Quantifying the Economic Effects of Invasive Species:
A Non-Market Valuation Analysis of Eurasian Watermilfoil

by

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Abstract

One consequence of our increasingly globalized world is the ease at which humans and other species can move or be moved around the planet. As a result, exotic species have been accidentally or intentionally introduced to non-native areas, many of which have become invasive. Consequently, vast sums of money are spent each year to control the spread of invasive species and to address their adverse effects on ecosystems and the economy.

Generally, the costs of invasive species are estimated based on the costs of managing species invasions, including the amount that must be spent to repair infrastructure damage. However, this is a conservative estimate of the social costs associated with invasive species as they also affect biodiversity, ecosystems, and other environmental amenities whose values are not readily observed in a market. Relatively little economic research has been done concerning the non-market effects of invasive species.

The purpose of this study is to estimate a hedonic pricing model of lakeshore property values to quantify the economic costs of a common aquatic invasive species, Eurasian watermilfoil (EWM), across an extensive lake system in the northern forest region of Wisconsin. The hedonic pricing model is estimated using a database on property sales and lake-specific characteristics over the period 1997-2006.

While the primary purpose of the hedonic analysis is to isolate the price effect associated with the presence and abundance of EWM, two major econometric challenges arise: spatial autocorrelation and the endogeneity of EWM. Spatial autocorrelation arises due to the fact that the prices associated with multiple parcels on the same lake are likely to be influenced by similar unobserved lake-specific characteristics. Endogeneity problems arise because EWM is typically spread by the movement of recreational boaters, where boaters are more likely to visit lakes with attractive characteristics. To the extent that the attractiveness of a lake is unobserved to the analyst, EWM will be correlated with the error term in the hedonic model and OLS estimation will produce coefficient estimates that are positively biased.

Both issues are accounted for, in part, by defining each lake as a natural neighborhood and estimating a fixed effect for each lake within the model. The endogeneity of EWM is further accounted for by exploiting recent EWM invasions as a natural experiment with a difference-in-difference approach to hedonic analysis. Since only a portion of properties in the data set are affected by EWM, this methodology is useful for identifying the unbiased effect of EWM, eliminating any differences that may have been present before its introduction. Thus, the methodology used requires a panel data set to ensure observations are present both before and after the introduction of EWM.

Results indicate that lakes invaded with EWM experienced an average decrease in land values by 13% *after* invasion. The EWM results are robust across linear and non-linear specifications. This study addresses a topic that is both unique to the current environmental economics literature and yet widely important for all natural resource management. Despite the documented prevalence and detrimental effects of EWM, the associated economic and social costs are yet to be understood. In addition, the econometric challenges seen in this study are highly relevant to the field in general, particularly with the growing focus on spatial econometrics. Solutions for the issues of spatial autocorrelation and endogeneity remain elusive. The spatial difference-in-difference specification presented in this study offers a unique solution to these challenges, yet is simple enough to be estimated with linear regression techniques.

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Chapter One: 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). Accordingly, countries around the world spend vast sums of money each year to control the spread of invasive species and to address their destructive effects on ecosystems and the economy. In particular, the United States spends approximately $120 billion each year due to invasive species (USDA 2007a). An invasive species is classified as a non-native species "whose introduction causes or is likely to cause harm to the economy, environment, or human health" (USDA 2006). One consequence of our increasingly globalized world is the ease at which humans and other species can move or be moved around the planet. As a result, exotic species are accidentally introduced to non-native areas—such as the zebra mussel that was inadvertently brought into the Great Lakes—or intentionally introduced, as was the cane toad in Australia for the purpose of agriculture. Many species have been spread throughout the world, but it is only those who can survive, thrive, and alter their new ecosystems that are considered invasive.

Generally, the costs of invasive species are estimated based on the economic losses that they cause or on the amount that must be spent to repair infrastructure damage (see Eiswerth and van Kooten 2002). However, this is a conservative estimate of their true costs to society because invasive species can affect environmental goods and services that have non-market characteristics. As is the case with other forms of environmental degradation, invasive species also affect biodiversity, ecosystems, and other environmental amenities. For example, a collapsed fishery in a recreational lake may not have an easily measured economic impact, but the loss in recreation is clearly a cost that should be considered.

There is still much work to be done to quantify the true social costs of invasive species, or the benefits from preventing or managing invasions. From a policy perspective, a clearer understanding of the benefits associated with avoidance and treatment of invasive species allows for more-informed policy decisions. While present expenditures are largely known, benefits remain elusive and difficult to quantify.

Non-market costs and benefits have been a focus of environmental economics for many years. Hedonic analysis is one technique often employed to determine the value of non-market goods, such as environmental quality or degradation. Hedonic analysis is a useful method for valuing non-market goods because it allows the researcher to use a differentiated good that has measurable economic value, such as property, and determine how any given characteristic of that good affects its price. For example, the selling price of a piece of property is influenced by the value of the structure, location, environmental goods, and other factors. If one can control for the effects of the non-environmental characteristics, the marginal contribution of the environmental good(s) of interest can be determined (Boyle and Kiel 2001, p. 117-118). This implies, all else equal, that consumers would generally be willing to pay more for a property with higher environmental quality than a similar property with lower environmental quality. The idea of hedonic analysis is to isolate this differential to quantify the value assigned to the non-market good.

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 (EWM). Our case study uses property transaction data across an extensive system of more than 170 lakes in the northern forest region of Wisconsin. EWM is a submerged aquatic plant characterized by dense stands that have a variety of negative effects on native plants and animals, along with its limiting effect on recreation activities. Once established, EWM is extremely difficult to remove without clearing native vegetation. The data used for estimation cover a period (1997-2006), in which several lakes in the study region become invaded with EWM. Hedonic results presented in this paper provide early evidence regarding the effects of invasive species on property values, and thus, should prove to be a useful input in designing efficient resource management strategies to control species invasions.

The econometric challenges explored in this paper are ubiquitous across hedonic pricing models and the empirical methods developed here have broader implications. Two major econometric challenges arise: spatial autocorrelation and endogeneity. Spatial autocorrelation arises because parcel values on the same lake are likely to be influenced by similar unobserved neighborhood or lake characteristics. Endogeneity problems arise because EWM is typically spread by the movement of recreational boaters, where boaters are more likely to visit lakes with attractive characteristics. To the extent that the attractiveness of a lake affects property values and is unobserved to the analyst, EWM will be correlated with the error term in the hedonic model and OLS estimation will produce coefficient estimates that are positively biased.

