What's in a Label? Distance Analysis of the Listing Effect of Hazardous Waste Remediation on Property Value; Great Lakes Areas of Concern

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Abstract

The AOC program is an internationally managed hazardous waste remediation program focusing on the Great Lakes Basin, yet since its inception in 1987 little concrete evidence of its effects have been documented. Using tract level data from the 1970, 1980 and 1990 decennial censuses, this study employs a fixed effects panel data model and difference in differences analysis in order to recover the effect of AOC Listing on local property values. The results show large and significant negative effects to a change in hazardous waste status, all while the hazardous waste condition itself remains constant. This effect extends beyond the AOC and suggests heterogeneous impacts at different distances. These findings are useful in policy implementation and analysis, as they demonstrate both a scope of influence and potential cost considerations, and information on such informational effects will aide attempts to recover net benefits of longstanding, mostly unfinished remediation efforts.

I. Introduction

The Great Lakes Areas of Concern program (AOC) officially began in 1987 with the listing of 43 sites that are "watersheds, or portions of watersheds, along the Great Lakes suffering from degraded environmental conditions stemming from historic and ongoing pollution."[1] Of these, 31 are either wholly within the United States or jointly managed between the US and Canada, and 4 of those have met their restoration goals and achieved "delisted" status-that is the completion of the AOC program and formal removal from AOC status. This program has provided the renewal of ecosystem services to the surrounding communities and the Great Lakes system as a whole, yet this has been at a cost of several million dollars across the sites and over the past 29 years. In continuing funding for this and other hazardous waste cleanup programs, a difficulty presents itself in comparing the cost inputs with

[1] EPA. Great Lakes Areas of Concern. *United States Environmental Protection Agency*. 13 January 2016. https://www.epa.gov/great-lakes-aocs

the non-market benefits of a restored environment. Within this realm there is also an issue in the fact that these valuations may reflect perceptions as much as services rendered, where the labeling effect of AOC status may obscure the benefits added through restoration. As only 4 sites have been delisted, the majority of AOC's are providing restored services that may be masked by the ongoing nature of the cleanups-that is the labelling effect of being listed as an AOC.

Attempts to estimate the value that individuals place on environmental goods and services have been myriad and methodologically diverse in the field of environmental economics. In order to value the provisioning of a good such as environmental quality (the expected output of remediation) no explicit market exists and thus techniques to recover individual willingness to pay (WTP) have focused on two chief methodologies: revealed preferences and stated preferences. The latter has its benefits yet requires heavy cost and time intensive generation of survey preference data that still has some limitations in using hypothetical rather than actual choices. Revealed preferences have become a preferred methodology for both cost and causal reasons, and these take advantage of other goods and services that have well defined markets in order to examine an environmental service as a price determining component of these marketed goods. The hedonic pricing methodology has been used often[2] in the literature analyzing hazardous waste as well as several other environmental disamenities, yet does not come without its own criticism. Misspecification is often cited by detractors, yet methodologies have improved and risen in application over the past 15 years[3] to correctly isolate and identify causally the desired effects.

Hazardous waste surrounding the Great Lakes has been a topic of great interest in the region. The 43 total AOC's are the most heavily contaminated hazardous waste sites that affect Great Lakes watersheds. AOC's were determined through a collaborative effort between local stakeholders,

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[2] See Gamper-Rabindran and Timmins (2013), Greenstone and Gallgher (2008), Muehlenbachs et al (2015)
[3] Kuminoff and Pope (2014)

scientific experts, state and national environmental groups and the International Joint Commission[4]. They were defined as "geographic areas designated by the Parties where significant impairment of beneficial uses has occurred as a result of human activities at the local level[5]," and were officially listed as actionable parcels under the 1987 amendments to the Great Lakes Water Quality Agreement between Canada and the United States.

This paper will implement a quasi-experimental approach based on difference-in-differences (DD) regression analysis exploiting the fact that an environmental disamenity has localized effects that should, at a certain distance from the site, go to zero. In a similar methodology to those such as Linden and Rockhoff (2008) and Muehlenbachs, Spiller and Timmins (2016), this paper will compare housing prices and neighborhood demographic characteristics at the 31 US AOC's at the local and distance adjusted non-local (control) level, and then evaluate their respective changes pre- and post-listing decision (1987) in order to recover this difference-in-differences. Utilizing this fixed effects model and distance-as-control, this methodology will correct for unobservables that may be correlated with listing status and with property determinants in order to identify the causal effects of AOC listing on property values.

It is posited that a stigma associated with clean up status may "turn on" at listing and off at delisting and that this titular disamenity may affect perceptions that are capitalized in the housing market. Delisting has not happened for the majority of both Superfund and AOC sites, but Gamper-Rabindrin and Timmins (2012) find evidence for a positive effect on those Superfund sites that were delisted. It is also possible that there is some forward-looking positive expectation of reestablished

[4] The International Joint Commission is an independent binational organization established by the United States and Canada under the Boundary Waters Treaty of 1909, and oversees the implementation of the Great Lakes Water Quality Agreement of 1978, as amended in 2012.
[5] EPA. Great Lakes Areas of Concern. *United States Environmental Protection Agency*. 13 January 2016. https://www.epa.gov/great-lakes-aocs

environmental services associated with listing, and thus the determination of the direction of the total listing effect should have significant impact on attempts to value cleanup programs that are more often than not ongoing.

This paper matches census tract level data, normalized from 1970-1990 via the Geolytics database, with individual AOC and state level fixed effects and time trends to evaluate changes in property value associated with the listing decision at certain buffer distances from the site. Exploiting the fact that houses can be viewed as goods composed of several characteristics, each with its own marginal WTP, Rosen (1974) found that through repeated interactions through buyers and sellers, a Hedonic Price Schedule (HPS) emerges at the tangencies between individual indifference curves and offer curves that can isolate the MWTP for any of these characteristics. This paper utilizes such intuition to investigate the characteristic trait (disamenity) of hazardous waste presence (and the sub-level environmental service detriments associated) and isolated its effect from other determinants of housing prices in order to recover the WTP at the margin related to new public information associated with AOC listing.

