The Effects of Aquatic Invasive Species on Property Values: Evidence from a Quasi-Random Experiment

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Abstract: The invasion of ecosystems by non-native species is widely considered to be a principal threat to global biological diversity, yet the social costs of invasive species are not well-understood. The purpose of this study is to estimate a hedonic model of lakeshore property values to quantify the effects of a common aquatic invasive species – Eurasian Watermilfoil – on property values across an extensive system of over 170 lakes in the northern forest region of Wisconsin. In addition to providing empirical evidence as to the potential benefits from reducing the spread of invasive species, this paper also develops a quasi-experimental methodology to identify the effects of changes in endogenous neighborhood amenities within the commonly estimated hedonic framework. In our application, a lake is more likely to be invaded with Milfoil if it is more popular with recreational boaters. Therefore, since lakes popular with recreational boaters are also likely to be popular with potential residents, and since many aspects of a lake's amenities may be difficult to quantify, the likelihood of Milfoil invasions is endogenous in a hedonic price equation. Our identification strategy is based on a spatial difference-in-difference specification, and uses fixed effects to control for observed and unobserved neighborhood effects, while exploiting changes in the Milfoil status of several lakes during the time period of our data. Results indicate that lakes invaded with Milfoil experienced an average 13% decrease in land values *after* invasion. The Milfoil results are robust across linear and non-linear specifications.

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I. Introduction

The invasion of ecosystems by non-native species is widely considered to be a principal threat to global biological diversity (Armsworth, Kendall, and Davis 2004). Invasive species alter ecological communities by competing or preying on native species, and can affect market-related enterprises such as agriculture, forestry, fisheries, and electric power production (Lovell and Stone 2005). Aquatic invasive species include a diversity of fish, crustaceans, mollusks, and plants, and are widely found in lakes, rivers, and coastal regions of the United States and throughout the world. Given the widespread importance of all types of water bodies as an amenity and a source for economic activity, developing a greater understanding of the relationship between invasive species and welfare is central to understanding the appropriate role of public policy.

The social costs of species invasions are not well understood (Lovell and Stone 2005). On the other hand, massive amounts of resources are diverted towards invasive species control and mitigation efforts. For example, the United States spends approximately $120 billion annually on various programs related to invasive species (USDA 2007). Generally, the costs of invasive species have been derived from estimates of the costs of managing species invasions, including the amount that must be spent to repair infrastructure damage. In addition, other commonly cited cost estimates of species invasions (e.g. Pimentel, Zuniga, and Morrison 2005) tend to be more anecdotal and not based on empirical methods grounded in economic theory (Lovell and Stone 2005).

The purpose of this study is to estimate a hedonic model of lakeshore property values to quantify the effects of a common aquatic invasive species – Eurasian Watermilfoil (hereafter labeled Milfoil) – on property values across an extensive system of over 170 lakes in the northern forest region of Wisconsin. Milfoil is a submerged aquatic plant characterized by dense stands that i) block sunlight and limit the ability of native plant species to grow, ii) affect fisheries by inhibiting the ability of larger fish to prey on smaller ones, iii) limit recreational activities such as swimming and boating, and iv) provide good habitat for mosquitoes. Once established, Milfoil is extremely difficult to remove without clearing native vegetation. The data used for estimation covers a period (1997-2006) that saw multiple lakes become invaded with Milfoil. Hedonic results presented in this paper provide the first evidence regarding the effects of invasive species on property values, and thus, should prove useful in designing efficient resource management strategies to control species invasions.

In addition to providing evidence on the costs of species invasions, the analysis in this paper makes a general contribution to the hedonic literature by setting up a quasi-random experiment to identify the effects of changes in an endogenous neighborhood amenity on property values. The methodology is based on a spatial difference-in-differences specification, and simultaneously accounts for both bias and inefficiency problems associated with spatially-correlated neighborhood unobservables, yet is simple enough to be estimated with well-known regression techniques. Although typically treated as an efficiency issue in econometric estimation, unobserved neighborhood characteristics are likely to be correlated with measurable neighborhood environmental amenities (Small 1975), resulting in biased estimates of such amenities in hedonic estimation. For example, neighborhoods with desirable unmeasured amenities, such as scenery and ambiance, may also have easily measurable amenities that are the focus of hedonic estimation, such as protected open space and clean air. A prominent recent example of correlated neighborhood effects comes from the hedonic application by Leggett and Bockstael (2000), who account for the fact that sources of water pollution, in addition to emitting undesirable pollution, are also likely to be unpleasant neighbors.

The problem of unobserved neighborhood effects arises in the present application because the property values associated with multiple parcels on the same lake are influenced by the same lake-specific unobservables, such as fishing quality or the scenic views of the surrounding landscape. In addition to the well-known efficiency issues, the presence of such spatially-correlated unobservables calls into question the exogeneity of variables aimed at measuring the presence and abundance of Milfoil on a lake. Milfoil is typically spread from lake to lake by the movement of recreational boaters,[1] creating a direct link between the spread of Milfoil and the recreation decisions of boaters. Since boaters are more likely to visit popular lakes with desirable amenities, and since many of these amenities may be unobservable to the analyst, the likelihood that any particular lake is invaded with Milfoil will be correlated with the error term in the hedonic model; thus, conventional OLS estimation of cross-sectional data will produce coefficient estimates that are positively biased. To support this claim, we present results from a cross-sectional hedonic analysis that suggest an increase in property values arising from Milfoil invasions.

Our strategy for identifying the effects of Milfoil invasions on property values is based on a difference-in-differences analysis specified with fixed neighborhood effects. The fixed neighborhood effects specification exploits the natural panel structure of the data, where each lake is defined as a natural neighborhood. Identification of the effects of Milfoil on property

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[1] In particular, Milfoil fragments get stuck on boats, boat motors, boat trailers, and get into bait buckets. Individuals who launch boats in multiple lakes can inadvertently spread the plant.

values is achieved because the fixed effects control for all observable and unobservable lake (neighborhood) amenities that affect property values, while the difference-in-differences specification exploits the fact that our dataset spans a period where multiple lakes were invaded by Milfoil. The spatial difference-in-differences methodology isolates the negative effect of Milfoil invasions on property values by isolating the source of estimation bias arising from unobserved neighborhood effects, and exploits the natural experiment inherent in the before-and-after nature of Milfoil invasions present in the dataset. Further, we show that when unobserved and observed neighborhood effects are correlated, identification using a difference-in-differences framework requires a fixed neighborhood effects specification for unbiased estimation. Results indicate that a Milfoil invasion reduces average land values by approximately 13%.

The paper is organized as follows. Section 2 places the present work in the larger context of estimating the effects of spatial amenities in hedonic models, and argues for the general applicability of our approach. Section 3 presents background information on aquatic invasive species, particularly Milfoil. Section 4 presents the application and the data used for estimation. Sections 5 and 6 present modeling approaches and estimation results while concluding thoughts are offered in section 7.

