effect of distance to the nearest gravel pit is as expected, which indicates that households prefer to select houses with longer distance to the gravel pit operation.

References

Allen Klaiber, H., and D.J. Phaneuf. 2010. "Valuing Open Space in A Residential Sorting Model of the Twin Cities." *Journal of Environmental Economics and Management* 60(2):57–77.

Banzhaf, H.S., and R.P. Walsh. 2008. "Do People Vote with Their Feet ? An Empirical Test of Tiebout ' s Mechanism." *The American Economic Review* 98(3):843–863.

Bayer, P., F. Ferreira, R. Mcmillan, J. Altonji, P. Bajari, S. Berry, S. Black, D. Card, K. Chay, D. Cutler, H. Fang, D. Figlio, E. Glaeser, D. Lee, E. Moretti, T. Nechyba, J. Rothstein, K.

Rueben, and H. Sieg. 2007. "A Unified Framework for Measuring Preferences for Schools and Neighborhoods." *Journal of Political Economy* 115(4):588–638.

Bayer, P., N. Keohane, and C. Timmins. 2009. "Migration and hedonic valuation: The case of air quality." *Journal of Environmental Economics and Management* 58(1):1–14.

Bouvier, R.A., J.M. Halstead, K.S. Conway, and A.B. Manalo. 2000. "The Effect of Landfills on Rural Residential Property Values : Some Empirical Evidence." *The Journal of Reginal Analysis and Policy* 30(2).

Hite, D. 2001. "Property-Value Impacts of an Environmental Disamenity : The Case of Landfills." *Journal of Real Estate Finance and Economics* 22(2/3):185–202.

Kinnaman, T.C. 2009. "a Landfill Closure and Housing Values." *Contemporary Economic Policy* 27(3):380–389.

McFadden, D. 1978. *Modeling the choice of residential location.pdf*. Amsterdam.

Ready, R.C. 2010. "Do Landfills Always Depress Nearby Property Values?" *Journal of Real Estate Research* 32(3):321–339.

Sieg, H., V.K. Smith, H.S. Banzhaf, and R. Walsh. 2004. "Economics Department of the University of Pennsylvania Institute of Social and Economic Research -- Osaka University Estimating the General Equilibrium Benefits of Large Changes in Spatially Delineated Public Goods." *International Economic Review* 45(4):1047–1077.

Tra, C.I. 2010. "A discrete choice equilibrium approach to valuing large environmental changes." *Journal of Public Economics* 94(1-2):183–196.

Tra, C.I. 2007. *Equilibrium Welfare Impacts of the 1990 Clean Air Act Amendments in the Los Angeles Area by Equilibrium Welfare Impacts of the 1990 Clean Air Act Amendments in the Los Angeles Area 1*. University of Maryland.

Tra, C.I. 2013. "Measuring the General Equilibrium Benefits of Air Quality Regulation in Small Urban Areas." 89(2):291–307.