The findings of this paper suggest a strong and negative relationship between the AOC listing decision and tract average property value changes. This effect is heterogeneous, but negative, at different buffer distances away from an AOC, suggesting a differential impact of the information effect at different distances, or levels of local. The results also demonstrate some interplay between forward looking positive effects and negative perception effects. Given that hazardous waste remediation efforts take decades to reach completion, it is vital to the policy context that evaluators and decision makers understand the overall negative impact that certain aspects of ongoing remediation have in order to make optimum listing and funding decisions.

This paper proceeds as follows: section II covers relevant background information on the AOC program; section III provides an overview of previous literature investigating the economic benefits of hazardous waste cleanup sites and AOC's, and other related studies; section IV overviews the data sources; section V reviews the adjacency buffer; section VI covers the econometric methodology and model; section VII analyzes results; and section VIII concludes.

II. Background on the Areas of Concern Program

The remediation of the 31 Great Lakes Areas of Concern (AOC) under USEPA jurisdiction has been projected to cost upwards of $4.5 billion (2005 USD) (ref), and the program has seen increased attention and funding since that estimate leading to significant interest in finding a causal estimate of benefits. Within this broader question, and given the ongoing nature of the majority of the AOC sites, the issue of a labeling effect becomes prominent. This is the question of the stigma that may be associated with a site formally entering a hazardous waste remediation program, the positive forward looking effects combat that stigma, and the overall direction of said effect.

In a 2016 consideration of applying for Superfund remediation funding to deal with historical hazardous waste in Ann Arbor, MI, Mayor Christopher Taylor "said in an interview with the Daily that while the EPA would likely lead to a more comprehensive cleanup of the contaminated water, the stigma of Superfund status could damage property values in the city."[6] It is intuitive that labelling comes with a price, and this price may impact the economic viability of remediation.

[6] Kuang, Brian. "Ann Arbor Township Considers Federal Intervention Groundwater Contamination." *Michigan Daily.* 23 March 2016.

The AOC program was first suggested in the 1972 Great Lakes Water Quality Agreement between the United States and Canada, where both nations had seen significant environmental degradation of the shared Great Lakes resource and proposed a series of studies to motivate the listing of sites in most dire need of remediation. From 1972 to 1987, 111 sites were considered that had had former or ongoing industrial or municipal waste issues that contributed directly to one of the five Great Lakes watersheds. Forty-two made the final list in 1987, and a 43rd was added in 1992.[7]

As this program came about in similar timing with the national and more publicized Superfund program, it is important to note a few distinctions. First, unlike Superfund sites, AOC's are non-binding designations that open up channels of public funding that are managed hierarchically from state environmental quality agencies down to the local sites themselves. This is as opposed to the mandatory responsible party system of Superfund which enforces private payment for restoration. Second, Superfund sites utilize a fairly well defined hazardous waste ranking score system to identify any site that meets a certain numerical threshold, whereas AOC's have more individualized site analyses and, again, only focus on the Great Lakes basin. That being said, it is the case that Superfund sites have overlapped with or abutted AOC sites, and thus this is an important variable that will be controlled for in the analysis to follow.

Following from this discussion, there are many entangled effects surrounding hazardous waste cleanup sites that make proper specification and analysis challenging. Beyond the existence of Superfund sites, there are community based efforts and other funding sources that can overlap with AOC and Superfund programs alike, and there is a certain caveat to the idea that remediation begins in absolute upon listing. During the period 1972-1987 while potential AOC sites were considered, it was

[7] International Joint Commission Data Portal. "Great Lakes Water Quality Reports, 1972-1987." www.ijc.org/en_/reports_and_publications

not the case that sites were simply analyzed and left alone, but efforts both through the GLWQA and other local and federal programs existed in hard to quantify fashions. There were sites that improved enough over this period to be omitted from the final list, and there were sites on the final list that had been invested in over this period before the 1987 listing, thus the consideration of not “on the list” sites as untreated is dubious, and the consideration of sites as treated after listing is likely equally so.

This is also true of the Superfund program and yet has not been discussed in the literature, where not only do existing National Priorities List (NPL) sites overlap with other programs and monies, but the sites that did not make that list and often serve as control groups are rarely left untreated by those other programs and their local communities. While this presents problems for isolating when exactly one can say a site begins remediation and can be labeled as treated, it does not do the same for the listing decision. The official listing of AOC’s is unfettered by the activities before and after, and simply reflects a titular change that may have affected the perception of individuals in regards to those activities. Thus, while this issue is potentially confounding (and unconsidered) in the previous literature, it is a point of motivation for this paper as the listing effect did “turn on” at a single point.

As of the present, only 4 AOC’s have been delisted in the United States, and these delistings are also too recent to yield the amount of data needed for proper analysis. Thus an examination of the listing decision is warranted in order to capture effects that delisting could reverse, and add preciseness to the discussion of the benefits of remediation programs that are often calculated before that delisting happens.

Through focusing on the effects of listing decisions as treatment, this paper seeks to uncover the potential biasing effects of remediation as it is occurring, disentangling the effects of improved environmental services from the effects of the improvement process itself. In the context of justifying expenses and correctly allocating funding towards improving environmental services, the validity of these techniques and their findings will be paramount.

III. Literature Review

Despite its long history, only a few studies, and all in the past decade, have rigorously attempted to evaluate the benefits of the AOC program. However, the few studies which exist and determine WTP for AOC remediation have focused at the individual AOC level and have fallen short of the statistical and quasi-experimental rigor necessary for causal inference and suffer from the same misspecification issues typically cited[8]. A holistic evaluation of the benefits of the AOC program has yet to be endeavored. However, the findings of these reports all suggest higher benefits than costs and motivate further, more extensive analysis.

Recent literature at the forefront of hedonic pricing analysis has examined other hazardous waste cleanup programs, and most often the USEPA Superfund program. Despite the usage of similar and currently favored methodologies, the results have pointed in multiple directions. Greenstone and Gallagher (2008) found little to no positive effects on housing prices due to Superfund cleanup. However they analyze sites as treated upon listing which could potentially be missing the actual benefits of the program and also may not be able to reconcile the labeling effects that this paper seeks to analyze. Greenstone and Gallagher also do not employ detailed spatial analysis, which may have led to a muting of the observed effect. Finally, this study also utilizes a regression discontinuity strategy that may not

[8] See Braden et al, (2008), (2004) and Isley et al, (2011).

create a completely valid counterfactual, as unlisted sites may need to be more rigorously proved as untreated due to the existence of other cleanup efforts, as explained in section II.