2. Estimating the Effects of Neighborhood Amenities in Hedonic Models

Hedonic modeling is one of the most widespread techniques used to estimate the economic value of non-market amenities to individuals. The theoretical foundation of hedonic modeling is elegantly laid out by Rosen (1974) and is based on the insight that the price of a differentiated product can be decomposed into the price for individual characteristics of the good. Despite the well-understood theoretical foundation underlying hedonic modeling, empirical application of the method forces researchers to grapple with a number of well-known econometric challenges, such as an arbitrary choice of functional form, defining the spatial and temporal extent of land markets, heteroskedasticity, and multicollinearity. While a perusal of the hedonic literature suggests that issues associated with unobserved neighborhood effects are a recent concern, the issue was originally broached by Small (1975). In discussing the use of hedonic models to quantify the effects of air pollution on property values, Small (1975) questions "whether the empirical difficulties, especially correlation between pollution and unmeasured neighborhood characteristics, are so overwhelming as to render the entire method useless" (p. 107).

As argued by Chay and Greenstone (2005), the problem of omitted variable bias, such as induced by correlation between unobserved neighborhood effects and observable environmental amenities, has received little attention in the hedonic literature. The recent literature treats the estimation problems associated with unobserved neighborhood characteristics primarily as an inefficiency problem, induced by spatial correlation in the error terms of hedonic models.[2] While models of spatial autocorrelation are well-established and can be estimated (Anselin and Bera 1998) to correct for correlation in the error terms, such approaches still assume no correlation between the observed and unobserved neighborhood effects, and thus fail to address Small's (1975) original critique.

One approach to dealing with the correlation between observed and unobserved neighborhood characteristics is to include additional variables measuring neighborhood characteristics directly in the hedonic model. For example, Leggett and Bockstael (2000) show that omitting variables that measure the distance from homes to unpleasant sources of water pollution induces bias in estimates of the effects of the water pollution itself on property values.

[2] Examples include Bell and Bockstael (2000), Kim, Phipps, and Anselin (2003), Wu, Adams, and Platinga (2004), and Donovan, Champ, and Butry (2007).

A second approach to handling correlation between observed and unobserved neighborhood characteristics is to instrument for the environmental amenity of interest. For example, Chay and Greenstone (2005) use exogenous changes to federal air pollution control policy to instrument for air quality in a national analysis with aggregate county-data, while Irwin (2002) uses measures of the soil quality of neighboring parcels to instrument for endogenous variables measuring the amount of open space within a particular parcel's neighborhood. However, as described by Irwin (2002), "while the IV estimation controls for the bias introduced by the endogenous variables and unobserved spatial correlation, it does not correct for the inefficiency of the estimates caused by the remaining spatial error correlation" (p. 473). In an attempt to rectify this problem, Irwin (2002) randomly draws a subset of her data and drops all nearest neighbors, essentially eliminating the potential for spatial autocorrelation. Unfortunately, this approach loses information and Irwin (2002) concludes that her estimates lack robustness and calls for additional research on the identification issue that arises from unobserved neighborhood effects.

A quasi-experimental approach to handling correlation between observed and unobserved neighborhood effects is difference-in-differences analysis (Greenstone and Gayer 2007). Difference-in-differences analysis exploits before-and-after effects of changes in neighborhood amenities for identification. Examples of difference-in-differences hedonic models include analyses of supportive housing (Galster, Tatian, and Pettit 2004), hurricanes (Hallstrom and Smith 2005), and the effects of new sports stadiums (Tu 2005) on property values. While all three of the above difference-in-differences models account for the inefficiency problems associated with spatially correlated errors, they also assume no correlation between the unobserved neighborhood effects and the change in neighborhood amenities.[3] In the context of the treatment evaluation literature, the assumption is one of "selection on observables", whereby selection into the "treatment" is based on observable factors that can be controlled for econometrically.

The approach taken in this paper defines a fixed time-invariant neighborhood effect to control for all neighborhood characteristics that do not change over the time period of the dataset (ten years in this application). As such, the model is only capable of separately estimating the effects of individual neighborhood characteristics that vary over the time period of the dataset, as the effects of all time-invariant neighborhood characteristics (e.g. lake size, distance to nearest town, etc.) will be accounted for by the fixed effects. The effects of Milfoil can be identified because our data set covers a period where multiple lakes were invaded. The spatial difference-in-differences specification estimates how the premium between a Milfoil lake and a non-Milfoil lake changes due to the invasion. Since Milfoil is more likely to spread on popular recreational lakes with attractive unobserved neighborhood effects, the fixed neighborhood effect specification controls for spatial correlation that would otherwise plague the estimated covariance matrix, and relaxes the independence assumption between variables measuring Milfoil and unobserved neighborhood effects. This approach provides consistent estimates even when a Milfoil invasion on a lake is subject to "selection on unobservables", since the unobservables are controlled with the fixed neighborhood effects.

3. Invasive Species as a Resource Management Problem

In the United States, about 50,000 exotic species are now established, roughly half of which are plants. While many exotic species yield substantial economic benefits (e.g. wheat,

[3] This assumption is quite reasonable in the case of Hallstrom and Smith (2005), given that their change in neighborhood amenity is based on the truly random path of a hurricane.

rice, domestic cattle, etc.), others become a nuisance and require management. One of the more serious ecological effects of aquatic invasive species is their ability to drive native species to extinction, as "40% of native species extinction has been attributed to predation, parasitism, and competition from biological invaders" (SGNIS 2008). Many aquatic invasive species, including Milfoil, are believed to have been transported to the United States via the ballast tanks of foreign ships, and the regulation of discharges from ballast tanks has become a major policy initiative for the federal Environmental Protection Agency.

Eurasian Watermilfoil – the focus of the present study – is a submersed plant that is native to Europe, Asia, and North Africa (Seely 2007), yet has been widely spread across North American lakes and rivers. The plant reproduces through fragmentation, creating shoots that can be carried naturally by a stream or river to other bodies of water, or by "boats, motors, trailers, bilges, live wells, or bait buckets, and can stay alive for weeks if kept moist" (Wisconsin DNR 2007). Milfoil is an opportunistic species that thrives in many different environments and can reproduce rapidly. Milfoil was first discovered in the Chesapeake Bay in the late 19th century and is now known to exist in at least 45 states. In its worst form, Milfoil can create dense mats that inhibit many forms of water-based recreation, such as boating, fishing, and swimming.

The time-growth relationship for Milfoil has shown significant variability in the different bodies of water that have been invaded. One of the first places to become infested with Milfoil, Chesapeake Bay, showed few signs of the species for over sixty years, until its growth finally took off and became a major nuisance. In other cases, Milfoil populations have taken little time to take over their host body of water. While there is considerable uncertainty regarding the ability of Milfoil to become a nuisance in particular types of water bodies, in general, it is believed that Milfoil prefers highly disturbed lake beds and lakes receiving nitrogen and phosphorous-laden runoff. Higher water temperatures promote multiple periods of flowering and fragmentation, and it appears that Milfoil is a particular problem in nutrient-rich lakes.