Spatial autocorrelation is accounted for by defining each lake as a natural neighborhood, where a fixed effect is specified for each lake within the model. All properties on a given lake are assumed to share this fixed effect since many spatial characteristics are lake-specific. The endogeneity of EWM is resolved by exploiting recent EWM invasions as a natural experiment with a difference-in-difference approach to hedonic analysis. This methodology is useful for estimating an unbiased effect of an EWM invasion, eliminating any differences that may have been present between affected and unaffected lakes before invasions took place. Intuitively this approach looks at the difference in price premium before and after invasions for properties on affected lakes, relative to those on unaffected lakes. When unobserved and observed neighborhood effects are correlated, this study demonstrates the necessity of both a difference-in-difference framework combined with a fixed neighborhood effects econometric specification in order to achieve identification.[1]

Solutions for the issues of spatial autocorrelation and endogeneity have remained elusive in the hedonic pricing literature, as has been seen in a variety of studies. As a growing number of researchers continue to grapple with these issues, this study offers an opportunity to examine potential solutions to the spatial econometric challenges associated with hedonic models. Furthermore, 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. Relatively little economic research has addressed the true costs of invasive species by incorporating non-market values. This study helps to alleviate this deficiency of the literature by examining the case of EWM in several Vilas County, WI lakes.

The paper is organized as follows. Chapter Two is used to provide an overview of invasive species, highlighted by a subsection that focuses on EWM. A discussion of the study region, Vilas County, WI, is also presented. A review of the relevant literature is covered in Chapter Three, which is supported by a theoretical discussion of hedonic pricing models. A discussion of the data used is provided in Chapter Four. Chapter Five provides an outline of the cross-sectional model that is estimated, while the results of this estimation are explored in Chapter Six. Chapter Seven moves into alternative modeling approaches, using the results in Chapter Six to motivate the econometric challenges dealt with in these latter models. Finally,

[1] Fixed effects results are contrasted with a random effects approach, revealing that unobserved spatial heterogeneity is an issue of both inefficiency *and* bias when the fixed component is correlated with observed characteristics.

Chapter Eight is used to provide an analysis of the results from these final estimations, while conclusions are offered in Chapter Nine.

Chapter Two: Purpose and Motivation

2.1 Invasive Species

Nationwide, about 50,000 exotic species are now established, roughly half of which are plants. There are two important distinctions to make concerning invasive species. First, not all exotic introductions are detrimental to society. About "98% of the US food supply, including wheat, rice, domestic cattle, and poultry, come from introduced plants and animals" (SGNIS 2008). Second, only about 10% of non-native species become a nuisance (Cornell 2008). Thus, of the 50,000 introduced species, about 5,000 have been deemed invasive.

While the vast majority of non-native introductions die off or fail to flourish in their new environment, the invasive pests that emerge share several characteristics that help them adapt to their new habitat (Pimentel, Zuniga, and Morrison 2005, p. 82). First, if there is no biological control or natural predator for the non-native species, it is more likely to multiply and spread. Similarly, the species is more likely to flourish if it encounters a natural advantage in predation in its new habitat. If the affected ecosystem is disturbed, weak, or amenable to a variety of new species, or if the introduced species is highly adaptable in general, the exotic species is also more likely to thrive.

The effects of invasive species can be far-reaching, from displacing native species, disrupting ecosystems, and limiting recreational activities, to the more general damage they cause commercial, agricultural, and aquacultural resources (Wisconsin DNR 2008). Once an invasive species is in place, it can become very difficult, if not impossible, to remove. Moreover, costs of management and control are often incurred in perpetuity and vary directly with the population size of the species. For this reason, it is more prudent and less costly to prevent an invasion than to eradicate or manage an existing invasive species (NOAA 2008).

Thus, recent efforts have been directed at technologies or other policy measures that reduce the risk of an introduction.

It is clear that non-native introductions, particularly those that are intentional, may not have the intended outcome. The case of the cane toad in Australia is a clear example of this. Introduced in Australia around 1935 for the purpose of controlling greyback cane beetle pests, the cane toad ultimately did little to control the pest population and has a become an invasive species of its own. These toads have severely upset the food web and local ecosystems by preying on and competing for small animals and poisoning larger predators when eaten.

The cane toads were introduced for the purpose of reducing variation in agricultural yields due to pests. Broadly speaking, agriculture is one of the critical areas of concern associated with terrestrial invasive species. In the US, "about 40% of our insect pests are exotic, costing $14.5 billion annually in damage" (SGNIS 2008). In turn, billions of pounds of pesticides are now applied each year, which has had further ecological consequences. One of the greatest emerging threats to agriculture and food security is the invasive parasite mite, varroa destructor (often associated with colony collapse disorder), which has decimated honey bee populations, leading to reductions in pollination and dependant crop yields.

With the exception of natural boundaries, terrestrial-based invasive species, such as the ones mentioned above can spread across land-locked areas almost at will. For this reason, terrestrial invasive species pose a great challenge, perhaps even greater than that faced by aquatic invasive species (AIS), as climate serves as the lone mechanism for reducing further spread. AIS, while certainly capable of spreading on their own, have a much more difficult time doing so without the help of humans or other organisms. This is not to say that AIS are easy to prevent or control, but perhaps easier so than their terrestrial counterparts. From this standpoint, policies aimed at controlling AIS may have sizable associated benefits.

2.2 Aquatic Invasive Species

Since EWM is the species of interest in this study, it is worth examining the nature of AIS more closely. AIS 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. The associated damages and costs of controlling aquatic invaders in the United States are estimated to be $9.2 billion annually, as shown in Table 1.

Table 1. Summary of Damages and Costs Associated with Aquatic Invasive Species

Fish	$5.4 billion
Zebra and quagga mussels	$1 billion
Asiatic clam	$1 billion
West Nile Virus (WNV)	$1 billion
Aquatic plants	$500 million
Shipworm	$205 million
Green crab	$100 million

(SGNIS 2008)

One of the more serious ecological effects of invasive species is their ability to drive native species to extinction. With AIS, "40% of native species extinction has been attributed to predation, parasitism, and competition from biological invaders" (SGNIS 2008). AIS also disrupt aquatic ecosystems and a variety of valuable economic resources.