Gamper-Rabindran and Timmins (2012) cite some of these factors, and reinvestigate the same question utilizing delisting and finer spatial and distance based analysis in order to recover findings of significant gains in property value associated with Superfund cleanup. While they utilize the same sample and a similar RDD strategy as Greenstone and Gallagher, the spatial component is a key difference. By examining within tract variation, they investigate the distribution of housing value changes in order to recover spatially localized benefits to cleanup efforts. This paper adds to the dialogue surrounding contradictory findings regarding hazardous waste cleanup and suggests that via proper spatial analysis a better estimate can be recovered. This paper also does some preliminary analysis of the listing decision, as it breaks treatment down into a composite variable including proposition, listing, constructing, completion and delisting. While they recover small but positive listing effects, the negative proposition effect may explain some of this. Furthermore, the spatial boundary used as the “end of the local effect” is taken from an external study, which precludes a robust or program specific evaluation of that boundary, something that this paper focuses on.

The analysis of the AOC program will employ similar hedonic methodologies to the above mentioned papers, but will exploit spatial variation in order to establish a control, and will focus on hazardous waste listing status as a price determinant that mediates the relationship between improvements in environmental quality and marginal WTP (i.e. housing value). This distance-as-control method is supported by Muehlenbachs et al (2015) and Linden and Rockoff (2008). Muehlenbachs et al, in examining shale gas development, find that the effects of a localized amenity go to zero at a certain buffer distance, and exploit that distance to isolate the effect of well installation on treated vs. untreated properties. The key elements of this paper, which motivate the control strategy for the oncoming analysis, is that an environmental (dis)amenity has localized effects that stop at a certain buffer distance away from the source, and that those properties outside of that buffer can serve as a control group.

IV. Data

A large dataset was compiled from several sources for the analysis. The data on the AOC sites came from the International Joint Commission's library and the EPA-managed individual AOC websites. AOC specific information on site location, size and history was found through these two resources. This included 31 individual site shapefiles that were necessary for spatial analysis. Additionally, as noted above, original consideration dates under the GLWQA were found for each site that predated the 1987 official listing decision. It is possible that these activities may have led to stigmatization or restored services that happened prior to the official listing, and thus allows for a control of that potential effect.

USEPA Superfund data was obtained from the NPL and EPA data stores, including shape files and historical information pertinent to the analysis. This was done to address overlaps between AOC's and Superfund sites and to control for potentially biased results. Only those Superfund sites that were within the utilized buffer distances and had been listed before 1987 were considered for each AOC. The timing of this listing was included to better measure the preciseness of this effect.

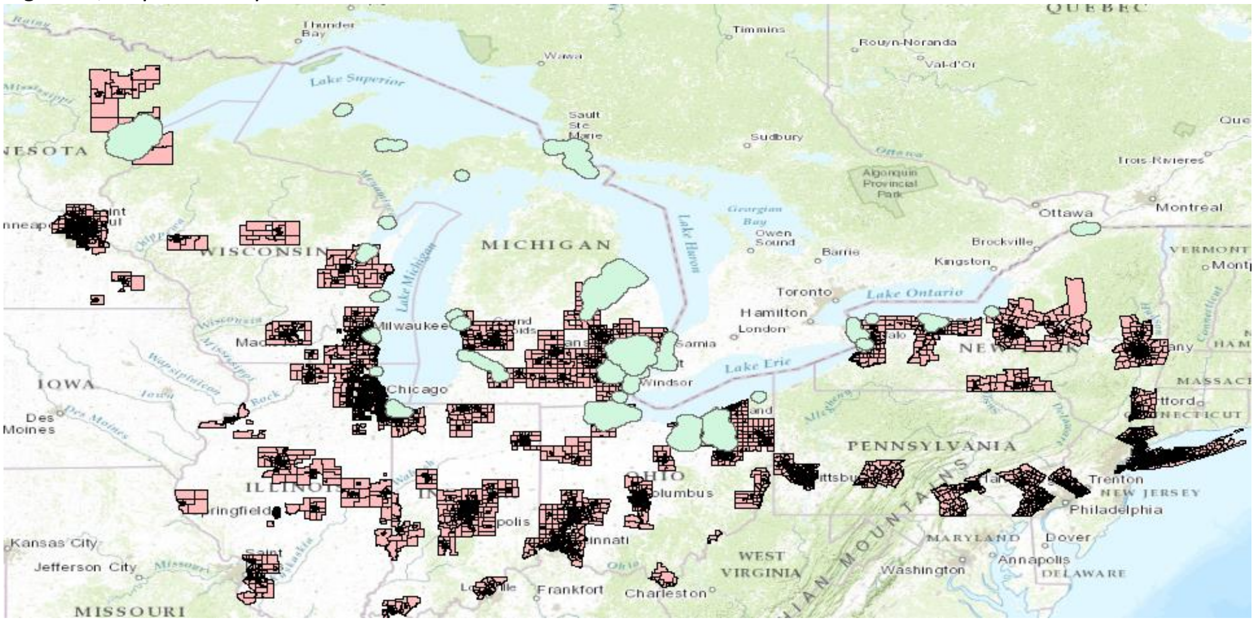
Demographic information as well as housing price and characteristics information was collected from the Geolytics *Neighborhood Change Database*. This data came from the 1970, 1980 and 1990 Decennial Censuses. These data have been normalized to the 2010 census tract boundaries which represent 4,000 person density centroids, and was taken within varying buffer distances of each AOC, the full extent of the data set is the seven-state Great Lakes region. Distance was measured, using ArcGIS, from AOC feature border to census tract centroid. Only those tracts with complete data from

1970-1990 were considered for the main analysis, though separate regression of just 1980-1990 data is also included. Through this, the proper explanatory variables were identified that contribute to the model's understanding of shifting house prices as measured in the decennial census.