Once Milfoil is established in a lake, it is quite difficult, if not impossible, to remove without clearing native vegetation. Given the uncertainty associated with predicting the growth rate of Milfoil across similar types of water bodies, and the irreversibility associated with a Milfoil invasion, its mere presence in a lake is a chief concern to many individuals as opposed to the degree of Milfoil abundance at any particular point in time. Therefore, since property prices capitalize current and expected future levels of environmental quality, even a lake with relatively low levels of Milfoil may experience a negative price premium due to its quasi-irreversibility and the uncertainty associated with how Milfoil populations may change over time.

4. Study Area and Variables Used in Estimation

This study focuses on the property price effects of Milfoil on lakes within Vilas County, Wisconsin. Vilas County is located in the northern forest region of Wisconsin and is widely considered to have the highest concentration of freshwater lakes in the world. This region is mostly forested and its rural economy is heavily influenced by the preponderance of second homes located along the shorelines of the region's many lakes.

The data used for this study were compiled from a variety of sources. Data on arms-length lakefront property transactions were collected from the Wisconsin State Bureau of Revenue for the years of 1997-2006. Assessed structural values were taken from annual tax rolls, obtained from the Vilas County Information Technology Department.[4] GIS tax parcel and county-wide spatial water data were obtained from the Vilas County Mapping Department.[5] Lake characteristics and ecological variables were collected from the Wisconsin Department of

[4] We thank Mike Duening for supplying these data.
[5] We thank Barb Gibson for supplying these data.

Natural Resources (DNR)[6] and the Environmental Remote Sensing Center at the University of Wisconsin, Madison. Data on fisheries quality,[7] the presence of Milfoil, and the year of Milfoil invasion were gathered from the Wisconsin DNR.[8] Milfoil abundance data were compiled with the help of Jen Hauxwell and her staff at the Wisconsin DNR. The entire panel of data represents transactions on 172 lakes in Vilas County

There are 17 lakes in the dataset that have been invaded by Milfoil.[9] Eight out of the seventeen lakes were invaded during the period 1992-1995, while the other nine lakes were invaded during 2000-2005. Recent invasions have been a primary concern of lakefront property owners in this region, as residents are concerned about the potential for Milfoil to adversely affect the recreational opportunities on their lakes. Anecdotally, a local realtor[10] estimates that a $250,000 home on a Vilas County lake with severe Milfoil problems, such as Big Sand Lake, sells for $30,000-$40,000 less than if it were on a similar lake without Milfoil. Despite the speculation by local realtors, the average sales price of a property on a lake with Milfoil was about $18,000 above the average sales price on a lake without Milfoil during the period 1997-2006, suggesting that lakes with a price premium may also be more likely to be invaded with Milfoil.

The literature does not provide concrete guidance on the selection of variables or functional form in hedonic models, although in general, property prices are determined by their structural and lot characteristics, neighborhood characteristics, and spatial attributes. Table 1

[6] See Wisconsin Lakes Book at http://www.dnr.state.wi.us/org/water/fhp/lakes/list/#lakebook
[7] See Wisconsin Lakes Book (cited in previous footnote) and Wisconsin Muskellunge Waters: Vilas County at http://www.dnr.state.wi.us/fish/musky/lakes/vilas.html
[8] See Listing of Wisconsin Waters with EWM at http://dnr.wi.gov/invasives/fact/milfoil/charts/ewm2006_by_county.pdf
[9] Lakes infested with Milfoil in the data set include: Arrowhead Lake, Boot Lake, Catfish Lake, Cranberry Lake, Duck Lake, Eagle Lake, Forest Lake, Little Saint Germain Lake, North Twin Lake, Otter Lake, Scattering Rice Lake, Silver Lake, South Twin Lake, Upper Gresham Lake, Voyageur Lake, Watersmeet Lake, and Yellow Birch Lake.
[10] We thank realtor Jim Mulleady for helpful discussions regarding the effects of Milfoil on the local land market.

presents a comprehensive list of the variables included. Structural and lot characteristics include assessed structure value, size of lot, frontage, and frontage-squared. Due to data limitations, structural characteristics are lumped into one variable: assessed structural value. Frontage and frontage-squared are included to provide flexibility in functional form, since additional feet of frontage likely bring about diminishing contributions to price. Lot size is also included in a linear form. All structural and lot variables are expected to make positive contributions to the dependent variable.

Several lake-specific variables are included to account for observable variation in neighborhood characteristics: lake area, water clarity, fishing quality variables, and maximum depth. Depth and area are important if Milfoil is present. The fishing quality variables (muskie, pike, walleye, bass, and panfish) are rankings determined by the Wisconsin DNR. Muskie ratings range from 0-4, while rankings for other species range from 0-3. Water clarity is a continuous measure based off secchi disk readings. Also included are two dummy variables accounting for the presence/absence of a lake association and the possibility of public access. Since many households prefer to locate on a relatively pristine lake with significant amounts of open space, we include a variable measuring the number of private parcels along a lake's shoreline divided by the size of the lake. Distance and distance-squared (in miles) to either Eagle River or Minocqua are included to proxy for convenience of the property to services.

We account for the presence/abundance of Milfoil with several different combinations of the Milfoil measures—a continuous relative frequency measure, three dummy variables based off relative frequency, and a presence/absence dummy variable. The continuous variable is the relative frequency of Milfoil lake-wide, standardized using all other present species. The dummies are grouped into categories based on the continuous variable, providing low, medium, and high abundance categories. Unfortunately, the DNR and other organizations that do lake surveys only began a state-wide sampling of lakes believed to be infested with Milfoil in 2005. Consequently, abundance data cannot be retrieved from years past. However, the presence/absence measure of Milfoil has been documented for several years. All of the Milfoil variables are expected to have a negative impact on selling price.

Any measure of Milfoil (continuous abundance measure, discrete categories based on abundance, or presence/absence) is interacted with a variable called, treatment. Properties on lakes with Milfoil that have been treated will likely suffer a moderated negative price effect, relative to untreated lakes, when comparing to lakes that have no Milfoil at all. While treatments ranging from herbicides to mechanical cutters can lower the abundance of Milfoil, these treatments are rarely successful at removing the plant. The variable is defined in such a way that requires a treatment to have taken place on a given lake with Milfoil and before the transaction, but within the same year. If both constraints are satisfied, the variable is coded as a 1. If the treatment were to take place after the transaction, the associated benefit to a selling property would not yet be capitalized into property price (ignoring expectations or knowledge of a pending treatment). In addition to the Milfoil variables and treatment, a variable called, prime, is included, indicating whether or not a transaction took place during the prime months that Milfoil affects lakes.

5. Cross-Sectional Hedonic Model (2005-2006)

We begin estimation by exploring the effects of Milfoil on property values with the most common hedonic specification, using 457 cross-sectional arms-length transactions for the years 2005-2006. This model is estimated to take advantage of the only years in which Milfoil abundance data are available.

