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

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Abstract: This study uses hedonic analysis to estimate the effects of a common aquatic invasive species – Eurasian Watermilfoil (milfoil) – on property values across an extensive system of over 170 lakes in the northern forest region of Wisconsin. Since milfoil is inadvertently spread by recreational boaters, and since boaters are more likely to visit attractive lakes, variables indicating the presence of milfoil are endogenous in a hedonic model. Using an identification strategy based on a spatial difference-in-differences specification, results indicate that lakes invaded with milfoil experienced an average 13% decrease in land values *after* invasion.

JEL Codes: Q24, Q51, Q57

Keywords: invasive species, hedonic, spatial model, difference-in-differences, Eurasian watermilfoil, *Myriophyllum spicatum*, lakes.

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I. INTRODUCTION

The invasion of ecosystems by non-native species is considered to be second only to habitat loss as the greatest threat to biological diversity (Wilcove et al. 1998). Freshwater rivers and lakes have been particularly susceptible to species invasions, and have recently attracted the attention of large environmental regulatory bodies.[1] Invasive species can i) alter ecological communities by competing or preying on native species, ii) affect market-related enterprises such as agriculture, forestry, fisheries, and electric power production, and iii) affect non-market resources such as recreational fisheries. Despite significant advances in understanding the ecology of invasive species, the economic costs of invasive species are not generally understood (Lovell and Stone 2006). The most commonly cited estimate of the costs of invasive species for the United States is $120 billion per year (Pimentel, Zuniga, and Morrison 2005), which is derived from estimates of the costs of managing species invasions, including the amount that must be spent to repair infrastructure damage. However, such cost estimates tend to be more anecdotal and not based on empirical methods grounded in economic theory (Lovell and Stone 2006). Developing a greater understanding of the relationship between invasive species and welfare is central to understanding the appropriate role of public policy.

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 (*Myriophyllum spicatum*, hereafter labeled milfoil) – on property values across an extensive system of over 170 lakes in the northern forest region of Wisconsin. Milfoil has been labeled as “among the most troublesome submersed aquatic plants in North America” (Smith and Barko 1990, p. 55), and is 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, the presence of milfoil is quasi-irreversible, as the plant is extremely difficult to remove without clearing native vegetation. The data used for estimation covers more than 1,800 lakeshore property transactions across 172 lakes within a single county in the northern forest region of Wisconsin. The sheer variation in lakes within one land market makes this dataset particularly unique for hedonic analyses of water-based amenities. Further, the dataset covers a period (1997-2006) that coincides with multiple lakes becoming invaded with milfoil. Hedonic results presented in this paper provide unique evidence regarding the effects of aquatic invasive species on property values, and thus, should prove useful in designing efficient strategies to manage species invasions.

In addition to providing evidence on the costs of species invasions, the analysis in this paper provides a general contribution by designing 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 unobserved neighborhood effects. Although typically treated as an efficiency issue in econometric estimation, unobserved (or unmeasured) neighborhood effects can be correlated with measurable neighborhood environmental amenities (Small 1975), resulting in biased estimates of such amenities in hedonic estimation. One example of correlated neighborhood effects in hedonic applications is the observation that sources of water pollution, in addition to emitting undesirable pollution, are also likely to be unpleasant neighbors (Leggett and Bockstael 2000). A second example derives from the observation that the negative property price effects of being located in a flood plain can be confounded by the amenity effects of being located close to streams and lakes (Bin and Polasky 2004; Pope 2008).

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 unobserved lake-specific characteristics. For example, fishing quality and the scenic views of the surrounding landscape affect property values and will be spatially correlated within a lake, yet are difficult to measure. In addition to 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. Many of the most problematic aquatic invasive species – including milfoil, zebra mussels, rainbow smelt, rusty crayfish, and spiny water flea – are spread from lake to lake by the movement of recreational boaters and anglers (Vander Zanden et al. 2004), creating a direct link between the spread of the invasive and the recreation decisions of boaters.[2] Since boaters are more likely to visit popular lakes with desirable amenities, and since many of these amenities are difficult to quantify and are therefore unobservable to the analyst, the likelihood that any particular lake is invaded will be correlated with the error term in a hedonic property value model. Thus, conventional OLS estimation of cross-sectional hedonic data will likely produce positively biased coefficient estimates on variables indicating a lake's milfoil status.[3] 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 difference-in-differences analysis is based on a relatively long time-series consisting of ten years of property transactions that include observations on lakes before and after milfoil invasions. The fixed neighborhood effects specification exploits the panel structure of the data, where each lake is defined as a natural neighborhood, or cluster. Identification of the effects of milfoil on property 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 natural experiment inherent in the before-and-after nature of milfoil invasions present in the dataset. Further, the clustering of properties by lake allows us to estimate cluster-robust standard errors, which ensures that inference is robust to any form of spatial correlation across properties within lakes. Results indicate that a milfoil invasion reduces average *property values* by approximately 8%, and reduces average *land values* net of the value of any structure by approximately 13%. Since a time-series dataset is necessary for our identification strategy, we demonstrate that our results are robust to handling the temporal aspects of the data with either time-specific dummy variables or a simple time trend in either linear or non-linear forms.