This demographic data started with 21,261 tracts, which is all of the seven states of IL, IN, MI, MN, NY, OH, WI, as they were fully tracted by 1990. Removing "absent tracts" from each decade, 1970 yielded 4907, the 1980 census 7 and the 1990 census 1 additional, leaving 16,346 tracts that had data during each census. Then, 980, 28, and 19 tracts from the 1970, 1980, 1990 censuses, respectively, were removed where aggregate housing value data was missing, leaving 15,319 tracts. Finally, 1,538, 425 and 3 tracts from the 1970, 1980 and 1990 censuses, respectively, were removed where the number of housing units was missing (meaning there was no way to calculate average value), leaving 13,353 tracts. Each tract was decomposed into three long form data observations, one for each census, yielding 40,056 observations for the analysis.

Due to the heterogeneous nature of census collection, especially in more rural areas, and also the reporting nature of the key statistic (aggregate housing value) during the 1970's and 1980's, certain tracts are missing from the data set (in fact the majority). See Figure 1 for a mapping of included tracts. There is no reason to suspect endogenous tract placement that coincides with AOC listing and distance, as the sites are varyingly affected by the amount of missing tracts, but this is discussed further in section VII. Additionally, the dependent variable of interest is housing value, yet given the nature of census data the best representation of this was "owner occupied non condo housing units". While a good proxy, this obviously restricts the dataset to only those properties, and was an often omitted question that reduced the sample size. A final note is on the coarseness of the data. While the previous literature mentioned uses individual house transaction data and block level census data, this analysis uses tract level data and average tract housing value.

Figure 1, Repeat Sample Tracts 1970-1990



Map of Tracts (red) overlaid with 10km buffer AOC suites (green).
Data Source: USEPA

V. Distance Strategy

This section investigates the relationship between distance and the effect of an environmental disamenity. In this case, the identification strategy seeks to find localized informational effects that correlate with the AOC listing decision. The effects can be either positive of negative, as there could be some forward looking expectation of improved conditions or there could be an increased awareness of the environmental disamenity and forecasting of the negative aspects of restoration activities (noise, obscured views, increased traffic). The key assumption tested here is that this informational effect should vary with distance in two important ways: that different distance bins can proxy for different sets of localized effects and that the effect goes to zero at a certain distance. This section will provide evidence for a buffer distance from an AOC that signifies the distance at which localized effects go to zero, which is a foundational element of the control strategy employed via the difference in differences estimation in section VII.

This test is conducted via the utilization of repeat observation census tracts, creating a fully balanced panel data set with each observation being decomposed into long form data including the 1970, 1980 and 1990 years. This strategy is consistent with Linden and Rockoff (2008) and Muehlenbachs, et al (2015) in determining where a localized (dis)amenity no longer has localized effects.

First, a linear regression of the log of price controls for various time variant and invariant effects including property, AOC, lake, and county by year effects. Leaving “distance to nearest AOC” out of the initial regression, the resulting residuals are stored and a second, polynomial, regression of the residuals on distance from the nearest AOC examines the extent to which the heterogeneity in property values surrounding AOC’s can be explained by distance to the nearest AOC. This second regression is in fact a composite of several regressions taken at different bandwidths along the independent variable. Figure 2 depicts this relationship, using both an algorithmically generated bandwidth of around 3KM and also 1KM, similarly to that of Muehlenbachs et al (2015), the results below demonstrate a positive effect to proximity prior to listing (1970 and 1980) which becomes much closer to zero post-listing (1990), signifying a negative effect on housing values post-listing for within-boundary properties.

The observed temporal relationship is weaker closest to the AOC sites and becomes increasingly stronger until it disappears at around 30-35 KM. Gamper-Rabindran and Timmins (2015) utilize a figure of 3 miles (approximately 5KM) as an upper bound of their effect, taken from a panel data study of the relationship between housing prices and hazardous waste site placement (Jenkins et al. 2006). Muehlenbachs et al use two different localized effects for their model, where an adjacency effect is found to be bounded at 2KM and a further vicinity effect at 20KM. The AOC listing effect is shown here to extend past 30KM, which is an order of magnitude larger Jenkins’ figure and Muehlenbachs’ adjacency figure, but is not much further than their vicinity figure. Although those studies were investigating the full effect and not the listing effect per se, robustness checks will utilize a series of different buffer distances, including the aforementioned 2 and 5 KM, as the effect of listing a hazardous waste site should, intuitively, go no further than the full effect of said site.

The aforementioned distance strategy employed by Muehlenbachs et al (2015) and Linden and Rockoff (2008) utilizes a two tiered distance buffer strategy that decomposes their effects into adjacency and vicinity effects. There is no similar intuition, and little additional information to be gleaned, from such a distinction for this paper, however. The effect of listing is not assumed to be heterogeneous within 32KM (the figure to be used subsequently), but the motivation and intuition behind where effects could be direct and indirect is lacking in this instance. The previous literature also does not employ nearly as rigorous of a strategy on the extent of the vicinity buffer (which essentially is the extent of the effect being studied) as they do on the end of the adjacency buffer, and this lax approach fails to convincingly identify extent of the effect and its full impact. That being said, the findings in this section suggest a further scope of influence for the AOC program, but this will be tested later on. Section VII will include a secondary investigation of the possibility of a decomposed vicinity and adjacency effect, yet it is the total effect and its distance-extent that are of key interest.

In identifying the distance beyond which localized effects of AOC listing go to zero, this strategy allows those tracts outside the effect-buffer to serve as controls in the following regressions in section 6. The summary statistics under the ideal buffer specification are included in the appendix.