5.1 Econometric Considerations for Cross-Sectional Model

A number of functional forms were considered in this research. The first was a linear-linear model, as many hedonic models appear in the literature. The second was an inverse semi-logarithmic model, in which the dependent variable is transformed using the natural log operator and the independent variables are linear in the parameters. In addition, non-linear forms and a variety of Box-Cox models were estimated to add flexibility to the functional form, given the absence of a priori information on the structure of the hedonic price function[11] (Bender, Gronberg, and Hwang 1980; Sakia 1992).

In selecting a model, two issues arise. The first concerns a criterion for goodness-of fit, which are often used when specifying hedonic price functions (Cropper, Deck, and McConnell 1988). Two criteria were used: Akaike's Information Criterion and the Schwartz Information Criterion (see Greene 2003, 159-160). Although crude measures with no statistical power, the rule of thumb for these measures is the lower the value, the better the fit. Second, the ease of interpretation for a given model is considered; the linear, semi-log, and non-linear specifications are not of concern, thus, this consideration applies only to Box-Cox models. Several variations of this transformation were estimated using maximum likelihood techniques.[12] While the less restrictive model always fits best, the most flexible forms were not chosen due to interpretation problems.[13] Moreover, "when variables are omitted or replaced by proxies, the simpler forms—the linear, semi-log, double-log, and the Box-Cox linear—do best" (Cropper, Deck, and

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[11] A Box-Cox transformation can be applied to non-binary independent variables and the dependent variable. The transformation looks as follows: $(X^{\lambda}-1)/\lambda$ (Greene 2003, 173).

[12] The first of these models transformed the non-binary independent variables with a constant value of lambda, another allowed lambda to vary over the independent variables, and others included transformations of the dependent and independent variables, allowing lambda to vary for all parameters in the most flexible case

[13] For example, the lambda coefficients associated with some variables were estimated to be greater than 5, implying that a given variable should be raised to its 5th power or greater. There seems to be little economic meaning in such estimates. Rasmussen and Zuehlke (1990) characterize this issue as follows: "unnecessary non-linearities may 'over-parameterize' the problem, resulting in less precise point estimates" (p. 431).

McConnell 1988, 674). As it turns outs, all specifications have a relatively similar fit, with the linear Box-Cox (constant lambda transformation on non-binary independent variables) fitting best. Thus, the linear-linear model is given preference because of its prevalence in the literature and straight-forward interpretation.

Multicollinearity is often a problem with hedonic models, as has been established throughout the literature. This is generally caused by the lack of model specification guidance, resulting in the inclusion of numerous variables that are often highly collinear, such as square footage and number of bedrooms. We examined multicollinearity with pair-wise correlation analysis and by calculating variance inflation factors and tolerances for each variable (see Gujarati 2004, 350-353). Results indicate that multicollinearity is not a serious problem. The above models were also tested for the presence of heteroskedasticity with a Breusch-Pagan test statistic for each model. The test statistics were highly significant. Following Gujarati (2004), we found that outliers were causing the heteroskedasticity and we dropped observations with a transaction price outside two standard deviations of the mean. This was done for both the 2005-2006 data and the panel data in section 6. While omitting observations is rarely preferred, doing so in this case clears up the problem of heteroskedasticity. For the first model, 23 observations were omitted.[14] The threshold of two standard deviations was chosen because this was the first point where heteroskedasticity was no longer a problem.

5.2 Cross-Sectional Hedonic Results

Three cross-sectional models were estimated using the following linear specification:

$$P_i = X_i^{'}\beta + Z_{j(i)}^{'}\phi + \varepsilon_i \tag{1.1}$$

[14] In later estimations when the full panel data set is used, 92 observations (of 1841 total) were omitted to mitigate heteroskedasticity in a similar fashion. Moreover, White's robust standard errors are used in these later estimations to further deal with this issue. These robust errors allow for reliable statistical inference tests to be carried out.

where X_i is a matrix of variables specific to parcel i, and $Z_{j(i)}$ is a matrix of variables specific to lake j(i) that contains parcel i (Table 1). The results for these models are presented in Table 2.[15] From these simple results, we see that over 73% of the variation in price is explained by the models, which can be inferred using the adjusted-R^2 measure. In terms of the coefficients, the interpretation of the model is straight-forward. The coefficients reflect the marginal change in selling price resulting from a one unit change in a given attribute, holding all else constant. The coefficients appear to be somewhat unstable across the above models, an issue resolved in later estimations. Several non-Milfoil variables are significant at the 95% confidence level in Table 2, including assessed structure value, lot size, frontage, frontage-squared, water clarity, muskie, and pike. Moreover, development density is significant at the 90% level or greater in two of the models. In general, the parameter estimates for the non-Milfoil variables conform reasonably well to expectations, though the magnitudes are not always robust.

The Milfoil-variables differ across the above cross-sectional models, but in each case, illustrate the likely endogeneity of Milfoil. Looking first at Model 1 in Table 2, a continuous measure of relative frequency is used to gauge the effect of Milfoil. The coefficient on this variable represents the change in price from an additional percentage of Milfoil, relative to all other species in the lake. Curiously, the results indicate a small price premium as Milfoil increases at the margin. However, this price effect is statistically insignificant. Additionally, the model captures the price effect associated with an infested lake that has been treated, relative to uninfested lakes. This price effect makes little sense, indicating that a lake treated for Milfoil sells for a statistically significant premium relative to lakes that are not infested. In other words, the model says it is beneficial to a property owner to have Milfoil in the lake *and* to treat it, then to not have Milfoil at all.

[15] All results presented in this paper are in real 2006 dollars.

Moving onto Models 2 and 3, we reach a similar conclusion. Model 2 uses two dummy variables to indicate if a lake has low abundance levels of Milfoil (<3% relative frequency) or medium/high levels (>3%). From these variables we get mixed results. The low levels have the expected sign and are statistically significant, indicating that a property on a lake with low levels of Milfoil suffers a negative price effect relative to lakes without Milfoil. However, the medium/high coefficient indicates a positive price premium relative to lakes without Milfoil (significant at the 90% confidence level). As in Model 1, a statistically significant premium is associated with treated, infested lakes as compared to those free of Milfoil. Model 3 aggregates the dummy variables seen in Model 2 into one presence/absence measure and the same results are found. A negative, but statistically insignificant price effect is found for properties on lakes with Milfoil. However, once these lakes are treated, a statically significant premium is associated with properties on these lakes, relative to properties on uninfested waters. There is little intuition to be offered for a positive price effect from the presence of Milfoil, and this result is likely confounded by the presence of unobservable neighborhood attributes that are correlated with variables indicating the presence of Milfoil on a lake.