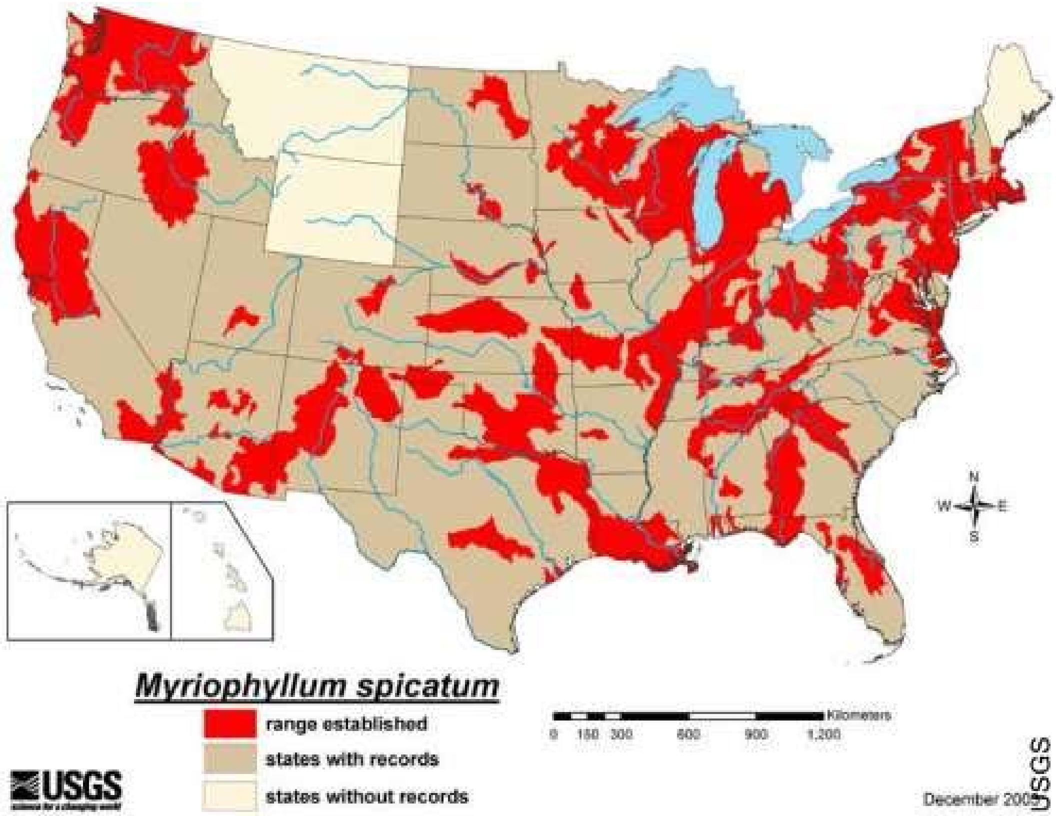
Many AIS, including EWM, are believed to have been transported to the United States via the ballast tanks of foreign ships (WSJ Editorial 2008). Ballast water is used by boats of all sizes for stability and improved control, among other reasons. Large cargo vessels take in water to store in ballast tanks when the load is light and discharge the water when heavily laden with cargo. Since ballast water is often discharged in a body of water different from where it originated, foreign species can be introduced to the site of discharge. The EPA has previously exempted the discharge of ballast water from the Clean Water Act, but will develop regulations that will take effect September 30, 2008. Under the proposed Vessel Discharge Permit Program, the EPA estimates “approximately 143,000 commercial vessels and potentially more than 13 million state-registered recreational boats and more than 25 different types of vessel discharges could be affected” (EPA 2008).

Once established along coastal bodies of water, the Great Lakes, the Mississippi River, or other major waterways, EWM and other AIS have been spread inland, primarily by recreational boaters and fisherman. Due to its importance as a trade route, “the Great Lakes basin is the aquatic gateway to the heartland of America and a hot spot for aquatic invasive species” (NOAA 2008). The Great Lakes basin provides a home for over 162 AIS; the earliest invasive species in these waters was the sea lamprey, having been established since the 1820s (NOAA 2008). With its eastern and northern boundaries bordering Lake Michigan and Lake Superior respectively, Wisconsin is a prime target for invasive species seeking to expand inland.

2.3 Eurasian Watermilfoil in the United States

While EWM is a particular issue of concern for Wisconsin, it is a problem faced more broadly in this country, as shown in Figure 1.

Figure 1. Distribution Map of Eurasian Watermilfoil



(USGS 2003)

Currently, EWM is known to exist in 45 states. It is likely present in the five remaining states, but no records exist to confirm this. EWM is "a submersed aquatic plant native to Europe, Asia, and Northern Africa" (Seely 2007). It is "among the most troublesome submerged aquatic plants in North America" (Smith and Barko 1990, p. 55). 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). EWM was first discovered in the Chesapeake Bay in the late 19th century and has been spread and found around the country ever since.

EWM is an opportunistic species that thrives in many different environments and reproduces rapidly and successfully. This often leads to dense stands of EWM that have a variety of negative effects on lake ecosystems and recreation. These stands block out sunlight, limiting the ability of native plant species to grow. They also inhibit the ability of larger fish to prey on smaller ones. Furthermore, they limit recreational activities and can "interfere with power generation and irrigation by clogging water intakes" (Washington 2006). Dense mats of EWM also provide a good habitat for mosquitoes and can increase the sedimentation rate (Washington 2006).

It is not clear which characteristics of a lake, if any, cause a lake to be more venerable to infestations of EWM. In general, it is believed that EWM prefers highly disturbed lake beds and lakes receiving nitrogen and phosphorous-laden runoff. Higher water temperatures promote multiple periods of flowering and fragmentation. Based on past infestations, it appears that EWM has become a distinct problem in nutrient-rich lakes. However, there have certainly been exceptions to this trend. A variety of factors are at work within any lake, complicating the predictive power about future infestations and the associated severity thereof.

Once established, EWM is quite difficult to remove without clearing native vegetation. Thus, efforts have been made to educate boaters and fishermen on how further spread can be avoided. This point about the persistence of EWM is central to this paper because it demonstrates that the mere presence of EWM is the greatest concern of lakefront property owners, as opposed to the level of infestation at any given time. Certainly concerns about abundance levels exist, but the prevention of EWM is crucial to homeowners and policy-makers. In fact, the time-growth relationship for EWM has been well-documented and remains unclear. One of the first places to become infested with EWM, Chesapeake Bay, showed few signs of the species for over sixty years, before EWM exploded and became a major nuisance. In other cases, EWM populations have taken little time to take over their host body of water (see

Maryland DNR 2008; Smith and Barko 1990; Vermont DEC 2008; and Wisconsin DNR 2007). With this type of uncertainty, the presence-absence criteria is of chief concern

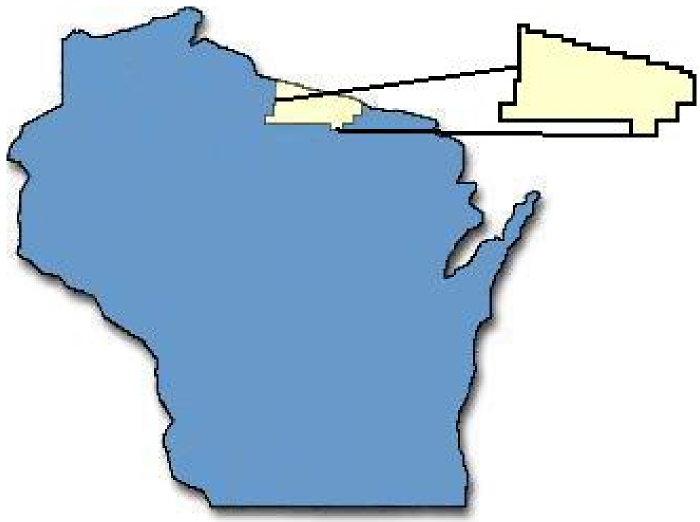
2.4 Eurasian Watermilfoil in Vilas County, WI: Description of the Study Region