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 provides background information on milfoil, while section 4 presents the application and the data used for estimation. Sections 5 and 6 presents estimation results while concluding thoughts are offered in section 7.

II. 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 provides the conceptual basis for estimating landowners' revealed preference for the neighborhood amenities surrounding their land. 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), who questioned whether unobserved neighborhood effects would substantially bias hedonic estimates of air quality.

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.[4] While models of spatial autocorrelation are well-established and can be readily estimated (e.g. see 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 (e.g. Leggett and Bockstael 2000). 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 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 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. Difference-in-differences analysis can be used to exploit 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 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.[5] In the language of the treatment evaluation literature (e.g. see Ch. 25 in Cameron and Trivedi (2005)), the assumption is one of "selection on observables", whereby the "treatment" is the change in neighborhood amenities, and 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) will be accounted for by the fixed effects. Given the change in milfoil status on multiple lakes in the sample, 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 assumption that variables measuring a lake's milfoil status are uncorrelated with the unobserved neighborhood effects. Again adopting the language of the treatment evaluation literature, our approach produces consistent estimates of the price effects of milfoil even when a milfoil invasion on a lake is subject to "selection on unobservables", provided that the unobservables are controlled with the fixed neighborhood effects.

III. EURASIAN WATERMILFOIL

Eurasian Watermilfoil (milfoil) is a submersed plant that is native to Europe, Asia, and North Africa. Milfoil was first discovered in the United States in the late 19th century and is now known to exist in at least 45 states. The invasion of a lake by milfoil has four effects that are particularly relevant for property values. First, the species has the ability to rapidly cover a water body with vegetation, potentially reducing the quality of many types of recreation (e.g. swimming, boating, fishing, etc.). Second, the presence of milfoil in a lake is generally thought to be quasi-irreversible (Smith and Barko 1990). Third, the increase in submerged biomass from a milfoil infestation can accelerate eutrophication (Carpenter 1980). Fourth, the ability of milfoil to rapidly cover large portions of lakes is highly uncertain and difficult to predict (Smith and Barko 1990).

Milfoil is an opportunistic species that thrives in many different environments and primarily reproduces through fragmentation, a characteristic that greatly drives the spread of the species through the movement of boaters. The time-growth relationship for milfoil has shown significant variability in the different bodies of water that have been invaded – e.g. see Smith and Barko (1990) for an extended discussion of the ecology of milfoil. One of the first places to become infested with milfoil, Chesapeake Bay, showed few signs of the species for over sixty years. However, its abundance roughly doubled between 1960 and 1961 to cover 100,000 acres across the bay (Orth and Moore 1984). 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 the species 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.

Given the uncertainty associated with predicting the growth rate of milfoil across similar types of water bodies, and the quasi-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 the quasi-irreversibility of its invasion, and the uncertainty associated with how milfoil populations may change over time.

IV. HEDONIC APPLICATION

This study focuses on the property price effects of milfoil on lakes within Vilas County, Wisconsin (Figure 1). 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.

Data and Variables Used in Estimation

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.[6] GIS tax parcel and county-wide spatial water data were obtained from the Vilas County Mapping Department.[7] Lake characteristics and ecological variables were collected from the Wisconsin Department of Natural Resources (DNR)[8] and the Environmental Remote Sensing Center at the University of Wisconsin, Madison. Data on the presence of milfoil and the year of milfoil invasion were gathered from the Wisconsin DNR's website.[9] Data on fisheries quality were gathered from the Wisconsin DNR and a widely read guidebook of fishing quality in northern Wisconsin (Sportsman's Connection 2002).[10] Milfoil abundance data were compiled with the help of staff at the Wisconsin DNR and other contracting firms.[11] The entire panel of data represents transactions on 172 lakes in Vilas County

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. The dependent variable in all models is the observed arms-length transaction price of the property deflated with the consumer price index (2006 dollars). Table 1 presents a comprehensive list of the independent variables included. Structural and lot characteristics include assessed structure value (*Structure*), the size of the lot (*Lot size*), shoreline frontage (*Frontage*), and frontage-squared ($Frontage^2$). Due to data limitations, the value of characteristics associated with a property's housing structure are lumped into an assessed structural value. All structural and lot variables are expected to make positive contributions to the dependent variable.

In an attempt to alleviate omitted variable bias, we include many lake-specific variables to account for observable variation in lake characteristics: *Lake area*, *Water clarity*, and *Max depth*. Fishing quality variables included (*Muskie*, *Pike*, *Walleye*, *Bass*, and *Panfish*) are based on species-specific rankings determined by the Wisconsin DNR. The ratings for *Muskie* – muskellunge (or muskie) are the premiere sport fish in this region – range from 0 to 4 and are based on angler surveys and observations made by biologists.[12] Also included are two dummy variables accounting for the presence/absence of a lake association (*Assoc*) and the possibility of public access through a boat ramp (*Access*). Since many households prefer to locate on a relatively pristine lake with significant amounts of open space (Spalatro and Provencher 2001), we include a variable measuring the number of private parcels along a lake's shoreline divided by the size of the lake (*Parcel density*),[13] and the minimum frontage zoning regulation of the lake (*Zone*). *Distance* and $distance^2$ are variables that measure the distance (in miles) to either Eagle River or Minocqua to proxy for convenience of the property to services.