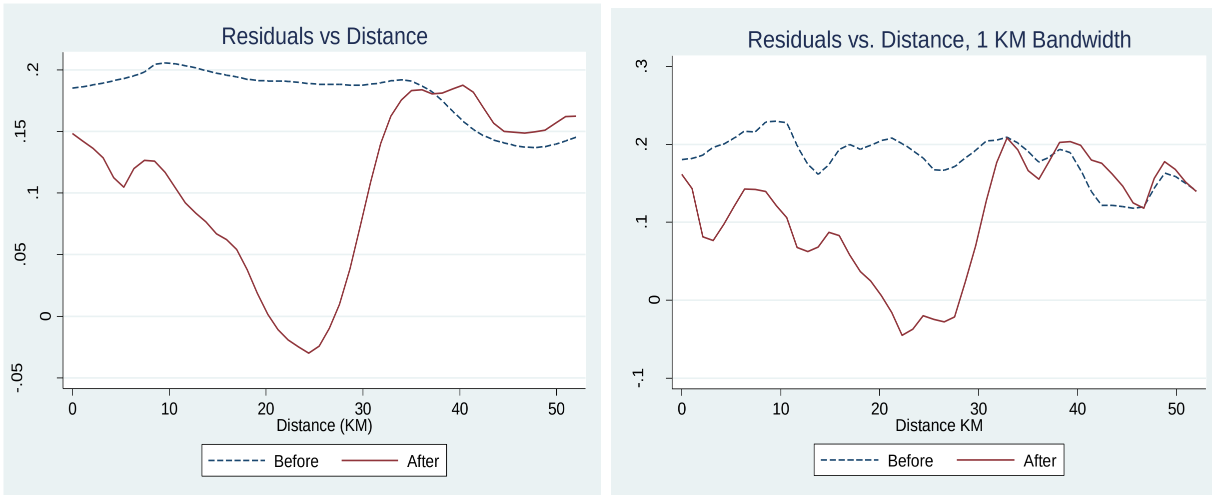


Figure 2: Price Gradient of Distance from AOC

VI. Econometric Strategy and Model

1. Fixed Effect Model

The section describes the strategy employed to explain the changes in a tract's average property value over time. Utilizing the distance control strategy described in the previous section, a fixed effects model and difference-in-differences analysis, a single regression controls for time variant and invariant effects, tract effects, AOC effects and other probed variables in order to reach an estimate of the effect of AOC listing on individual tract level property value changes. The model is follows as below.

$$\ln(Price)=\alpha_0 + \alpha_1 \gamma_i^{<DIST} p_i + \mu_i + v_{it} + \varepsilon_i \quad (1)$$

In equation (1) α_0 is a constant term, μ_i is a vector of time invariant fixed effects including tract effects (summary statistics in appendix 1), v_{it} is a vector of time variant and interactional effects including county x year effects, and ε_i is a residual term. p_i is the effect of the presence of an AOC on housing value, interacted with, and mediated by, a distance buffer.

$$\ln(Price) = \alpha_0 + \alpha_1\gamma_i^{<ADJ} + \alpha_2\gamma_i^{<PROX} + \alpha_3\gamma_i^{<MACRO} + \mu_i + v_{it} + \varepsilon_i \quad (2)$$

In equation (2) effect p_i has been decomposed into three effects, and thus three dummy $\gamma's$ for adjacency, proximity and a macro effect that represents larger, regional trends. This third effect, α_3 ,is absent in the regression, as county level effects are collinear with state level effects, and larger Great Lakes Basin effects are not observed as the sample is fully contained within the GLB. The model will be tested with and without the proximity effect, as explained in section 6.

2. Difference in Differences Strategy

Here the differencing strategy is outlined, where treatment, as a temporal marker, allows an isolation of the listing effect via the assumption of similar pre-treatment.

- $\Delta_{DISTANCE} = \alpha_1 + \alpha_3$
- $\Delta_{MACRO} = \alpha_3$
- $\alpha_1 = \Delta_{DIST} - \Delta_{MACRO} = (\alpha_1 + \alpha_3) - (\alpha_3)$

This is the strategy employed with equation (1), α_1 represents the informational effect on housing price change pre and post listing for all tracts within the treatment buffer.

2.1 Proximity Effects Difference in Differences:

- $\Delta_{ADJ} = \alpha_1 + \alpha_2 + \alpha_3$
- $\Delta_{PROX} = \alpha_2 + \alpha_3$
- $\Delta_{MACRO} = \alpha_3$

For the strategy in line with equation (2), the effect of being within an adjacent tract is the sum of adjacency, proximity and macro effects. The effect of being in the proximal tracts is decomposed into two effects, proximity and macro effects. Broader regional trends for the 7 Great Lakes Basin States correspond to the macro effect.

- $\alpha_1 = \Delta_{ADJ} - \Delta_{PROX} = (\alpha_1 + \alpha_2 + \alpha_3) - (\alpha_2 + \alpha_3)$

In this differencing strategy α_1 represents the effect of adjacency, α_2 represents the effect of adjacency and $(\alpha_1 + \alpha_2)$ represent the total effect for tracts within the localized buffer. As stated previously, there is little motivation for focusing on the difference between the proximity and adjacency effects in the AOC context as their combination should be the full listing effect, but such an analysis could prove informational through the decomposition of the effect.

2.2 Final Equation

The final equations used in the results section are presented below, as taken from a combination of equations (1) and (2) and their respective DD strategies.

$$\ln(Price) = \alpha_0 + \alpha_1 \gamma_i^{<DIST} * \delta_{1990} + \mu_i + v_{it} + \varepsilon_i \qquad (3)$$

Equation (3) represents a single buffer distance regression, where δ_{1990} is an interactional dummy for the treatment period (1990 observations) on the distance-based listing effect, $\gamma_i^{<DIST}$.

$$\ln(Price) = \alpha_0 + \alpha_1 \gamma_i^{<ADJ} * \delta_{1990} + \alpha_2 \gamma_i^{<PROX} * \delta_{1990} + \mu_i + v_{it} + \varepsilon_i \qquad (4)$$

Equation (4) has decomposed the buffer distance variable into adjacency and proximity effects, both using δ_{1990} as an interactional dummy for the treatment period.

VII. Results

The first set of regressions shown in Table 1 show a probe of different buffer distances, utilizing numbers taken from the literature and from the polynomial regression output from section 5. This regression reflects equation (3) from section 6, and uses normal OLS standard errors, tract effects and county x year effects. The results demonstrate a negative effect of being within any of the specified buffer distances, compared to those outside, for the post listing period (i.e. 1990 observations). This effect ranges between -.0508 and -.074, translating to a -5.2% to -7.6% decrease in average housing price post AOC listing, within buffer census tracts. This result is significant to the 1% level for all distances tested.