EWM has been detected in about 500 lakes (or about 3.3%) throughout Wisconsin (Wisconsin DNR 2007). It is distributed fairly evenly from north to south, but is more prevalent in the eastern half of Wisconsin due to its proximity to Lake Michigan. It was originally detected in southern counties, as early as the 1960s, and moved north and elsewhere across the state over time (Vilas County 2000). While EWM is certainly a national concern, this study focuses particularly on the presence of EWM in several lakes within Vilas County, WI.[2]

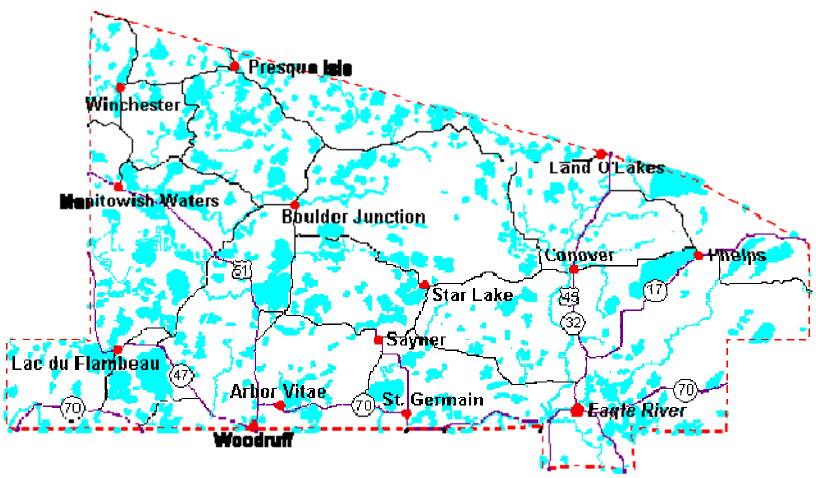
Vilas County is located in Northern Wisconsin, bordering the Upper Peninsula of Michigan. As shown in Figure 2, Vilas County boasts one of the densest collections of freshwater lakes in the world. Of the 1018 square miles that the county covers, 14.2%, or 144 square miles (about 94,000 acres), is water, which is composed of 1318 lakes (Wisconsin Online 2008). The largest of these lakes is Trout Lake at about 3800 acres. Most of the county is dotted with small lakes, fragmenting the landscape and shaping the focus of local residents and tourists.

[2] This is, in part, because hedonic analysis requires a common land market.

Figure 2. Map of Vilas County



(Wisconsin's Work.net 2008)



(Vilas County 2008)

Northern Wisconsin, and Vilas County in particular, has become Wisconsin's playground for Wisconsinites and other Midwesterners. This area has historically served as a weekend getaway for urbanites from the south, such as those from Milwaukee, Madison, and even Chicago. Many have put down a second set of roots, buying property in Vilas County, much of which is lakefront. These second-homes have spurred much development in the county that is not without controversy. Since 1960, 60% of previously undeveloped lakes have been developed and density has increased from five to nearly forty houses per mile of lakefront frontage (Wisconsin DNR 1996). This robust growth led to the passage of a county-wide zoning ordinance in 1999, aimed at controlling lakefront development.

In 1965, the State of Wisconsin passed a statute (Wisconsin Administrative Code NR 1965), mandating that all residential shoreline properties have at least 100ft of frontage. Before that time, the state had no mandate on minimum frontage for such properties. In Vilas County, Presque Isle had its own township-wide requirement of 200ft before the state minimum went into effect, passing this zoning law in 1959. Six of the remaining 14 townships passed similar mandates throughout the following decades (see Table 2).

Table 2. Zoning Regimes in Vilas County

Town	Year Enacted	Min. Width (ft.)	Min. Area (sq. ft.)
Boulder Junction	1972	200	40,000
Conover	1977	200	40,000
Lac du Flambeau	1994	200	30,000
Land O'Lakes	1972	200	40,000
Manitowish Waters	1986	200	50,000
Presque Isle	1959	200	65,340
Winchester	1995	200	60,000

Despite the zoning restriction placed on development density in these townships, development in Vilas County continued. Concern for deteriorating lake quality and over-congestion of lakes grew to the point where a county-wide zoning code was needed. To support this process, the Wisconsin DNR developed a grant program in the mid-1990s to help counties classify lakes according to the current level of development and ecological sensitivity. These characteristics would be the chief criterion for rezoning lakes under the Vilas County Shoreland Zoning Ordinance, which went into effect May 1, 1999. The ordinance was established to:

> …further the maintenance of safe and healthful conditions; protect spawning grounds, fish and aquatic life; preserve shore cover and natural beauty; prevent and control water

> pollution; prevent erosion of the soil; preserve the compatibility of proposed development with existing land and water usage; and control building sites, placement of structures and land uses. (Vilas County 1999, p. 3)

According to the classification work that was done, it was determined that lakes should be zoned such that minimum frontage would be 150, 200, or 300 feet. For townships that had previously established a 200ft minimum, those laws would supersede the ordinance, allowing more strict zoning, but keeping the minimum frontage at 200ft.

Instead of a one-size fits all approach to zoning, as had previously been in effect at the township level, the classification scheme was used to establish zoning at the lake-level. In theory, this should maximize the efficiency of zoning laws. If a lake is very sensitive to development, the restriction on density would be understandably greater, and vice versa. With a one-size fits all approach, many lakes would be zoned too strictly, while others would be zoned with too much leniency.

The classification itself is shown below as Figure 3. Lakes can fall into one of nine cells of the matrix, depending on the current level of development and ecological sensitivity. Ecological sensitivity includes aspects such as lake area, shape of shoreline, soil sensitivity, among others. Development level was determined using a measure of structures per mile of privately owned frontage (Vilas County 1999).