5.3 Spatially Correlated Unobservables

Unobservable neighborhood effects are typically explored by examining potential spatial autocorrelation in the estimated covariance matrix. To test for the presence of spatial autocorrelation, Moran's I statistic is generated: $I = e_s{}'We_s / e_s{}'e_s$ (Anselin and Bera 1998, 265). This statistic is relatively easy to compute because it uses the OLS errors (e_s), leaving only the weight matrix, W, to be defined. The weight matrix is used to define the relationship between observations based on their locations and is up to the discretion of the researcher. To construct it, neighbors of a given property must be defined. A distance threshold is often used to define neighbors, but a strong argument can be made in the case of lake-related data to define one's neighbor as anyone else who lives on the same lake. Intuitively, one would expect the error terms to be correlated within a lake because many of the lake characteristics are shared – as seen by the fact that our primary specification includes multiple lake-specific characteristics as explanatory variables. The null hypothesis is that no spatial dependence exists, and the null is rejected at the 99% confidence level for all cross-sectional specifications, confirming the presence of spatial autocorrelation.

6. Spatial Difference-in-Differences Hedonic Model (1997-2006)

The second set of models is estimated using the entire panel data set from 1997-2006. Our strategy for identifying the price effects of Milfoil relies on a difference-in-differences specification that exploits the fact that several lakes in our dataset were invaded by Milfoil during the time frame of our dataset.

6.1 Econometric Considerations for Spatial Difference-in-differences Model

The full dataset consists of a total of 1841 observations, spanning 172 lakes. The price of parcel i on lake j during time t takes one of two general forms:

Random effects: $$P_{it} = X_{it}^{'}\beta + Z_{j(i)t}^{'}\phi + \delta_1 \cdot impact_{j(i)} + \delta_2 \cdot before_{j(i)t} + \mu_{j(i)} + \varepsilon_{it} \qquad (1.2)$$

Fixed effects: $$P_{it} = X_{it}^{'}\beta + \delta_2 \cdot before_{j(i)t} + D_{j(i)}^{'}\alpha + \varepsilon_{it} \qquad (1.3)$$

In (1.2), $\mu_{j(i)}$ is the neighborhood (lake) specific random error associated with lake j(i) where parcel i is located. Consistent estimation of β with (1.2) requires the assumption that the set of independent variables $\{X_{it}, Z_{j(i)t}, impact_{j(i)}, before_{j(i)}\}$ are uncorrelated with both $\mu_{j(i)}$ and ε_{it}. In (1.3), $D_{j(i)}$ is a matrix of dummy variables associated with lake j(i) where parcel i is located. Table 3 presents a description of additional variables specific to the difference-in-differences specification. The key difference between the fixed and random effects models is that the fixed effects are not present in the error term and so correlation can still exist between the fixed effects and independent variables without violating the assumption of no correlation between observable and unobservable determinants of land prices. The purpose of the fixed or random effects is to soak up any unobserved (and observed in the fixed effects case) spatial heterogeneity that is clustered within lakes (neighborhoods). The fixed effects specification has far fewer variables than the random effects model because any lake-time invariant characteristic is absorbed by the fixed effect. Only variables that vary within a lake or over time are included.[16]

Both the fixed and random effects models outlined above use a difference-in-differences specification to estimate the effects of Milfoil on property values. In particular, nine lakes became infested with Milfoil after 1999.[17] Given the above specifications, the coefficient on $impact_{j(i)}$ (δ_1) will specify the premium/discount that properties on lakes with Milfoil sell for, relative to those on non-infested lakes. Because the $impact_{j(i)}$ variable is lake-invariant over time, the dummy variable matrix $D_{j(i)}$ accounts for this variable in the fixed effect model. The additive result of $impact_{j(i)}$ and $before_{j(i)}$[18] (($\delta_1 + \delta_2$) in the random effects model) will specify the premium/discount that properties on lakes with Milfoil sell for before infestation, relative to properties on non-infested lakes. Finally, the difference-in-differences component follows from this; the before infestation premium ($\delta_1 + \delta_2$) minus the after infestation premium (δ_1) is simply

[16] *Parcel_dens* does vary over time, but is relatively constant for most lakes. Thus, the variable is considered lake-invariant and is absorbed by the fixed effects.
[17] Lakes infested with Milfoil after 1999 include: Arrowhead Lake, Boot Lake, Cranberry Lake, Forest Lake, Little Saint Germain Lake, North Twin Lake, Silver Lake, South Twin Lake, and Upper Gresham Lake.
[18] The *before* variable is an interaction of *impact* and a variable that designates whether or not the ith transaction occurs before the infestation. Therefore the partial derivative of price with respect to *impact* is $\partial Price/\partial impact = \delta_1 + \delta_2$ in the random effects model. The second component of this effect, δ_2, is turned on or of depending if the ith transaction took place before or after an infestation.

δ_2. Therefore, the parameter δ_2 allows the researcher to back out the difference in premium of now-infested lakes, before they became infested.[19]

Many lakes in the dataset underwent a change related to minimum frontage zoning in May, 1999, and we account for this temporal variation in the above specification to see how the premium/discount of lakes differs after the zoning change. In general, strict minimum frontage zoning can either decrease property values by restricting subdivision opportunities, or increase property values by restricting the development opportunities of other lakefront parcels (Spalatro and Provencher 2001). Analogous to the difference-in-differences specification for the Milfoil variables, we estimate the average price effects of all the possible minimum frontage zoning changes: 100 ft. to either 150 ft., 200 ft., or 300 ft., and from 200 ft. to 300 ft. Not all lakes underwent a change in zoning, as some lakes were zoned 200 ft. minimum frontage before the new ordinance went into effect and ended up 200 ft. under the new classification.

There are two additional points to justify our identification strategy with respect to Milfoil. First is the variation in year of invasion. The nine lakes became infested over a five-year period, 2000-2005, with each lake becoming infested at a time distinct from any other. Conversely, in Tu (2005), for example, the construction of the sports stadium (the event of interest in that study) occurred within one time period. While it is unlikely that some other coinciding events or regional effects plagued Tu's identification of the sports stadium effect, it is worthy to note that the likelihood of a confounding event occurring concurrent to the various years that Milfoil invasions occurred is highly unlikely. Second, identification of the effect of Milfoil is enhanced by the quasi-random nature of the time of a Milfoil invasion, relative to other changes in lake characteristics. As a contrasting example, zoning laws are put in place over time

[19] The Milfoil variables that appeared as continuous abundance measures in the cross-sectional model are purely presence/absence indicators in the difference-in-difference models. This is primarily because abundance data are unavailable for years prior to 2005.

and expectations about the laws may be captured in real estate values well before the laws actually go into effect. In that sense, identification of a change in zoning can be a challenging task due to expectations, and as such, we recommend caution in interpreting our difference-in-differences estimates of the effects of the zoning changes. On the contrary, lake owners are unlikely to believe their lake will be affected by Milfoil if the species is not already present. While we argue that Milfoil is more likely to show up in lakes highly popular for recreational activities, particularly boating and fishing, the vast majority of "popular" lakes in Vilas County are still free of Milfoil. Therefore, the effects associated with an invasion are unlikely to be diluted by any previous expectations about such an event, as we maintain an assumption that these expectations are unlikely to exist.