Milfoil Variables Used in Estimation

There are 17 lakes in the dataset that have been invaded by milfoil.[14] 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.[15] Despite the concerns of local residents, the average sales price of a property on a lake with Milfoil was about $15,000 above the average sales price on a lake without milfoil during the period 1997-2006, suggesting that lakes with a price premium (i.e. popular lakes) may also be more likely to be invaded with milfoil.

We account for the presence/abundance of milfoil with several different combinations of the milfoil measures—a continuous relative frequency measure (*Milfoil_freq*), two dummy variables based off relative frequency, and a presence/absence dummy variable. The continuous variable is the relative frequency of milfoil lake-wide. The dummies are grouped into categories based on the continuous variable, providing low (*Milfoil_low*) and high (*Milfoil_high*) abundance categories. Unfortunately, the Wisconsin 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 (*Milfoil_pres*) has been documented for several years and is publicly available on the Wisconsin DNR's website.

Properties on lakes with milfoil that have been treated will likely suffer a moderated negative price effect. While treatments ranging from herbicides to mechanical cutters can lower the abundance of milfoil, these treatments are rarely successful at removing the plant. A treatment variable (*Treat*) 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.[16] 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 to indicate whether or not a transaction took place during the prime months that milfoil affects lakes.

V. 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 cross-sectional arms-length transaction data for the years 2005-2006. In addition to demonstrating the endogeneity of milfoil in a hedonic equation, this model is estimated to take advantage of the only years in which milfoil abundance data are available.

Econometric Considerations for Cross-Sectional Model

A number of functional forms are considered. The first was a linear-linear model, as found in many hedonic applications 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 are estimated to add flexibility to the functional form, given the absence of a priori information on the structure of the hedonic price function (Bender, Gronberg, and Hwang 1980; Sakia 1992).[17] We considered criteria for goodness-of-fit and ease-of-interpretation in selecting a model for the cross-sectional data. However, all specifications have a very similar fit, with the linear Box-Cox (constant lambda transformation on non-binary independent variables) fitting just slightly better than a linear-linear model.[18] We chose the linear-linear model because of its prevalence in the literature and straight-forward interpretation, although we also examine a non-linear specification with the panel data in section 6.[19] Pair-wise correlation analysis and calculation of variance inflation factors and tolerances for each variable fail to indicate that multicollinearity is a serious problem. Lastly, White's robust standard errors are used to account for potential heteroskedasticity.

Cross-Sectional Hedonic Results

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

$$P_i = X_i^{'}\beta + Z_{j(i)}^{'}\phi + \varepsilon_i \qquad (1)$$

where X_i is a Kx1 vector of variables specific to parcel *i*, $Z_{j(i)}$ is an Lx1 vector of variables specific to lake *j* that contains parcel *i* (Table 1), and $\{\beta, \phi\}$ is a set of K+L parameters to be estimated. Results from estimating (1) with ordinary least squares are presented in Table 2, and 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 models in Table 2. Several non-milfoil variables are generally significant from zero at the 90% confidence level or higher, including *Structure*, *Lot size*, *Frontage*, *Frontage*^{2}, *Water clarity*, *Parcel density*, *Muskie*, *Pike,* and *Distance*. In general, the parameter estimates for the non-milfoil variables conform reasonably well to expectations, though the estimated magnitudes are not always robust across the three milfoil specifications.

The milfoil-variables differ across the cross-sectional models, but in each case, illustrate the likely endogeneity of milfoil. When a continuous measure of relative frequency is used to gauge the effect of milfoil (model 1), the results indicate a small price premium on a milfoil lake, and a larger premium for a milfoil lake that has been treated. Switching to model 2 and using dummy variables to indicate if a lake has low abundance levels of milfoil (<3% relative frequency) or high levels (>3%) yields similar findings. Model 3 aggregates the dummy variables seen in model 2 into one presence/absence measure, and similar results are found. A negative price effect not significant from zero is found for properties on lakes with milfoil. However, once these lakes are treated, a positive premium significantly different from zero is associated with properties on treated milfoil lakes relative to properties on milfoil-free waters. There is little intuition to be offered for a positive price effect from the presence of milfoil, and despite the inclusion of an unusually rich set of control variables, 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.

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, p. 265). This statistic is computed with the OLS errors (e_s) and a spatial weight matrix (W) that specifies neighbors and is pre-defined by the researcher. Recent work with micro-level data has specified W with distance relationships (e.g. Donovan, Champ, and Butry 2007). However, distance-defined spatial weight matrices can result in a variety of problems in hedonic models. For example, Bell and Bockstael (2000) found that hedonic estimates are quite sensitive to the assumed structure of a distance-defined W, which is problematic since the specification of W is typically treated as a maintained assumption. Further, the process of row-standardizing a distance-defined W (which is required for a well-defined econometric problem) is ad-hoc and places too much weight on the neighbors of rural houses when the dataset represents a mix of dense and rural housing developments (Bell and Bockstael 2000).