Figure 3. Vilas County Lakes Classification Matrix

Lake Classification Matrix for Lakes Greater than 50 Acres			
Sensitivity to Development	**Current Level of Development**		
	Low Development Level	**Medium Development Level**	**High Development Level**
High Sensitivity	Minimum lot area = 60,000 ft^2 Minimum frontage width = 300 feet Minimum lot width = 270 feet	Minimum lot area = 40,000 ft^2 Minimum frontage width = 200 feet Minimum lot width = 180 feet	Minimum lot area = 40,000 ft^2 Minimum frontage width = 200 feet Minimum lot width = 180 feet
Medium Sensitivity	Minimum lot area = 40,000 ft^2 Minimum frontage width = 200 feet Minimum lot width = 180 feet	Minimum lot area = 40,000 ft^2 Minimum frontage width = 200 feet Minimum lot width = 180 feet	Minimum lot area = 30,000 ft^2 Minimum frontage width = 150 feet Minimum lot width = 135 feet
Low Sensitivity	Minimum lot area = 30,000 ft^2 Minimum frontage width = 150 feet Minimum lot width = 135 feet	Minimum lot area = 30,000 ft^2 Minimum frontage width = 150 feet Minimum lot width = 135 feet	Minimum lot area = 30,000 ft^2 Minimum frontage width = 150 feet Minimum lot width = 135 feet

(Vilas County 1999)

The lakes classification matrix applies only to lakes over 50 acres. Anything smaller is zoned at the strictest level.

As of the 2000 census, there were 21,033 people, 9,066 households, and 6,300 families in Vilas County. The population density was 10 households per square mile. There were 22,397 housing units at an average density of 26 per square mile (Wikipedia 2008). Notice the curious discrepancy between houses and households. Houses actually exceed the number of households, emphasizing the fact that many Vilas County dwellings are second homes or cottages. Population data by decade for the 20th century appear in Table 3 below:

Table 3. Vilas County Population Data over Time

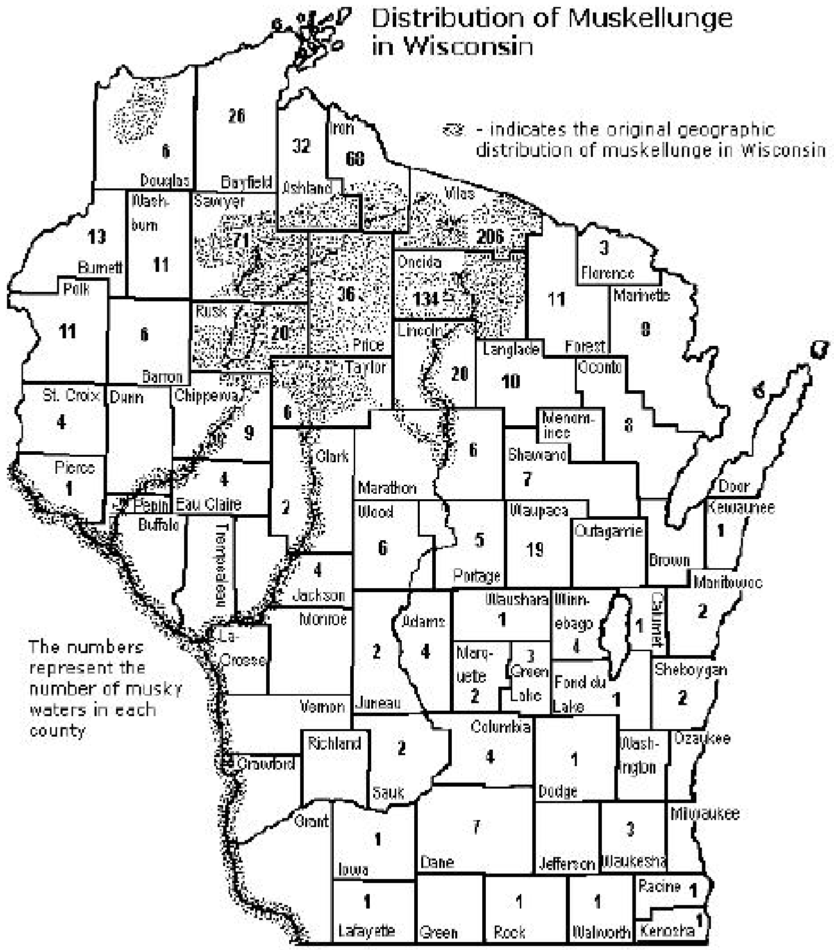
Historical Populations		
Census	Pop.	% (+/-)
1900	4,929	--
1910	6,019	22.1%
1920	5,649	-6.1%
1930	7,294	29.1%
1940	8,894	21.9%
1950	9,363	5.3%
1960	9,332	-0.3%
1970	10,958	17.4%
1980	16,535	50.9%
1990	17,707	7.1%
2000	21,033	18.8%

(Wikipedia 2008)

The county is clearly rural given its area and population size. Its only city, Eagle River, serves as the county seat. Fourteen small towns compliment Eagle River, providing basic goods and services to the county's residents.

While recreation opportunities range from hiking, snowmobiling, and cross-country skiing to boating, fishing, and swimming, the focus of Vilas County residents and visitors is on its lakes. One of the more unique characteristics of these lakes, other than the pure abundance of them, is the fact that muskellunge are present in many of them. A muskellunge, or muskie, is the largest member of the pike family and are relatively uncommon in North America. Within Wisconsin, the species occurs naturally in the north-central region, with Vilas County having the largest collection of muskie waters (see Figure 4).

Figure 4. Distribution of Muskellunge in Wisconsin



(Wisconsin DNR 2008c)

Muskie range from 1-5ft in length and can weigh over 65 pounds. Anglers are attracted to muskie both for their uniqueness, but also for the challenge and awe that they provide. They have been called, "the fish of a thousand casts" and are known for their strength and acrobatic leaping ability when under duress. Of the 1318 lakes in Vilas County, 53 lakes are classified as trophy waters for muskie, where exceptionally large fish are known to exist (Wisconsin DNRb 2008). Besides these trophy waters, several other lakes boast muskie fisheries of various quality, bringing the total to 206 lakes. Moreover 73 rivers and streams compliment the lakes with additional fish species including panfish, bass, walleye, trout, and northern pike.

2.5 Recent Efforts in Managing EWM

In Wisconsin, EWM is estimated to cost citizens millions of dollars in treatment, prevention programs, and lost tourism revenue annually (UW-Extension 2004). Similar estimates exist for other states (University of Minnesota 2008). In Wisconsin, $4.3 million is allocated annually by the state for an invasive species grant program that the DNR manages. The purpose of this budget is to "establish procedures to award cost-sharing grants to public and private entities for up to 75% of the costs of projects to control aquatic invasive species" (UW-Extension 2008). Grant projects should be designed to focus on one or more of the following categories:

1) Education, prevention and planning,

2) Early detection and rapid response, and

3) Controlling established infestations (UW-Extension 2008).

Similar dollar amounts and programs exist in other states for the purpose of managing AIS (Idaho State Department of Agriculture 2006; South Carolina DNR 2008). Expenditures on EWM in particular are difficult to disaggregate as funds are usually allocated for managing all or several invasive species. Nonetheless, the previous discussion provides a sense of scope of current expenditures.