Table 2 represents the same regression, but employs robust standard error estimation. This simply relaxes the assumption that variance is equal across all observations, and uses White's estimator that allows variance to be different at each observation point, creating an equally unbiased but better fitted estimate of standard error. This specification makes sense as there could be some unobserved heterogeneity within the data that is correlated with any of the control variables, distance making the most sense, and this simply corrects for possible heteroskedasticity. The results from Table 2 show equal effects to table one (as it is only the standard error calculation that has changed), but find smaller standard error terms. The potential for heteroskedastic error terms is certainly viable, and therefore robust standard errors will be the preferred calculation throughout the remaining regressions.

The 32 KM buffer distance, as observed in section 5, is found to have the largest effect. The effect tails off immediately, and this lines up with the prediction from the polynomial regression, lending confidence to the usage of 32KM as the preferred distance specification throughout the remaining regressions. The observation of the effect being larger at further distances makes some intuitive sense when considering how the listing effect should function. As an informational effect, the change observed is not in hazardous waste condition, but merely in the labelling of an area as such. It seems that for those tracts closest to an AOC, their main method of awareness would be in direct observation of AOC effects and they are likely to have been more severely aware prior to listing. For those tracts further out, however, information (of a secondary nature) is likely the main source of AOC awareness, and thus the labelling effect is likely stronger at medium versus short distances within the total effect buffer. This observation also creates some motivation for the investigation of an adjacency (direction observation) and proximity (informational awareness) pair of buffer distances, as will be examined further on.

Table 1

	2 KM	5 KM	10 KM	18 KM	32 KM
Ln(Price)	-0.0508***	-0.0521***	-0.0483***	-0.0647***	-0.0740***
	(0.0103)	(0.0100)	(0.0096)	(0.0091)	(0.0090)
Observations	40056	40056	40056	40056	40056
Adjusted R^2	0.8543	0.8543	0.8543	0.8544	0.8544

Standard errors in parentheses
Decennial Census 1970, 1980 and 1990
Single distance buffer (tract centroid to AOC edge), county x year, property, AOC x year effects
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2

	2 KM	5 KM	10 KM	18 KM	32 KM
Ln(Price)	-0.0508***	-0.0521***	-0.0483***	-0.0647***	-0.0740***
	(0.0094)	(0.0095)	(0.0100)	(0.0093)	(0.0098)
Observations	40056	40056	40056	40056	40056
Adjusted R^2	0.8543	0.8543	0.8543	0.8544	0.8544

Robust Standard errors in parentheses
Decennial Census 1970, 1980 and 1990
Single distance buffer (tract centroid to AOC edge), county x year, property, AOC x year effects
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3 represents the same regression model as table 2, but with added effects. This similarly utilizes equation (3), but adds “full suite” effects-a set of controls that isn’t utilized in the general literature but makes intuitive sense in the AOC context. Lake x year effects are used to control for Great

Lake specific confounders and distance to nearest water feature is included to control for the package of effects that water proximity has on property value that may be lost in a simple distance-based regression. Distance to nearest Superfund site is included to control for the effects of overlapping programmatic efforts. Additionally, a variable for the number of beneficial use impairments (BUI) that ranges from 0-14 is included to investigate perception responses to the number of detrimental effects that are present. Finally, a running variable for the number of years an AOC had been considered before being added to the list is included to control for confounds such as earlier informational campaigns. The coefficient on the distance term is lower at each distance tested, but again the effects are all negative, significant to the 1% level and the 32 KM specification has the largest (in magnitude) effect. The breakdown of the suite effects is discussed with table 5 below.

Table 3

	2 KM	5 KM	10 KM	18 KM	32 KM
Distance	-0.0472***	-0.0485***	-0.0432***	-0.0597***	-0.0714***
	(0.0095)	(0.0096)	(0.0102)	(0.0096)	(0.0102)
Years Considered	0.0288	0.0255	0.0246	0.0300	0.0371
	(0.0672)	(0.0672)	(0.0671)	(0.0674)	(0.0676)
Distance Superfund	0.000000741***	0.000000745***	0.000000743***	0.000000744***	0.000000769***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Distance Water	-6.90e-08	-7.40e-08*	-7.67e-08*	-8.79e-08**	0.000000109**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
BUI #	0.124***	0.122***	0.122***	0.121***	0.119***
	(0.0151)	(0.0152)	(0.0152)	(0.0153)	(0.0152)
Observations	40056	40056	40056	40056	40056
Adjusted R^2	0.8546	0.8546	0.8546	0.8547	0.8548

Robust Standard errors in parentheses
Decennial Census 1970, 1980 and 1990
Single distance buffer (tract centroid to AOC edge), county x year, property, AOC x year effects
Full Suite Effects: Years considered, distance to nearest water feature, distance to nearest Superfund site, lake x year effects, BUI effects
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4

	Ln(Price)	Ln(Price)	Ln(Price)	Ln(Price)	Ln(Price)	FS	FS	FS	FS	FS
2 KM	-0.0194**					-0.0176*				
	(0.0092)					(0.0093)				
5 KM		-0.0157*					-0.0140			
		(0.0092)					(0.0092)			
10 KM			-0.00268					0.000891		
			(0.0101)					(0.0101)		
18 KM				-0.0254**					-0.0207**	
				(0.0101)					(0.0101)	
32 KM	-0.0671***	-0.0671***	-0.0726***	-0.0566***	-0.0104	-0.0651***	-0.0652***	-0.0719***	-0.0573***	-0.00985
	(0.0099)	(0.0099)	(0.0101)	(0.0110)	(0.0111)	(0.0103)	(0.0102)	(0.0104)	(0.0112)	(0.0111)
50 KM					-0.0832***					-0.0819***
					(0.0123)					(0.0126)
Observations	40056	40056	40056	40056	40056	40056	40056	40056	40056	40056
Adjusted R^2	0.8544	0.8544	0.8544	0.8544	0.8545	0.8548	0.8548	0.8548	0.8548	0.8549

Robust Standard errors in parentheses
Decennial Census 1970, 1980 and 1990
Single distance buffer and Proximity buffer (tract centroid to AOC edge), county x year, property, AOC x year effects
Full Suite (FS) Effects: Years considered, distance to nearest water feature, distance to nearest Superfund site, lake x year effects, BUI effects
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4 shows both a testing of buffer distances as specified in section VI equation (4), probing a few different sets of adjacency and proximity effects. While this binary distinction is not as strongly motivated as in the literature, there is some evidence for a heterogeneous listing effect based on distance within the treatment boundary. Table 4 tests proximity buffers of 32 and 50 KM while using 2, 5, 10, 18 and 32 KM adjacency buffers, consistent with the previous analysis. At the same time, the indicators from the full suite of controls are tested across the different proximity specifications, with the full suite results as the final 5 columns presented. For the 32 KM specification, a proximity buffer of 50 was set to test for further effects.