Fixed neighborhood effects have recently emerged as an alternative to distance-defined weight matrices, and neighborhoods are typically defined by boundaries such as those used to define census tracts (e.g. see Pope 2008a, 2008b). In our application for lakeshore property, the most plausible theoretical argument regarding the spatial relationships between parcels is that each lake represents a natural neighborhood.[20] Therefore, W is defined such that all parcels within each lake are neighbors. Intuitively, one would expect the error terms to be correlated within a lake because many lake-specific characteristics are shared – as reflected in our primary specification which includes multiple lake-specific characteristics as explanatory variables. Further, given our interest in estimating the price effects of a lake-specific amenity (a lake free of milfoil), the presence of unobserved lake-effects is of particular consequence for our results. The null hypothesis for the Moran's I statistic is that no spatial correlation exists, and the null is rejected at the 99% confidence level, confirming the presence of unobserved neighborhood effects.

VI. SPATIAL DIFFERENCE-IN-DIFFERENCES HEDONIC MODEL (1997-2006)

The second set of models is estimated using the entire panel dataset from 1997-2006. Our strategy for identifying the price effects of milfoil exploits the substantial spatial and temporal variation present in the full panel dataset. Further, the structure of our data allows us to exploit developments in panel data methods and estimate cluster-robust standard errors, where each lake is a natural cluster. Inference with cluster-robust standard errors requires no assumptions on correlation within a cluster, and places no assumptions on the form of heteroskedasticity (Cameron and Trivedi 2005; Ch. 24). Since clusters are defined as spatial neighborhoods of property transactions, cluster-robust standard errors allow for inference robust to any form of spatial correlation within each lake without introducing additional structure to the model.

Econometric Identification Strategy

The full dataset consists of a total of 1,841 observations, spanning 172 lakes. The price of parcel *i* on lake *j* during time *t* takes one of two general forms:

$$\underline{\text{Random effects:}}\quad P_{it} = X_{it}^{'}\beta + Z_{j(i)t}^{'}\phi + \delta_1 \cdot Impact_{j(i)} + \delta_2 \cdot Before_{j(i)t} + T_t^{'}\delta_3 + \mu_{j(i)} + \varepsilon_{it} \qquad (2)$$

$$\underline{\text{Fixed effects:}}\quad P_{it} = X_{it}^{'}\beta + \delta_2 \cdot Before_{j(i)t} + T_t^{'}\delta_3 + D_{j(i)}^{'}\alpha + \varepsilon_{it} \qquad (3)$$

where X_{it} is a Kx1 vector of variables specific to parcel *i*, $Z_{j(i)t}$ is an Lx1 vector of variables specific to lake *j* that contains parcel *i*, T_t is a Jx1 vector of year-specific dummy variables that accounts for year-specific price shocks that affect all parcels, and $Impact_{j(i)}$ and $Before_{j(i)t}$ are variables included to identify the difference-in-differences effect of milfoil (discussed below). In (2), $\mu_{j(i)}$ is the lake (neighborhood) specific random error associated with lake *j* where parcel *i* is located. In (3), $D_{j(i)}$ is an NLx1 vector of dummy variables associated with lake *j* where parcel *i* is located, where NL indicates the number of distinct lakes in the sample. Table 3 presents a description of additional variables specific to the difference-in-differences specification.

The purpose of the fixed and random effects is to absorb any unobserved (and observed in the fixed effects case) spatial heterogeneity that is clustered within lakes. Consistent estimation of all parameters with equation (2) requires the assumption that the set of independent variables $\left\{X_{it}, Z_{j(i)t}, Impact_{j(i)}, Before_{j(i)t}, T_t\right\}$ are uncorrelated with both $\mu_{j(i)}$ and ε_{it}. The key difference between the fixed and random effects models is that the fixed effects are not present in the error term, and so consistent parameter estimates are possible even if correlation exists between the fixed effects and independent variables. 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 separately included.

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 were invaded with milfoil after 1999.[21] For the nine lakes invaded during 2000-2005, the dataset contains 81 transactions before invasion and 80 transactions after invasion. 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 effects model. The additive result of the coefficients on $Impact_{j(i)}$ and $Before_{j(i)t}$[22] – ($\delta_1 + \delta_2$) 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 δ_2. Therefore, the parameter on the variable $Before_{j(i)t}$ (δ_2) enables us to back out the difference in premium on milfoil lakes relative to non-milfoil lakes, before they became infested.[23]

Many lakes in the dataset underwent a change related to minimum frontage zoning in May, 1999, creating a potential temporal confounding factor. We account for temporal variation in zoning 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 remained zoned at 200 ft. minimum frontage before and after the new ordinance.

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 the precise year of invasion varying across lakes. Conversely, in the difference-in-difference hedonic model of 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 on each lake 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.[24] As a contrasting example, zoning laws are put in place over time 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 confounded by prior expectations of the zoning change, and as such, we have less confidence in our difference-in-differences estimates of the effects of the zoning change. In the case of milfoil, 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 the study region are free of milfoil. Therefore, the effects associated with an invasion are unlikely to be diluted by any previous expectations about such an event.