Property owners in Vilas County have already begun work with state and local government, along with private contractors to track the progress of EWM in infested lakes. Numerous volunteers are providing workshops and posting signs at boat landings for educational purposes, while the DNR and other private firms continue lake surveys to monitor the presence of EWM (Vilas County 2000). In addition, the use of herbicides or mechanical methods for controlling the spread of EWM has become common practice, particularly when grant money is available to cover the costs associated with treatments (Ritter 2007). While herbicide treatments cannot be perfectly selective, they have been effective in controlling isolated regions of lakes that have EWM. Mechanical treatments can be successful in breaking up and removing the species, but eradication is not a realistic goal.

These treatments need to be done year after year, possibly many times within a year, leading to increasing costs as a result of this problem. On a per acre basis, mechanical harvesting costs range from $500-$800, while chemical treatments range from $900-$1,400 (SFEI 2008). Additional costs may be incurred though plant disposal fees, equipment costs, and other services unique to certain infestations. Alternatively, a native herbivorous weevil, Eurhychiopsis lecontei, has emerged as a potential biological treatment (Wisconsin DNR 2007). The species prefers EWM and has been documented to decrease abundance of EWM, but additional research is needed on this potential solution, along with the logistics of how introduction of weevils would be managed.

Concerns about EWM are not unique to scientists and other researchers. Local citizens in Vilas County have expressed their own concerns on this issue. In a recent survey sent to lakefront property, 18% of respondents believed that EWM was in their lake (Provencher 2005). Moreover, numerous respondents wrote comments into space available at the end of the survey, highlighting their concerns about invasive species, particularly EWM. Many of the comments expressed a desire for more cooperation and planning between lake owners/lake associations and the state. Suggestions for controlling future invasions ranged from boat inspections at launches and increased launch fee permits to restricted access, essentially closing lakes off to visitors.

Anecdotal evidence for concern is provided by a realtor who works in the North Woods region, where Vilas County is located. This realtor often fields questions from potential property buyers on the presence and abundance of EWM. He estimates that a $250,000 home on a lake with severe EWM problems, such as Big Sand Lake, sells for $30,000-$40,000 less than if it were on a similar lake without EWM (Mulleady 2007).

Through the use of hedonic analysis, the negative impacts associated with EWM can be quantified. EWM is an invasive species most likely to be picked up in hedonic analysis because it not only has negative effects on the native ecosystem, but also causes direct damage to humans through its limiting effect on recreation activities, such as boating, fishing, and swimming. We now turn to a review of the relevant literature.

Chapter Three: Literature Review

The economic literature remains sparse with studies that examine the costs of invasive species, with hardly any using hedonic analysis for lakefront properties. Lovell and Stone (2005) remark, “The costs of preventing and controlling invasive species are not well understood or documented” (p. 1). They go on further to conclude, “The most obvious point…is that the literature is still in its infancy. There are few theoretical, and even fewer empirical studies, dealing with the economic costs of invasive species” (p. 50). Economic studies that have focused on invasive species have largely been concerned with trade and thus, further empirical work is needed outside this area. While the scientific literature discusses the ecological effects of AIS, including EWM, there has been little work done to quantify these effects.

The economic literature, however, is full of studies that examine the impacts of other changes in environmental quality—such as air quality, water quality, undesirable land use (industry, sprawl, etc.)—and their effects on nearby property values. Therefore, this paper relies heavily on these related studies in developing a model, as many use hedonic analysis to quantify environmental problems, specifically on lakes. Since many of the variables used across hedonic analyses are similar, this methodology for model development is not problematic. The literature review focuses first on a number of studies that use hedonic analysis to examine environmental quality with lakefront properties and then expands this focus to include other hedonic models that are related, but not specific to lakefront properties. Included is a subset of studies that have grappled with the challenges of endogeneity and spatial correlation, which are relevant for this study. Next, a brief overview of the scientific literature is offered, as it pertains to EWM. Finally, a theoretical discussion of hedonic pricing theory is presented.

3.1 Economic Literature

Boyle and Kiel (2001) offer an overview of several studies that use hedonic analysis to evaluate the impact of environmental changes. Although their review spans a variety of environmental issues, the relevant portion concerns their section on water quality studies. An early study in this area by David (1968) tested the effects of water quality on lakefront property values for sixty Wisconsin lakes in the late 1950s and early 1960s. In her simplistic model, water quality was measured using a discrete variable with values of poor, moderate, or good (Boyle and Kiel 2001, p. 123). The study does not include many of the traditional variables seen in hedonic analyses that are used to control for differences in property characteristics. It may be due to this omitted variable bias that she did not find the differing levels of water quality to be significant. Future studies would look to improve upon this limited model.

Young (1984) added housing characteristics and lot attributes to David's basic model, using hedonic analysis to test the effect of water quality on property values near Lake Champlain in Vermont. In addition, Young altered the definition of the water quality variable, allowing the score to range from one to ten, with higher water quality receiving a higher score (Boyle and Kiel 2001, p. 125). Young's findings differ from David's, as his paper finds water quality to have a statistically significant effect on property value. Steinnes (1992) reached a similar conclusion in terms of the significance of water quality, but used a truncated hedonic model. Steinnes omitted structural characteristics and used only land characteristics as primary determinants of property value. However, it will soon be discussed that most modern hedonic studies include structural/housing characteristics to control for variation of those attributes. In fact, most recent studies use a similar set of variables that are believed to affect property values.

Michael, Boyle, and Bouchard (1996) use hedonic analysis to quantify the effect of water clarity in a study that includes thirty-four Maine lakes. Their environmental variable is assigned a continuous value based on the reading of a secchi disk, an instrument often used to calculate water clarity. In addition to the secchi disk readings, the authors gathered data on property transactions for sales occurring between January 1, 1990 and June 1, 1994. Tax records were used to obtain data on property characteristics (Michael, Boyle, and Bouchard 1996, p. 9-10). The authors use sales price per foot of lake frontage as the dependent variable in their regression model. To control for variations in property characteristics, the authors include structural and lot attributes (such as the number of stories in a structure, living area, a dummy for the presence of a garage, size of lot, etc.) and locational/neighborhood variables (such as distance to nearest city, area of the lake, tax rate, and development density) (p. 6-7). The functional form used in their study is quite simple, as the model estimated is linear in the variables and parameters with the exception of water clarity, on which a natural log transformation is used. As with previous studies, the authors find a statistically significant effect of water clarity on property values. In particular, they find that a one unit improvement in lake water clarity increases the average property value by $11 to $200 per foot of lake frontage (p. 14).