Looking at the proximity buffers, the setting of 32KM is significant at the 1% level, and it represents 5.8% to 7.5% reduction in tract average housing value across the basic and full suite regressions. For the basic specification, proximity is significant for the 2KM, 5KM and 18KM adjacency buffers. It is significant for the 2KM and 18KM adjacency buffers for the full suite specification. Under both, the 32KM adjacency buffer is no longer significant, and the 50KM proximity region is, with an impact of around -8.5% on housing price. It is interesting to note that the sum of significant adjacent and proximity effects is larger than the single boundary effect, but this is difficult to explain. The notion of direct observation effects versus informational effects can explain some of the story, but not entirely. While the proximity results are significant in some places, the intuition is slightly lacking and thus the preferred specification still remains the single distance buffer.

Table 5	Ln(Price)		Ln(Price)
32 KM	-0.0704***		
	(0.0087)		
ResC	0	Eutr	0.00475
	(.)		(0.0252)
Tain	-0.0303	ResW	-0.0160
	(0.1029)		(0.0617)
DegF	-0.294**	Beac	0.175***
	(0.1240)		(0.0479)
Fish	0.0637	DegA	-0.0789*
	(0.0423)		(0.0423)
Bird	0.198**	AddC	-0.00603
	(0.0777)		(0.0405)
DegB	0	DegP	-0.123***
	(.)		(0.0394)
ResD	-0.104*	Loss	0
	(0.0543)		(.)
Observations	40056		
Adjusted R^2	0.8644		

Robust Standard errors in parentheses
Decennial Census 1970, 1980 and 1990
Single distance buffer (tract centroid to AOC edge), county x year, property, AOC x year effects
Full Suite (FS) Effects: Years considered, distance to nearest water feature, distance to nearest Superfund site, lake x year effects, BUI effects
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5 shows a breakdown on the full suite effects, but they are slightly mixed, a discussion of the results of table 3 will also follow. The distance to nearest water feature is significant across most specifications, but is very small. Yet it is in the predicted direction (the further out from water the less housing price should be). A problem is likely that the USGS hydrological data used to generate this indicator included every body of water from small ponds to backyard creeks to Great Lakes, and thus an indicator that represented distance from the affected AOC water feature would likely yield stronger results. Distance to Superfund is significant at the 1% level for all tests, yet it is a small effect of around .0001%. The magnitude of this effect is possibly due to the availability of centroid point files for Superfund sites, whereas the AOC files utilize full area shapefiles-thus the extent of overlap was unobserved-and also temporal data for the Superfund sites was not readily available. However, the notion of a positive Superfund effect makes intuitive sense, as this results in additional funding available, a potentially more recognizable brand of hazardous waste cleanup, and also a likelihood of alternative and possibly earlier informational effects, among other possibilities.

The years considered indicator represents how many years (some as high as 16) before listing an AOC was investigated. This oftentimes correlated with earlier cleanup efforts, earlier information dissemination and other potential confounds. This effect is not significant across all specifications, but is in the direction theorized. The effect of earlier consideration on the informational effect should intuitively be positive, as earlier information should reduce the impact of the listing effect, and because those tracts that had seen restoration may have become desensitized to its presence or seen its benefits. Finally, the coefficient on BUI presence is equal to a -12.0% effect on tract average property value. This effect is much larger than expected, but it is in the expected direction and significant at the 1% level across all specifications, but given its magnitude it should be interpreted cautiously.

Table 5 shows a regression under the preferred specification, equation (3), buffer distance of 32 KM and full suite effects. However, it breaks down the BUI figure into a dummy for each beneficial use impaired. A coded list of BUI's is in appendix 2. Degraded fish populations, bird and animal deformities, restricted dredging activities, beach closures, degraded aesthetics and degradation of phytoplankton populations are all significant. While it is a little ambitious to attempt to understand how these effects are demonstrating heterogeneous informational effects, it is a worthy exercise and there are some intuitive results. Each BUI represents an environmental amenity that is in disrepair, and thus the informational effect could be that citizens are finding out about this effect for the first time, it could be that they are finding out that there is a program to fix this problem, or it could be both. Thus a positive coefficient on something like beach closures makes sense in the forward looking sense as it was likely something citizens were already aware of and the listing effect is a prediction that beaches will be more likely to be open in the future. The information effect of degraded fish populations could have that same forward looking result, but it could also be something that non-fishers were not aware of, it could immediately reduce tourism etc. It is with caution that these results are presented and interpreted individually, but this breakdown lends some credence to the intuition behind forward looking versus negative perception effects, and perhaps the relative magnitudes is also informative.

VIII. Discussion

The results found are large and significant and in the hypothesized direction across specifications, demonstrating a strong negative informational effect on tract average property value after AOC listing. While this finding is meaningful, there are some important caveats in the methodology that should be refined in future efforts. The first is the coarseness of the data. Utilizing decennial census information (3 cross sections) and tract level effects, the data are not nearly as finely grained as that of the preexisting literature, which use individual housing transaction data and block level characteristics. Another caveat is in the AOC spatial data, where the extent of an AOC is seemingly up to the associated parties (State, local, EPA) and some follow exact water features while others cover larger and landed areas. This would spatial aspect would in fact make the estimations more conservative, but is still something that needs to be addressed in future work. This is also slightly under examined in the literature, as it is unclear exactly what kinds of spatial files Superfund has made available, and whether they are property boundaries, affected areas or something else. In the AOC context, it makes sense to think about the broader impacts that water based contamination could have, and future studies should include more uniform determinations.