The last econometric issue to discuss is the use of a ten year time-series of property transaction sales. Given the lack of theoretical guidance in addressing temporal variation in the data, we account for price inflation in two ways. First, a vector of dummy variables T_t is included for each observation to specify the year a given transaction takes place. This specification absorbs any year-specific effects on price. Second, we re-define T_t as a trend variable 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 with the linear specification 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:

$$P_{it} = \beta_1 \cdot (Structure) + e^{X'_{it}\beta + \delta_2 \cdot Before_{j(i)t} + T'_t \delta_3 + D'_{j(i)}\alpha} + \varepsilon_{it} \tag{4}$$

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.[25] The assumption that the assessed structural effects are independent of land-based attributes is consistent with the explicit assumptions used in property assessments.

Spatial Difference-in-Differences Results

Tables 4 and 5 summarize the results from the spatial difference-in-differences model[26], where the non-linear form (4) is estimated with non-linear least squares (NLLS). 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 linear and non-linear forms (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 time variable 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 *Structure*, *Lot size*, *Frontage*, *Frontage*^{2}, and the time variables are nearly identical and of the same order of statistical significance.

Robustness in functional form is illustrated 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. Given the sensitivity of the gradient algorithm used to solve the non-linear model, lakes with fewer than five transactions were omitted, resulting in a loss of 127 observations. We also examine the possibility of an incidental parameters problem – common in non-linear fixed effects models with short panels (Greene 2003, p. 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. In addition to the parcel-specific and time variables, the variables *Access*, *Parcel density*, and *Muskie* are significantly different from zero 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, or across 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 linear fixed effects model—a statistically significant premium of approximately $28,000 with the time-dummies, and approximately $29,500 with the trend variable. The estimated milfoil premium from the non-linear model is a discrete-change effect: the difference in predicted price between milfoil lakes before and after infestation using the sample mean value of all other exogenous variables. The average price premium that existed on milfoil lakes before infestation is $32,087 and is significantly different from zero at a 95% confidence level for the non-linear models.[27]

It was argued above that any correlation between the milfoil variable and the error term in the random effects model would render the 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. In addition, the estimated standard error of the *Before* coefficient is higher in the random effects model than in the fixed effects model. 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 restrictive identification assumptions across all estimated models, and combined with our use of cluster-robust standard errors, 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.

Marginal Willingness-To-Pay to Avoid Milfoil Invasions

Using the results from the spatial difference-in-differences hedonic model, insights 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). Given our use of a presence/absence dummy variable indicating a lake's milfoil status, the localized amenity change in this paper is the invasion of one additional lake with milfoil.[28] 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, more than $28,000 for a property on a lake free of milfoil, all else equal (depending on specification, results range from $28,000 to $32,087). With the non-linear model, the estimated marginal willingness-to-pay depends on the value of the other exogenous variables, and the average varies across milfoil lakes from a low of approximately $13,700 to a high of $48,400.[29] Since the price of land is a stream of rents in perpetuity, we can calculate the average annual marginal willingness to pay as approximately $1,400 (assuming a 5% discount rate). 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 8% of total *property value*, or 13% of total *land value*, net of the value of any structure. 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 (including prevention efforts on lakes not yet invaded). While the results of our analysis for marginal changes in milfoil invasions cannot be aggregated to examine the economic cost of milfoil on all 500 lakes, the marginal willingness-to-pay estimates for preventing an additional lake from being infested are nevertheless useful for examining policies aimed at preventing the spread of milfoil.

VII. 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: aquatic invasive species can depress land values. This result complements prior analyses that quantify the effects of fecal coliform counts and water clarity on the values of shoreline property (Leggett and Bockstael 2000; Poor et al. 2001). 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 specification 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 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-differences 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 ten years of property transactions used in our dataset. In addition, the neighborhood clustering aspect of properties allows us to estimate cluster-robust standard errors with no restriction on spatial correlation within neighborhoods.

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 most obvious example would be hedonic analyses of the many other aquatic invasive species that are readily spread by the movement of recreational boaters and anglers (e.g. zebra mussels, rusty crayfish, etc.), as the same endogeneity problems highlighted in this paper may also plague other hedonic analyses of aquatic invasive species. 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. While specific applications may naturally lend themselves to particular spatial structures, 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

Variable Name	Mean	Std. Dev.	Variable Description
Price	268,034.57	175,629.23	selling price of the property in real dollars (2006)
Structure	79,422.13	77,145.21	assessed structure value before transaction of the property
Lot size	2.06	2.60	size (in acres) of the property
Frontage	185.65	151.93	frontage (in feet) of the property
Lake area	503.75	530.32	surface area (in acres) of the lake that the property borders
Assoc	0.39	0.49	=1 if the property is on a lake with an association and 0 otherwise
Access	0.86	0.35	=1 if the property is on a lake with public access and 0 otherwise
Parcel density	0.35	0.21	number of private parcels divided by the area of the lake that the property borders
Zone	180.04	42.15	minimum frontage requirement for the lake that the property borders
Max depth	36.14	18.83	maximum depth (in feet) of the lake that the property borders
Prime	0.04	0.20	=1 if transaction of the property takes place between June 1 and September 30 and is subjected to milfoil
Milfoil			represents multiple variables, including i) relative frequency—a continuous measure of lake-wide milfoil abundance, ii) dummy variables representing low (0%<relative frequency<3%), and 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.
*Frequency**	0.78	2.60	
*Low**	0.11	0.32	
*High**	0.09	0.28	
*Present**	0.20	0.40	
*Treat**	0.03	0.17	=1 if the lake the property borders was treated for milfoil before the transaction within the same calendar year
*2006**	0.47	0.50	= 1 if the transaction took place in 2006
Water clarity	3.04	1.19	water clarity (secchi depth) measure of the lake that the property borders
Fishing Indices			index for quality of each fishery (muskie, pike, walleye, bass, and panfish) on the lake the property borders
Muskie	2.53	1.37	
Pike	1.16	0.80	
Walleye	1.40	0.81	
Bass	1.27	0.50	
Panfish	1.84	0.75	
Distance	12.75	8.30	Distance to nearest town (in miles)