The last econometric issue to discuss is the use of a ten year time series of property transaction sales. Given the temporal variation in the data, we account for price inflation in two ways. First, dummy variables are included for the year a given transaction takes place to absorb any year-specific effects on price. Second, a trend variable is included to account for the general upward trends in price. Use of time-series data is necessary for our identification strategy, though it requires the potentially strong assumption that the price-differential across lakes is constant over time, and general inflationary pressures have the same effect on all properties. This assumption is relaxed somewhat with the following non-linear specification of the fixed effects model:

$$P_{it} = \beta_1 \cdot (Struc\_Val) + e^{X_{it}\beta + \delta_2 \cdot before_{j(i)t} + D_{j(i)}\alpha} + \varepsilon_{it} \qquad (1.4)$$

This specification assumes that assessed structural effects are independent of land-based attributes, while the marginal impact of any land-based attribute depends on the level of all other land characteristics: $\partial P_{it} \big/ \partial X_{it} = \beta e^{X_{it}\beta + \delta_2 before_{j(i)t} + D_{j(i)}\alpha}$. Therefore, in using equation (1.4) to estimate the hedonic price function, the effect of Milfoil (and other explanatory variables) on property values is not independent of the values of the other explanatory variables.

6.2. Spatial Difference-in-differences Results

Tables 4 and 5 summarize the results from the spatial difference-in-differences model. In Table 4, time influences are accounted for using a dummy variable for each transaction year, while a time trend variable is used for the results presented in Table 5. Results for the fixed effects model are presented in a linear and non-linear form (NLLS). The results are very similar across the two time variable specifications, with the year dummies yielding a slightly better fit. Nonetheless, the stability of coefficients is evident across the two specifications, indicating a certain degree of model robustness. The coefficients of the non-Milfoil variables are generally stable across the linear fixed effects and random effects specifications, with the zoning variables being the exception. For example, the coefficients on assessed structure value, lot size, frontage, frontage-squared, and the time variables are nearly identical and of the same order of statistical significance.

Robustness is illustrated further by comparing the linear fixed effects results with the non-linear fixed effects model. In general, the signs are the same across specifications and variables that are significant in one model are statistically significant in the other. There are a couple of notes to be made concerning the non-linear model. First, continuous independent variables have been scaled down by their maximum values. Second, lakes with fewer than five transactions were omitted from the model, resulting in a loss of 127 observations. Given the functional form of this model, the algorithm used to solve out the non-linear specification is very sensitive to large values of independent variables. We also examine the possibility of an incidental parameters problem – common in non-linear fixed effects models with short panels

(Greene 2003, 690) – by first dropping lakes with fewer than ten transactions, then dropping lakes with fewer than fifteen transactions, to ensure our results do not depend on a short panel. The conclusions with respect to the effects of Milfoil are robust across estimations that drop lakes with fewer than ten or fifteen transactions.

Given the robustness of these models, only the results from Table 4 will be discussed in depth. As seen in the results, 81.8% and 73.8% of the variation in selling price is explained by the fixed effects and random effects models respectively.[20] As in the cross-sectional results, several non-Milfoil variables are significant at the 95% confidence level in both the fixed and random effects models, including assessed structure value, lot size, frontage, the zoning change variables, and the time-related variables. In addition, access, parcel density, and muskie are significant in the random effects model at the 90% confidence level or greater. The zoning variables indicate a negative price effect from the county-wide zoning change in 1999, though this result is not robust to the non-linear models, and the coefficients do not appear robust across the fixed and random effects models in Tables 4 and 5.

For the Milfoil variables, *impact* and *before*, we see results counter to the cross-sectional model. Looking at the random effects model, we see from the *impact* coefficient that no statistically significant premium exists for properties affected by Milfoil relative to unaffected properties. However, a premium did exist before infestation, as indicated by the *before* coefficient in the fixed effects model—a statistically significant premium of approximately \$28,000 (\$32,000) in the linear (non-linear) model with the time-dummies, and approximately \$29,500 in the linear model with the trend variable. It was argued above that any correlation between the Milfoil variable and the error term in the random effects model would render the

[20] In the case of the fixed effects model, an F-test can be used to evaluate if the addition of the 172 fixed effects is significant or if they are jointly equal to zero. This test yields a test statistic of 202.42 and an associated p-value of 0.000, indicating that these additions are highly significant.

results inconsistent. Based on the empirical evidence presented in Tables 4 and 5, we see this lingering bias in the random effects model. The *before* coefficient in the fixed effects model, the key variable of interest in these results, is some 50% greater in magnitude than in the random effects model. The coefficient is also statistically insignificant in the latter case.[21] These results are consistent with the notion that there is correlation between the presence of Milfoil and unobserved characteristics related to the level of a lake's attractiveness. Coupled with a difference-in-differences approach, the fixed effects model has the least stringent identification assumptions across all estimated models, and appears to resolve the issues of bias and inefficiency brought about by the presence of Milfoil on a lake being correlated with unobserved neighborhood effects.

6.3 Marginal Willingness-to-pay to Avoid Milfoil Invasions

Using the results from the spatial difference-in-differences hedonic model, broader conclusions can be made concerning the marginal willingness-to-pay to prevent an additional Milfoil infestation on a lake. The hedonic price function can be used to approximate welfare effects for localized amenity changes when the number of parcels affected by a change in environmental quality is small relative to the land market (Palmquist 1992). The localized amenity change in this paper is the infestation of one additional lake with Milfoil. Given our set of 172 lakes in the same land market, evaluating the costs of one additional infested lake reasonably fits the criteria of a localized amenity change.

The results from Tables 4 and 5 indicate that lakefront property owners are willing to pay, on average, greater than $28,000 more for a property on a lake free of Milfoil, all else equal

[21] While confidence intervals surrounding these estimates are intersecting, indicating that one point estimate is not statistically different from another, the means of these intervals are markedly different, along with the discrepancy in statistical significance.

(depending on specification, results range from \$28,000 to \$32,000).[22] Since the price of land is a stream of rents in perpetuity, we can calculate the annual marginal willingness to pay as approximately \$1400 with a 5% discount rate. Of the twenty lakes infested with Milfoil in our sample, there were 2,637 parcels as of 2006. Multiplying the average marginal willingness to pay by the number of affected parcels on the average lake, we arrive at an aggregate cost of Milfoil of about \$187,600/year, on average, for one additional infested lake. This amounts to approximately 13% of total land value. For further perspective, consider that there are approximately 500 lakes in Wisconsin affected by Milfoil, and the State's Department of Natural Resources allocates approximately \$4 million dollars annually for the management of *all* aquatic invasive species across the entire state.