Figure 1. Example of Landfill Map

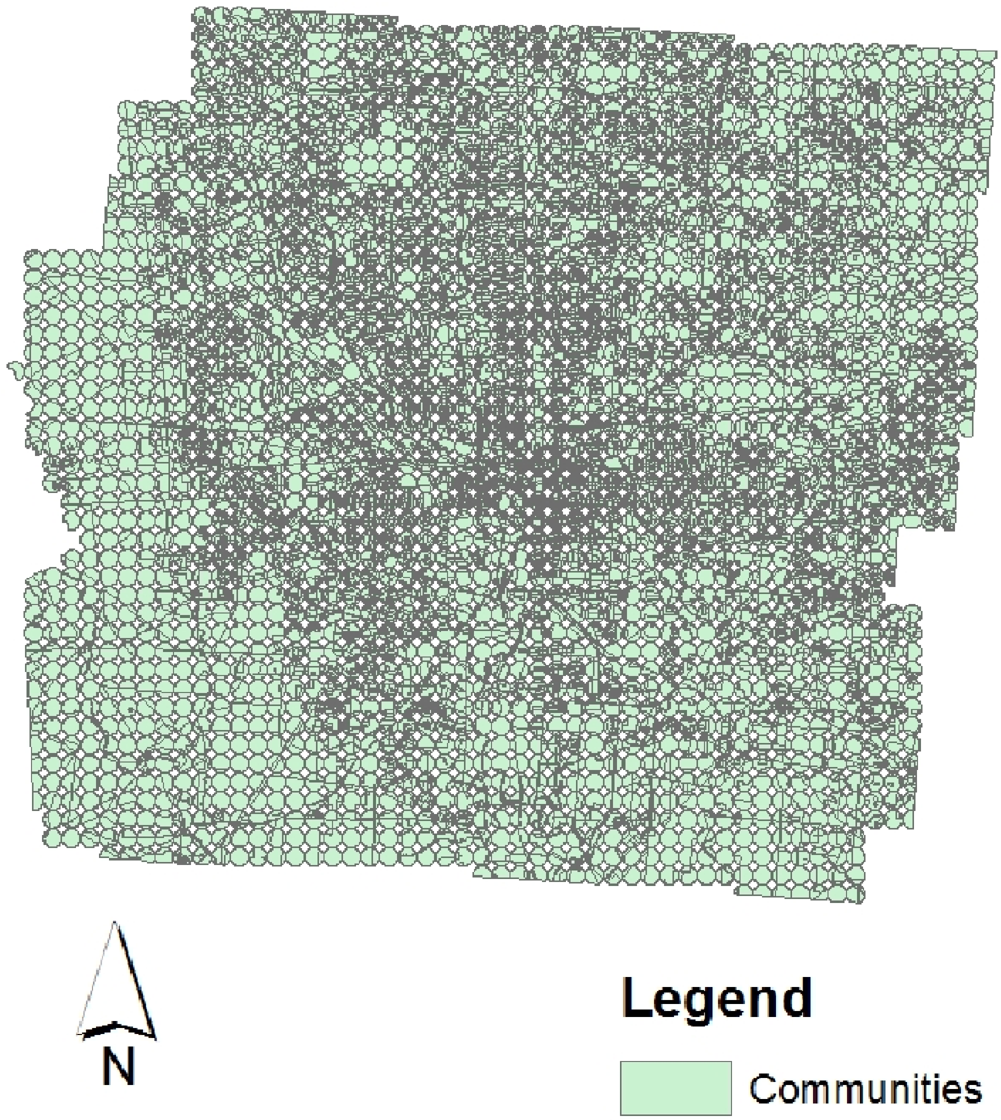

Figure 2. Community Creation

Table 1. Descriptive Statistics of the Data

	Mean	Std. Dev.
Descriptive Statistics for the Circle Communities:		
Population	419.55	517.41
White Population	290.44	383.81
Black Population	89.31	193.57
Household Income	64967.88	33884.31
Poor Population	71.94	179.34
Number of Observations	2171	
Descriptive Statistics for Housing Characteristics:		
Price	132746.10	62816.72
House Age	39.12	27.41
Bedrooms	3.13	0.61
Bathrooms	1.81	0.63
Air Conditioner	0.88	0.232
Fireplace	0.44	0.57
Gravel Distance (miles)	2.41	0.95
Landfill Distance (miles)	4.32	2.50
Number of Observations	1592	

Table 2. First Stage Estimation Results

Variable	Estimate	Std. Err.
Bathroom * Household Size	-0.0562***	0.0189
Distance to Landfill * Rich*Black	-1.854	421.37
Distance to Landfill * Rich*White	0.1623***	0.0183
Distance to Gravel Pit * Rich*Black	-3.4380	495.117
Distance to Gravel * Rich*White	0.1832***	0.0455
Income*Poverty	-0.801***	0.1804
Likelihood Ratio	173.73	

Note: *** means statistically significant at 99% and higher;

Table 3. Second Stage Estimation Results

	IV Estimation	
Variable	Estimate	t-Value
Intercept	-2.1958***	-13.51
Price	-1.5704***	-4.39
House Age	-0.0011	-1.19
Bedroom	0.0771**	2.44
Bathroom	0.1543***	0.0382
Air conditioner	0.0291	0.5
Fireplace	-0.04823	-1.52
Distance to the nearest gravel pit	0.1390***	7.85
Distance to the nearest landfill	0.3732***	49.23
Percentage of people in poverty	-0.1952	-0.98
Expenditure per Pupil	9.0420	12.93

Note: *** means statistically significant at 99% and higher; ** means statistically significant at 95%; and * means statistically significant at 90%.