Note: all descriptive statistics are based on the full panel data set unless denoted by an asterisk

TABLE 2
Cross-Sectional Estimation Results

	Model 1		**Model 2**		**Model 3**	
R^2	.7471		.7545		.7475	
	Coef.	**Robust Std. Err.**	**Coef.**	**Robust Std. Err.**	**Coef.**	**Robust Std. Err.**
Constant	-29323.54	40574.02	-46644.35	40329.50	-23471.11	39327.08
<u>Parcel-Specific Variables</u>						
Structure	1.59*	0.09	1.60*	0.09	1.58*	0.09
Lot size	7280.03**	4199.14	7835.79**	4079.69	7495.90**	4137.11
Frontage	580.67*	129.00	574.75*	125.47	599.83*	127.81
Frontage^2	-0.54*	0.13	-0.54*	0.13	-0.55*	0.13
<u>Milfoil Variables</u>						
Prime	-38.57	18517.67	8697.20	20222.73	16461.34	21061.81
Milfoil_freq	3057.69	2094.53	--	--	--	--
*Milfoil_freq*treat*	22698.47*	4760.33	--	--	--	--
Milfoil _low	--	--	-56054.44*	19706.23	--	--
Milfoil _high	--	--	53511.59*	26397.99	--	--
*Milfoil_low*treat*	--	--	169173.60*	47504.18	--	--
*Milfoil_high*treat*	--	--	101653.80*	26250.68	--	--
Milfoil_pres	--	--	--	--	-18008.47	19099.63
*Milfoil_pres*treat*	--	--	--	--	121779.30*	31329.00
<u>Other Lake-Specific Variables</u>						
Lake area	4.34	11.23	11.30	11.09	5.61	11.38
Assoc	-10757.95	11336.24	-12797.72	11579.82	-11829.46	11446.83
Access	19100.89	18263.10	21254.44	18406.01	18673.47	18193.20
Parcel density	-77277.76*	32256.91	-47817.36	32485.12	-57975.23**	32585.24
Zone	-129.09	170.94	-250.71	174.49	-164.23	172.35
Max depth	634.82	490.99	835.46**	493.72	588.28	478.08
Water clarity	13893.85*	6834.28	14355.30*	6771.99	13367.93*	6801.19
Muskie	16620.55*	5895.60	14011.07*	5818.25	16905.81*	5797.43
Pike	17715.32*	7275.70	15246.65*	7022.79	14762.55*	7262.75
Walleye	3250.71	9350.02	3273.84	9888.55	8776.44	9629.07
Bass	-2796.30	8579.56	-5530.87	8662.92	-3275.32	8613.91
Panfish	2269.80	7257.99	3552.07	7158.59	2309.16	7264.91
Distance	3708.20	2801.70	8089.48*	3043.95	2994.18	2756.78
Distance^2	-133.01	84.56	-247.78*	91.86	-117.09	84.03
<u>Time Variables</u>						
2006	-10896.12	10176.09	-13116.00	10108.00	-11277.33	10169.76

Note: n = 457 for all models. All standard errors are calculated with White's method. All dollar amounts in 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

Variable Name	Mean	Std. Dev.	Variable Description
Impact	0.21	0.41	= 1 if the property is on a milfoil-infested lake as of 2006 and 0 otherwise
Before	0.04	0.21	= 1 if the property is on a milfoil-infested lake AND the transaction occurs before infestation
Zone_100_any	0.47	0.50	= 1 if the 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
Zone_200_300	0.06	0.23	= 1 if the 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
Aft_100_any	0.39	0.49	= 1 if the property borders a lake that has undergone a zoning change from 100ft to some other amount AND the transaction takes place after the change
Aft_200_300	0.05	0.22	= 1 if the property borders a lake that has undergone a zoning change from 200ft to 300ft AND the transaction takes place after the change
Time			Represents two sets of variables: 1) In the first case, a dummy variable is used to designate the transaction year (=1 if the 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.
1998	0.09	0.29	
1999	0.09	0.29	
2000	0.08	0.27	
2001	0.10	0.29	
2002	0.10	0.31	
2003	0.12	0.33	
2004	0.11	0.31	
2005	0.13	0.34	
2006	0.12	0.32	
Trend	5.02	2.78	
$D_{j(i)}$	--	--	= 1 to designate which lake the property borders