7. Conclusions

The findings of this paper reveal that lakes invaded with the aquatic species Eurasian Watermilfoil experienced an average 13% decrease in land values *after* invasion. Therefore, we document a unique phenomenon in the environmental economics literature: invasive species can depress land values. Government agencies are spending significant dollars on invasive species management, despite the general lack of estimates on the costs of invasions derived from a rigorous economic framework. Our results provide some evidence as to the potential benefits derived from preventing the spread of Eurasian Watermilfoil, one of the most widespread and common aquatic invasive species in North America.

In addition to providing empirical evidence as to the potential benefits from reducing the spread of invasive species, this paper also develops a quasi-experimental methodology to

[22] For the non-linear model, the average price effects of Milfoil are represented as the discrete-change effect by taking the difference in predicted price between impacted lakes before and after infestation using the sample mean value of all other exogenous variables. Standard errors are calculated with the Delta Method (Greene 2003, p. 70), and the average price effect is significantly different from zero at the 5% level for the non-linear models.

identify the effects of changes in endogenous neighborhood amenities within the commonly estimated hedonic framework. In our application, a lake is more likely to be invaded with Milfoil if it is more popular with recreational boaters. Therefore, since lakes popular with recreational boaters are also likely to be popular with potential residents, and since many aspects of a lake's amenities may be difficult to quantify, the presence of Milfoil on a lake is an endogenous variable in the hedonic price equation. Our identification strategy is based on a spatial difference-in-difference specification, and isolates the source of endogeneity bias as arising from unobserved neighborhood effects. Although typically treated as an econometric efficiency issue in the literature, we highlight the estimation bias that ensues when a measurable neighborhood amenity is correlated with unobservable neighborhood effects. Our spatial difference-in-differences specification defines distinct neighborhood fixed effects to control for both observable and unobservable neighborhood effects, while exploiting the fact that the environmental amenity of interest (a lake free of Milfoil) varies over the time period of our dataset.

Given the potential for correlation between observed and unobserved neighborhood amenities in hedonic property value models, the identification strategy employed in this study could potentially be used in other settings. The fixed effects approach works best with clearly defined spatial neighborhoods. In this study, lakes give rise to natural neighborhoods, though such a clear definition of neighborhoods may not always exist for landscapes with less development fragmentation. However, it should be noted that all spatial econometric models face the problem of defining the relevant spatial neighborhood. Some studies use a distance-decay approach, others define neighbors by concentric rings of varying radius around a particular parcel, while others subjectively define a neighborhood to share a common error term. This paper demonstrates the potential of specifying fixed neighborhood effects jointly within a difference-and-differences framework as a strategy for identifying the effects of an endogenous neighborhood amenity on property values.

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Table 1. Description of Variables in Cross-Sectional Model

Descriptive Name	Variable Name	Variable Description
Selling price	$Price_i$	selling price of the ith property in real dollars (2006)
Assessed structure value	$Struc\_val_i$	assessed structure value before transaction of the ith property
Lot size	Lot_i	size (in acres) of the ith property
Frontage	$Front_i$	frontage (in feet) of the ith property
Lake area	$Lake\_area_i$	surface area (in acres) of the lake that the ith property borders
Association	$Assoc_i$	=1 if the ith property is on a lake with an association and 0 otherwise
Public access	$Access_i$	=1 if the ith property is on a lake with public access and 0 otherwise
Development density	$Parcel\_dens_i$	number of private parcels divided by the area of the lake that the ith property borders
Maximum depth	Max_dep_i	maximum depth (in feet) of the lake that the ith property borders
EWM prime season	$Prime_i$	=1 if transaction of the ith property takes place between June 1 and September 30 and is subjected to EWM
Eurasian Watermilfoil measures	EWM_i	represents multiple variables, including i) relative frequency—a continuous measure of lake-wide EWM abundance, ii) dummy variables representing low (0%<relative frequency<3%), medium (3%-9.99%), high frequency (>10%), and medium-high frequency (>3%), and iii) a presence/absence measure—present if relative frequency>0. Inclusion of these variables varies, but is made clear in the results.
Treatment	$Treatment_i$	=1 if the lake the ith property borders was treated for EWM before the transaction within the same calendar year
Year 2006	2006_i	= 1 if the ith transaction took place in 2006
Water clarity	$Water\_Clarity_i$	water clarity measure of the lake that the ith property borders
Fishery quality indices	$Muskie_i$ (and other fish)	index for quality of muskie fishery (or other fish) on the lake the ith property borders
Distance to nearest town	$Dist_i$	distance to nearest town (in miles) of the ith property

Table 2. Cross-Sectional Estimation Results

	Model 1		Model 2		Model 3	
R^2	.7468		.7534		.7471	
Adj-R^2	.7345		.7403		.7348	
	Coef.	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**
Constant	-46318.620	-1.16	-78349.400**	-1.90	-45569.740	-1.13
Struc_val	1.592*	28.43	1.599*	28.78	1.583*	28.29
Lot	7175.424*	3.15	7608.077*	3.37	7358.474*	3.23
Front	567.843*	5.11	551.288*	5.02	583.214*	5.28
$Front^2$	-0.523*	-4.14	-0.519*	-4.16	-0.533*	-4.23
Lake_area	3.809	0.36	9.598	0.89	4.644	0.43
Assoc	-10772.120	-0.92	-12388.240	-1.05	-11568.260	-0.97
Access	23328.840	1.27	28595.820	1.55	23648.090	1.28
Parcel_dens	-82919.150*	-2.24	-60433.110	-1.62	-66024.190**	-1.76
Max_dep	623.555	1.26	791.183	1.61	568.434	1.16
Prime	987.897	0.05	8867.079	0.39	16177.970	0.71
EWM_rel_freq	3130.613	1.21	--	--	--	--
Freq * treat	22634.900*	3.08	--	--	--	--
EWM_low	--	--	-49508.790*	-2.27	--	--
EWM_medhigh	--	--	53884.860**	1.94	--	--
Low * treat	--	--	163956.500*	3.61	--	--
Medhigh * treat	--	--	101679.600*	2.06	--	--
Impact	--	--	--	--	-14948.920	-0.77
Impact * treat	--	--	--	--	120459.500*	3.44
2006	-11037.060	-1.08	-13166.850	-1.30	-11373.930	-1.12
Water_Clarity	13462.160*	2.15	13628.190*	2.18	12924.180*	2.05
Muskie	16329.900*	2.82	13786.890*	2.38	16660.530*	2.88
Pike	18189.460*	2.45	16436.410*	2.21	15598.820*	2.07
Walleye	4091.533	0.46	4692.444	0.51	9500.241	1.03
Bass	-4818.475	-0.50	-8670.291	-0.88	-5438.350	-0.55
Panfish	2734.357	0.37	4359.438	0.59	2887.906	0.39
Dist	3294.444	1.13	6994.437*	2.28	2451.757	0.88
$Dist^2$	-128.439	-1.50	-230.309*	-2.58	-110.265	-1.34

Note: n = 457 for all models. All dollar amounts in real 2006 dollars. Single asterisk (*) denotes significance at the 95% level; double asterisk (**) denotes significance at the 90% level.