Hedonic analysis has also been used to examine the effects of environmental characteristics on property values for non-lakefront properties. These studies also provide a foundation from which a model for this study can be built. Geoghegan, Wainger, and Bockstael (1997) estimate the impacts of land use diversity and fragmentation on nearby parcel property values. The authors use GIS data from counties in the Patuxent Watershed in Maryland. Their model estimates housing values as a function of traditional variables, which include structural characteristics (such as lot size and age of structure/house), neighborhood characteristics (such as income level, tax rate, and school quality), and spatial characteristics (such as distance to nearby town or city), plus the ecological indicators (fragmentation and diversity) (p. 257). The authors use a double-log model so that all results are in terms of elasticities and find the ecological indicators to be statistically significant additions to the model.

Geoghegan (2002) expands on the 1997 paper, attempting to quantify the influence of open space amenities on a nearby parcel. In particular, the paper makes an effort to distinguish between the effects of nearby developable open space and permanent open space on property values. The data set used in the paper is a sample of 5599 property sales transactions that took place in Maryland between September of 1993 and June of 1996 (p. 94). Geoghegan's model is the same as in Geoghegan, Wainger, and Bockstael (1997), except for the variables of concern, which are the different open space variables relevant for her paper. The empirical results indicate that both types of nearby open space do indeed make positive contributions to property values, but the effect of permanent open space is much greater.

Several recent studies have made improvements to existing hedonic models, using a technique called difference-in-difference analysis. Tu (2005) uses this technique in estimating the effects of FedEx Field construction in Washington D.C on nearby property values. The study finds that a positive price premium exists for properties that are further away from the stadium. In other words, properties sold within a defined impact zone around the stadium are found to sell at a discount, relative to properties sold outside this buffer zone before and after construction. After construction, however, this premium has narrowed. This approach of comparing before and after price effects for an impact area relative to an area unaffected, called difference-in-difference analysis, can be used to estimate an unbiased effect of an event, when the event's occurrence or location may be endogenous. Thus, any unobserved characteristics that may have been present before the event of interest for affected and unaffected properties are differenced out of the effect. Had Tu (2005) only done a post-construction analysis, he would have simply found a price premium for properties located away from the field, perhaps leading one to conclude that the field has a negative effect on nearby property values. The difference-in-difference analysis allows for unbiased estimation of the effect of the stadium, indicating that the stadium actually has a positive effect on nearby property values.

Schwartz et al. (2006) and Galster, Tatian, and Pettit (2004) use a similar methodology to identify the effects of subsidized or supportive housing facilities on neighboring residential property values. Both studies assess before and after price levels for properties within close proximity to the construction sites of housing units, relative to properties further away that are unaffected. To accomplish this, fixed effects are estimated for mutually exclusive concentric rings, radiating out from a given construction site. These fixed effects are used to control for idiosyncratic neighborhood characteristics, but also for comparing price effects across neighborhoods, or areas that are affected at varying degrees based on their vicinity to the construction site (Schwartz et al. 2006, p. 684). Schwartz et al. (2006) compares the properties within a certain "ring" of the subsidized housing with the prices of comparable properties that are outside this ring, but still within the same land market. The magnitudes of these differences are assessed before and after the completion of the units.

The difference-in-difference aspect of this analysis can be summarized in its simplest form as follows: a variable denoting the presence of a property within the impact zone (IMPACT) of construction is used to differentiate affected and unaffected properties. Another variable denotes if the property is sold within the impact zone after construction takes place (AFTER). Using IMPACT and AFTER, three distinct effects can be deduced. The first, using the coefficient on IMPACT denotes the price differential between properties within the impact zone and outside, while IMPACT + AFTER denotes the difference between these properties after construction. The third and final effect is the result of difference-in-difference. The difference between these two effects (IMPACT +AFTER) – IMPACT, results in an unbiased estimate of the after construction effect on properties within the impact zone.

Galster, Tatian, and Pettit (2004) uses a slightly more complex version of this methodology, but the basic intuition remains the same. The study serves to debunk the myth that supportive housing units generate negative externalities with which they are generally associated (e.g. increased noise and crime, poorly maintained property, etc.). Adding to the simple logic set forth above, the authors argue that the analyst must also control for price trends in addition to the absolute level of prices in the neighborhoods surrounding a site, both before and after construction occurs (p. 37). Thus, it is precisely the spatial component of their research that gives rise to the endogeneity of supportive housing effects (these effects are correlated with unobserved attributes specific to the location of the property), but also to spatial autocorrelation in the error structure. The former is mitigated, at least in part, using the difference-in-difference approach, while the latter is incorporated into the model using a set of coordinate-based variables.

Dealing with the issues of spatial autocorrelation and endogeneity has been a challenge for many hedonic studies throughout the environmental economics literature. Since bias and inefficiency result if these problems are ignored or dealt with poorly, sound solutions must be developed (Irwin and Bockstael 2001, p. 698).[3] Irwin and Bockstael (2001) adopt an

[3] Endogeneity leads to bias, while spatial autocorrelation leads to unbiased, but inefficient estimates. In tandem, these issues lead to biased estimates with larger than optimal standard errors. For the purposes of this paper, 'biased and inefficient coefficients' refers to the scenario where both econometric issues are faced simultaneously.

instrumental variables approach to account for the endogeneity of open-space variables encountered in their study. However, as described in 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 (p. 474). Unfortunately, Irwin (2002) concludes that her estimates lack robustness and calls for additional research on the identification issue that arises due to problems of endogeneity and spatial autocorrelation. Recent difference-in-difference analysis is a thread of the literature moving toward a solution for these issues.

Hallstrom and Smith (2005) use a difference-in-difference hedonic framework to estimate an unbiased price effect of Hurricane Andrew on "near miss" residential properties—those projected to be in the path of the storm, but ultimately unaffected. Given that the gulf coast of Florida had experienced two decades of below average hurricane activity leading up to Andrew, the authors hypothesize that the effect of this hurricane would be capitalized into property values even for "near-miss" areas. The authors rely on repeat sales observations before and after the hurricane, arguing that the information effect associated with hurricane destruction may not be observable if confounded by the idiosyncratic features of individual properties (p. 543). This is a unique argument in the literature as most studies do not confine their data sets to repeat sales only. Instead, analysts try to account for idiosyncratic features specific to an individual property and to its location in space to get around this restriction. The authors also claim the use of repeat sales data reduces the effects of spatial autocorrelation, since over short periods of time these effects are likely to be constant (p. 550). Nonetheless, the authors use difference-in-difference analysis to difference out any unobserved characteristics that may be confounding the information effect on price. Despite being "near-miss" properties, the authors find the information effect associated with Hurricane Andrew (conveying the risk of future hurricanes) to reduce property values by nearly 20%.