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

	Fixed Effects		**NLLS Fixed Effects**		**Random Effects**	
	Coef.	**Robust Std. Err.**	**Coef.**	**Robust Std. Err.**	**Coef.**	**Robust Std. Err.**
Constant	--	--	--	--	-112349.00*	37987.74
Parcel-Specific Variables						
Structure	1.52*	0.05	1.51*	0.06	1.53*	0.05
Lot size	5006.16*	1532.17	1.29*	0.31	5506.89*	1558.12
Frontage	235.26*	38.69	3.47*	0.71	224.47*	37.17
Frontage^2	-0.03	0.02	-2.36*	0.71	-0.03	0.02
Milfoil Variables						
Prime	8772.96	11824.45	-0.01	0.09	9807.78	11883.62
Before	28294.20*	9509.41	0.21*	0.08	18880.71**	11308.22
Impact	--	--	--	--	9006.63	17961.4
Other Lake-Specific Variables						
Lake area	--	--	--	--	17.29	16.8
Assoc	--	--	--	--	-2617.92	9081.45
Access	--	--	--	--	25158.20*	10160.32
Parcel density	--	--	--	--	-25378.54**	13399.38
Zone_100_any	--	--	--	--	38992.96*	14753.87
Zone_200_300	--	--	--	--	47270.34*	17061.8
Aft_100_any	-38626.53*	10353.54	-0.22*	0.07	-37379.73*	9817.65
Aft_200_300	-59163.00*	11118.07	-0.20	0.13	-43602.31*	11596.76
Max depth	--	--	--	--	641.80	406.57
Water clarity	--	--	--	--	7072.71	6228.02
Muskie	--	--	--	--	8578.92*	4057.88
Pike	--	--	--	--	3916.67	5633.33
Walleye	--	--	--	--	7947.29	6959.83
Bass	--	--	--	--	-3712.71	7427.99
Panfish	--	--	--	--	1052.25	6936.19
Distance	--	--	--	--	3389.18	2167.68
Distance^2	--	--	--	--	-108.85	62.82
Time-Variables						
1998	10095.20	10868.14	0.12	0.14	10946.07	10604.32
1999	54634.80*	13027.25	0.39*	0.13	53292.81*	12464.55
2000	63306.83*	13330.03	0.54*	0.12	61937.59*	12793.04
2001	60896.67*	11873.06	0.48*	0.11	59634.27*	11308.58
2002	79208.17*	14979.5	0.65*	0.14	78290.49*	14376.71
2003	95634.54*	14933.23	0.73*	0.13	93705.30*	14542.26
2004	109544.10*	14186.6	0.83*	0.13	108652.70*	13620.54
2005	128563.20*	15380.94	0.97*	0.12	127870.50*	14553.28
2006	128854.00*	16939.86	0.95*	0.14	121101.90*	16230.88

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. Data is clustered by lake, and all standard errors are cluster robust. All dollar amounts in 2006 dollars. Single asterisk (*) denotes significance at the 95% level; double asterisk (**) denotes significance at the 90% level.

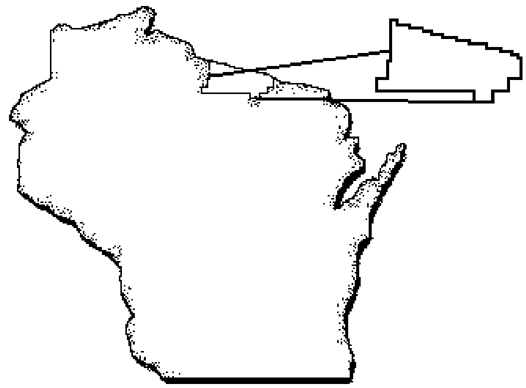
TABLE 5
Results for Spatial Difference-in-Differences Models with Year Trend Variable

	Fixed Effects		**NLLS Fixed Effects**		**Random Effects**	
	Coef.	**Robust Std. Err.**	**Coef.**	**Robust Std. Err.**	**Coef.**	**Robust Std. Err.**
Constant	--	--	--	--	-97264.30*	36375.36
<u>Parcel-Specific Variables</u>						
Structure	1.52*	0.06	1.51*	0.06	1.52*	0.05
Lot size	4928.06*	1483.99	1.28*	0.31	5379.84*	1516.35
Frontage	241.14*	39.0	3.57*	0.68	231.95*	37.51
Frontage^2	-0.04*	0.02	-2.51*	0.67	-0.03*	0.02
<u>Milfoil Variables</u>						
Prime	9471.35	11222.6	-0.02	0.09	9679.25	11266.38
Before	29518.13*	10425.13	0.2*	0.1	20893.91**	11720.78
Impact	--	--	--	--	8394.44	18146.18
<u>Other Lake-Specific Variables</u>						
Lake area	--	--	--	--	18.56	17.12
Assoc	--	--	--	--	-2438.35	9385.3
Access	--	--	--	--	24724.76*	10559.05
Parcel density	--	--	--	--	-24124.60**	13650.42
Zone_100_any	--	--	--	--	26024.91	15698.42
Zone_200_300	--	--	--	--	37591.62*	15450.28
Aft_100_any	-23783.32*	9097.6	-0.12**	0.07	-22806.40*	8839.28
Aft_200_300	-44400.53*	9533.34	-0.07	0.12	-31083.80*	8883.4
Max depth	--	--	--	--	614.54	428.78
Water clarity	--	--	--	--	6443.78	6628.68
Muskie	--	--	--	--	8303.25*	4144.46
Pike	--	--	--	--	3247.01	5840.7
Walleye	--	--	--	--	8587.34	7041.65
Bass	--	--	--	--	-3414.28	7612.22
Panfish	--	--	--	--	1404.82	7085.07
Distance	--	--	--	--	3203.29	2220.47
Distance^2	--	--	--	--	-102.55	64.35
<u>Time Variables</u>						
Trend	13537.41*	1265.53	0.1*	0.01	13105.92*	1201.68