Table 3. Description of Additional Variables in Spatial Difference-in-Differences Model

Descriptive Name	Variable Name	Variable Description
Lake that changes zoning from 100ft to other amount	$Zone\_100\_any_i$	= 1 if the ith property borders a lake that has undergone a zoning change from 100ft minimum frontage to some other category under the 1999 Vilas County Shoreland Zoning Ordinance
Lake that changes zoning from 200ft to 300ft	$Zone\_200\_300_i$	= 1 if the ith property borders a lake that has undergone a zoning change from 200ft minimum frontage to 300ft minimum frontage under the 1999 Vilas County Shoreland Zoning Ordinance
After zoning change from 100ft to other amount	$Aft\_100\_any_i$	= 1 if the ith property borders a lake that has undergone a zoning change from 100ft to some other amount AND the transaction takes place after the change
After zoning change from 200ft to 300ft	$Aft\_200\_300_i$	= 1 if the ith property borders a lake that has undergone a zoning change from 200ft to 300ft AND the transaction takes place after the change
EWM lake	$Impact_i$	= 1 if the ith property is on an EWM-infested lake as of 2006 and 0 otherwise
Before EWM	$Before_i$	= 1 if the ith property is on an EWM-infested lake AND the transaction occurs before infestation
Time	$Time_i$	Represents two sets of variables: 1) In the first case, a dummy variable is used to designate the transaction year (=1 if the ith property transaction took place in one of the given years and zero otherwise). 1997 is the omitted year. 2) In the second estimation, a continuous trend variable is used to give the average price change from year to year.
Fixed effect	D_{ji}	= 1 to designate which lake the ith property borders

Table 4. Results for Spatial Difference-in-Differences Models with Year Dummies

	Fixed Effects		NLLS Fixed Effects		Random Effects	
R^2	.8183		.8296		.7398	
	Coef.	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**
Constant	--	--	--	--	-112349.000*	-2.97
Struc_val	1.519*	27.48	1.513*	56.82	1.530*	29.15
Lot	5006.164*	3.41	1.293*	8.33	5506.886*	3.64
Front	235.263*	6.14	3.466*	12.59	224.474*	6.05
$Front^2$	-0.034	-1.37	-2.363*	-6.88	-0.030	-1.26
Lake_area	--	--	--	--	17.286	0.99
Assoc	--	--	--	--	-2617.920	-0.26
Access	--	--	--	--	25158.200*	2.21
Parcel_dens	--	--	--	--	-25378.540**	-1.78
Zone_100_any	--	--	--	--	38992.960*	2.52
Zone_200_300	--	--	--	--	47270.340*	2.56
Aft_100_any	-38626.530*	-4.40	-0.216*	-2.73	-37379.730*	-4.74
Aft_200_300	-59163.000*	-3.88	-0.202	-0.43	-43602.310*	-2.75
Max_dep	--	--	--	--	641.800	1.62
Prime	8772.964	0.81	-0.006	-0.10	9807.777	0.94
Before	28294.200**	1.90	0.210*	2.25	18880.710	1.38
Impact	--	--	--	--	9006.635	0.44
1998	10095.200	1.00	0.124	1.29	10946.070	1.23
1999	54634.800*	4.96	0.392*	4.13	53292.810*	5.27
2000	63306.830*	4.88	0.542*	5.72	61937.590*	5.19
2001	60896.670*	5.28	0.477*	5.08	59634.270*	5.68
2002	79208.170*	6.36	0.645*	7.11	78290.490*	6.86
2003	95634.540*	7.64	0.729*	8.26	93705.300*	7.94
2004	109544.100*	8.65	0.830*	9.37	108652.700*	9.26
2005	128563.200*	9.98	0.968*	11.06	127870.500*	10.73
2006	128854.000*	9.63	0.952*	10.93	121101.900*	9.63
Water_Clarity	--	--	--	--	7072.708	1.39
Muskie	--	--	--	--	8578.916**	1.82
Pike	--	--	--	--	3916.667	0.60
Walleye	--	--	--	--	7947.288	0.94
Bass	--	--	--	--	-3712.708	-0.48
Panfish	--	--	--	--	1052.253	0.16
Dist	--	--	--	--	3389.18	1.41
$Dist^2$	--	--	--	--	-108.848	-1.64

Note: n = 1841 for Fixed Effects and Random Effects models; n = 1714 for NLLS Fixed Effects Model. 172 fixed effects (106 for NLLS model) are not displayed for space. T-stats are calculated using White's robust standard errors. All dollar amounts in real 2006 dollars. Single asterisk (*) denotes significance at the 95% level; double asterisk (**) denotes significance at the 90% level.

Table 5. Results for Spatial Difference-in-Differences Models with Year Trend Variable

	Fixed Effects		NLLS Fixed Effects		Random Effects	
R^2	.8165		.8273		.7372	
	Coef.	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**
Constant	--	--	--	--	-97264.300*	-2.51
Struc_val	1.517*	27.27	1.512*	56.90	1.525*	28.95
Lot	4928.066*	3.48	1.277*	8.29	5379.838*	3.67
Front	241.142*	6.22	3.573*	13.10	231.950*	6.18
$Front^2$	-0.036	-1.45	-2.511*	-7.36	-0.033	-1.36
Lake_area	--	--	--	--	18.555	0.98
Assoc	--	--	--	--	-2438.350	-0.22
Access	--	--	--	--	24724.760*	2.01
Parcel_dens	--	--	--	--	-24124.600	-1.59
Zone_100_any	--	--	--	--	26024.910	1.59
Zone_200_300	--	--	--	--	37591.620*	2.08
Aft_100_any	-23783.320*	-3.49	-0.117**	-1.71	-22806.400*	-3.59
Aft_200_300	-44400.530*	-3.11	-0.073	-0.16	-31083.800*	-2.17
Max_dep	--	--	--	--	614.544	1.45
Prime	9471.351	0.89	-0.024	-0.41	9679.253	0.94
Before	29518.130**	1.93	0.201*	2.19	20893.910	1.48
Impact	--	--	--	--	8394.436	0.38
Trend	13537.410*	14.44	0.096*	17.94	13105.920*	15.04
Water_Clarity	--	--	--	--	6443.784	1.21
Muskie	--	--	--	--	8303.253	1.63
Pike	--	--	--	--	3247.011	0.46
Walleye	--	--	--	--	8587.339	0.95
Bass	--	--	--	--	-3414.280	-0.41
Panfish	--	--	--	--	1404.825	0.20
Dist	--	--	--	--	3203.286	1.24
$Dist^2$	--	--	--	--	-102.548	-1.44

Note: n = 1841 for Fixed Effects and Random Effects models; n = 1714 for NLLS Fixed Effects Model. 172 fixed effects (106 for NLLS model) are not displayed for space. T-stats are calculated using White's robust standard errors. All dollar amounts in real 2006 dollars. Single asterisk (*) denotes significance at the 95% level; double asterisk (**) denotes significance at the 90% level.