Additionally, a control strategy similar to the RDD work on Superfund sites could lend some additional confidence to the figures found here, as the distance-as-control methodology is second-best in some ways. Future work on AOC's should investigate the historical sites considered but not listed as AOC's as potential controls, but that data was not available for the purposes of this investigation.

A final caveat is related to the US Census. Before the 1990 census, the country was not fully tracted and large swathes of area (mostly rural) were not covered. This is further compounded by the questions asked, as property information and pricing were questions not asked/answered even in some tracted regions. Thus the sample of tracts with repeat housing value observation data from 1970-1990 was limited down to a fraction of the Great Lakes region. Thus some AOC's have very little data surrounding them. While it is unlikely that AOC placement/distance and tracting are endogenous, it is possible that it is correlated with other observed and unobserved variables. This problem could certainly be addressed with finer level, non-census housing transaction data, or perhaps an instrumental variables approach.

While there were some data limitations, the results were found to be robust and suggestive of a negative listing effect. These strong findings motivate future work using different data sources to further pin down the effect.

IX. Conclusion

The results demonstrate significant and negative impacts of the AOC listing decision on tract average housing value. This ranges from -4.4% to -7.6% under the various specifications examined (all significant at the 1% level), and is largest under the preferred specification of a 32 KM, single boundary effect. This finding begins to unravel the question of hazardous waste listing effects, pointing to the negative perception effects far outweighing any positive, forward looking effects.

Despite these caveats, the results are robust under various sets of tests and demonstrate a strong negative relationship between listing and property value. The results support an interpretation of a distance based information effect versus a hyper-local observational effect, which is certainly an important policy takeaway. The effects of specific beneficial use impairments is also an interesting point of discussion, as they demonstrate the ways in which forward looking effects interact with negative perception changing effects in order to create the informational effect. One of the key questions motivating this investigation was the composition of the listing effect, and thus an ability to decompose it and discuss competing sub-effects is an important policy takeaway.

The findings of this investigation suggest a large and negative listing effect that could potentially dwarf the positive effects of a restoration effort. This effect should, theoretically, be turned off at delisting, yet the case oftentimes is that a hazardous waste site, whether it's AOC, Superfund or something else, is under remediation efforts for several decades. Only 4 of the 41 international AOC's have been delisted, and thus an attempt to evaluate the economic impacts of remediation for all other sites is likely covered up by the deleterious effects of listing. The findings of this paper suggest that policy makers and evaluators should take the listing effect into account in order to understand the tradeoffs between remediation, property value change and project completion.

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A.1 Summary Statistics

	Within 18 KM		Outside 18 KM	
	Mean	SE	Mean	SE
Population	3658.646	1634.6	3504.087	1646.2
%Black	.1620381	.311	.0869876	.206
%Hispanic	.0288567	.080	.0389504	.089
%Under 18	.3021047	.080	.2903836	.082
%Foreign Born	.0557377	.055	.0753293	.099
%Female Head Household	.1847758	.183	.1470266	.138
Unemployment rate	.0766784	.063	.055258	.041
Poverty Rate	.1064931	.116	.090846	.090
% Welfare	.077289	.097	.056973	.067
Average HH Income	24624.89	16517.1	25667.4	18118.3
%Occupied homes	.9517074	.044	.9514936	.045
%Owner Occupied	.5658244	.240	.5289635	.249
Housing Density	827.2784	932.2	1268.211	2354.1
Population Density	2214.63	2374.0	3280.046	5720.8
HS Dropout	.1837504	.078	.1582706	.071
MS Dropout	.1622171	.116	.1615575	.114
Only HS	.3401712	.087	.3471797	.087
Some College	.1478906	.062	.1425129	.058
College Degree	.1663979	.142	.1910344	.146
%Attached homes	.6561238	.259	.6084082	.300
%Mobile Homes	.2201514	.325	.2063906	.314
% 0-2 Bedrooms	.4137672	.186	.4422327	.209
%3-4 Bedrooms	.5588158	.180	.5256489	.195
%Moved in last 5 yrs	.3411459	.235	.342067	.229
%Built w/in 5 yrs	.0956895	.132	.1040595	.130
%Built w/in 10 yrs	.1777652	.200	.1961442	.204
Observations	12126		27930	

A.2 Beneficial Use Impairment (BUI) Code

ResC	Restrictions on fish and wildlife consumption
Tain	Tainting of fish and wildlife flavor
DegF	Degraded fish and wildlife populations
Fish	Fish tumors or other deformities
Bird	Bird or animal deformities or reproductive problems
DegB	Degraded benthos
ResD	Restrictions on dredging activities
Eutr	Eutrophication or undesirable algae
ResW	Restrictions on drinking water consumption or taste and odor problems
Beac	Beach closings
DegA	Degradation of aesthetics
AddC	Added costs to agriculture or industry
DegP	Degradation of phytoplankton and zooplankton populations
Loss	Loss of fish and wildlife habitat

A.3 Balanced Data Set

Each tract observed in the panel data set was included as it had full information for all three decade censuses (1970, 1980 and 1990). Given that that the listing effect, or treatment, is both a distance buffer and a time stamp, the panel data is not fully balanced as there are twice as many pre listing observations as post. This remains the ideal specification as this additional 1970 data only adds further support to the change in trends post-listing, but Table 6 performs a balanced regression, under the specification of 18 KM distance buffer, full suite controls and equation (3) using only 1980 and 1990 data to investigate a fully balanced data set. Predictably, the effect is lower and represents a -2.5% change in tract average housing value due to listing effects for treatment distance bounded tracts. While the effect has lowered, it is still fairly large and significant at the 5% level, which supports the above findings

Table 6: Single Buffer, Full Suite

	Full Panel	1980 and 1990
18 KM	-0.0587^{***}	-0.0243^{**}
	(0.0087)	(0.0099)
BUI	-0.0197^{***}	-0.0255^{***}
	(0.0021)	(0.0021)
Observations	40056	26704
Adjusted R^2	0.8644	0.7821

Robust Standard errors in parentheses
Decennial Census 1970, 1980 and 1990
Single distance buffer (tract centroid to AOC edge), county x year, property, AOC x year effects
Full Suite (FS) Effects: Years considered, distance to nearest water feature, distance to nearest Superfund site, lake x year effects, BUI effects
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$