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. Data is clustered by lake, and all standard errors are cluster robust. All dollar amounts in 2006 dollars. Single asterisk (*) denotes significance at the 95% level; double asterisk (**) denotes significance at the 90% level.

FIGURE TITLES

Figure 1. Map of Vilas County, Wisconsin



Endnotes

[1] For example, the discharge of ballast water by ships into a different body of water from where the ship originates is thought to be a primary avenue of aquatic species invasions. In response, the United States Environmental Protection Agency is currently proposing extensive regulations governing the discharge of ballast water.

[2] 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.

[3] Endogeneity arising from correlated unobserved neighborhood effects was likely the primary reason why the cross-sectional analysis of Halstead et al. (2003) found no conclusive evidence of variable milfoil on shoreline prices in a set of ten New Hampshire lakes (variable milfoil is a different, though related, species to Eurasian Watermilfoil).

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

[5] 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.

[6] The authors thank Mike Duening for supplying these data.

[7] The authors thank Barb Gibson for supplying these data.

[8] See Wisconsin Lakes Book at http://www.dnr.state.wi.us/org/water/fhp/lakes/list/#lakebook

[9] See Listing of Wisconsin Waters with milfoil at http://dnr.wi.gov/invasives/fact/milfoil/charts/ewm2006_by_county.pdf

[10] See Wisconsin Lakes Book (cited above) and Wisconsin Muskellunge Waters: Vilas County at http://www.dnr.state.wi.us/fish/musky/lakes/vilas.html

[11] We thank Jen Hauxwell of the DNR, Crystal Koles and Melissa Davison of Northern Environmental, and Tim Hoyman of Onterra for assistance with the abundance data.

[12] The ratings distinguish lakes as: trophy fisheries, consistent action with strong populations, intermediate action, minor populations, and waters with no muskie. Rankings for other fish species are not based off surveys as detailed as the muskie ratings and range from 0 (not present) to 3 (abundant)

[13] A lake can be pristine because it either has significant amounts of publicly owned shoreline, or because the average privately owned parcel is large.

[14] Lakes infested with milfoil in the dataset 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.

[15] In a recent survey of shoreline property owners in the region, milfoil invasions were one of the most frequently voiced lake management concerns. Without prompting, many respondents mentioned milfoil concerns in a section requesting general comments. For more details on the survey, see the website: lter.limnology.wisc.edu/lakeresident_survey_summary.pdf..

[16] We thank Nicole Nikolaus and Jen Hauxwell of the Wisconsin DNR for their assistance with treatment records.

[17] 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, p. 173).

[18] The Akaike information criterion for the linear (Box-Cox) model is 16.35 (16.32), and all qualitative conclusions are identical across both specifications.

[19] See Horsch (2008) for more detail on other specifications.

[20] Given the presence of highly irregular lake shorelines with numerous bays and peninsulas, the use of a distance threshold is questionable in this application. Further, given the density of lakes in our study region, many parcels will be closer in Euclidean distance to parcels on other lakes than to parcels on their own lake, and so using Euclidean distances is also highly questionable.

[21] 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.

[22] 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 price premium with respect to *Impact* is $\delta_1 + \delta_2$ in the random effects model. The second component of this effect, δ_2, is turned on or off depending if the ith transaction took place before or after an infestation.

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

[24] One potential confounding variable would be if milfoil lakes experienced significantly more new development over this period, and hence, increases in nutrient loading that could be correlated with milfoil. However, this is unlikely since the lakes invaded with milfoil in our sample experienced a minor average development increase of approximately 2% in parcel density.

[25] An alternative to the linear and non-linear approaches employed here would be to estimate the difference-in-difference effects with Athey and Imbens' (2006) non-parametric estimator.

[26] The Within estimator is used to estimate coefficients in the linear fixed effects model (see Cameron and Trivedi 2005).

[27] Standard errors of the discrete-change effect are calculated with the Delta Method (Greene 2003, p. 70).

[28] Our results can only be used to derive the implicit price of being on a lake infested with milfoil, not the implicit price of reducing the abundance of milfoil on an already infested lake.

[29] The average willingness-to-pay for each milfoil lake is significantly different from zero at the 5% level and is calculated with the lake-specific sample mean values of the exogenous variables.