While the issues of endogeneity and spatial correlation, arising from unobserved spatial heterogeneity, are of great concern in many recent papers, the issue was originally broached by Small (1974). In discussing the use of a hedonic model that quantifies the effects of air pollution on property values, Small (1974) 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). In most cases, the issue of unobserved spatial heterogeneity is treated as an inefficiency problem, related to correlation in the error terms of hedonic models.[4] However, Chay and Greenstone (2005) suggest that bias can arise if unobserved characteristics are correlated with observable environmental amenities. Despite the concern raised by Chay and Greenstone (2005) and Small (1974), this issue has received little attention in the hedonic literature. While models of spatial autocorrelation can be estimated (Anselin 1998) to correct for correlation in the error terms, such approaches still assume no correlation between the observed and unobserved neighborhood characteristics, and thus fail to address Small's (1974) original critique.

Hedonic analysis has also been used in a variety of other contexts. Spalatro and Provencher (2001) use hedonic techniques to examine the effect of zoning regulation on property values. They use property transaction data for the period of January 1986 through December 1995 for lakefront properties in Vilas and Oneida Counties in Wisconsin. Due to the high rate of

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

development that had been occurring on lakes in Northern Wisconsin during the time period of interest, it was hypothesized that minimum lot zoning requirements would raise the value of nearby properties on the lakes relevant to the study (p. 471). Using a log-linear model with price per foot of frontage as the dependent variable and a set of independent variables similar to the above studies, the authors find that the zoning restriction adds value to the average property. In other words, they find that "the amenity effect dominates the development effect" and residents value low density development on their lakes (p. 480).

Other studies, such as Clark and Herrin (2000), use hedonics to explain how increasing school quality increases housing values, while Nelson (1981) uses a similar model to explain the lack of effect associated with the Three Mile Island nuclear accident on surrounding property values. With guidance from the reviewed studies, a model for this paper can now be constructed. Although the environmental variable of interest, the effect of invasive species, is different from many of the papers explored in the literature review, the basic hedonic framework is similar across all types of studies.

3.2 Natural Science Literature

The scientific literature has several studies that document the ecological effects of milfoil. In particular, Wetzel and Grace (1978) offer a discussion of factors that contribute to the growth of EWM, along with potential mechanisms for control. Madsen, Eichler, and Boylen (1988) study seasonal growth patterns on EWM in Lake George, New York, finding peak presence of the species in late summer months. Creed and Sheldon (1993) document the potential for a biological control of EWM in the form of the North American weevil. The weevil is found to prefer EWM over the native milfoil and has brought about declines in EWM populations through this feeding. In general, the biological characteristics and ecological effects associated with milfoil have been well-documented in the scientific literature for many years.

3.3 Hedonic Pricing Theory

Hedonic pricing theory is well-established and has been used across a variety of disciplines, including economics, for over forty years. The advantage of this form of modeling is that the logic is transparent and model interpretation is very intuitive. The basic intuition behind the theory was established originally by Lancaster (1966). Lancaster posited that a good itself does not provide utility, but rather the good possesses characteristics, which provide utility (Lancaster 1966, p. 133). When prices of goods are observed along with their attributes, a set of implicit or hedonic prices can be determined (Rosen 1974). Thus, for attributes that cannot be readily valued, such as environmental amenities, this technique of revealed preference proves useful for estimating implicit prices.

This theory has a direct application to a good such as property, as it is composed of a variety of attributes. In general, the property value of land can be represented as follows:

(3.1) $P_i = f(S_i, N_i, L_i \mid \beta)$

where P_i is the residential sales price of the property, S_i is a matrix of structural and lot characteristics, N_i is a matrix of neighborhood variables, L_i is a matrix of locational/spatial variables, and β is a vector of coefficients to be estimated (Freeman 1993, p. 125). Additional parameters may be introduced to allow further flexibility in the model, as will be discussed in subsequent sections.

Since P_i is a sales price, estimating the above equation yields a hedonic price curve that is a locus of equilibria in the housing market. In other words, the hedonic price function is based on transactions between buyers and sellers, resulting in a collection of equilibria in the data set.

This leads to a key assumption of this modeling approach, that is, the housing market is assumed to be in equilibrium. This implies that all individuals have made their utility-maximizing decisions given the existing stock of housing and their respective attributes (Freeman 1993, p. 371). Other assumptions that are generally made include: i) a common land market and ii) full information about prices and attributes. The first ensures that the region chosen, over which the hedonic price function is estimated, is a single land market with relatively homogenous characteristics. The researcher must decide on the extent of this land market because once the area of interest becomes too large, enough heterogeneity has probably been introduced to justify multiple land markets, and hence, the need to estimate additional hedonic price equations.

The implicit prices for non-market amenities (or disamenities), such as air quality or water clarity, should be treated as lower bound estimates (in absolute terms). In part, this is because some of the value from such goods will also be capitalized into wages. Roback (1982) finds that wages and environmental amenities can be considered substitutes as people usually accept lower wages to live in an area with more amenities. Moreover, values of such goods will also be held with non-property owners, such as tourists to the area. Lastly, other use and non-use values, such as water filtration, erosion control, and habitat for supporting biodiversity, may not be fully capitalized into land prices or wages, resulting in other unincorporated values associated with an environmental amenity. Thus, the derived implicit prices from any hedonic price study using land markets alone should not be recognized as the full value of the associated good.

Lastly, hedonic price equations can only be used to evaluate marginal changes in a good's characteristics. Assuming the function is smooth and twice differentiable, it can be differentiated with respect to any of the attributes (assuming linear in the parameters and variables) to derive the marginal implicit price of that attribute. However, without more information on the shape of the marginal willingness-to-pay curve, inferences cannot be made on non-marginal changes (Freeman 1974, p. 555).

Chapter Four: Data and Descriptive Statistics

4.1 Data

The data used for this study were compiled from a variety of sources. Data on lakefront property transactions in Vilas County, WI were collected from the Wisconsin Department of Revenue for the years 1997-2006. These data were used to select the transacted properties from annual tax rolls, obtained from the Vilas County Information Technology Department.[5] Assessed structural values were obtained from these tax rolls. GIS tax parcel and county-wide spatial water data were then obtained from the Vilas County Mapping Department.[6,7] Tax roll and GIS tax parcel data were linked together using a common pin identifier. After water data were associated with the data set, lot, neighborhood, and spatial attributes were calculated or added. Lake characteristics and ecological variables were collected from the Wisconsin Department of Natural Resources and the Environmental Remote Sensing Center of the University of Wisconsin-Madison.[8] Data on the presence of EWM and year of invasion were gathered from the Wisconsin DNR website.[9] EWM abundance data were then compiled with the help of Jen Hauxwell and her staff, of the Wisconsin DNR. Finally, data related to the quality of fisheries were obtained from the Wisconsin DNR website.[10] These data were merged using a unique lake identifier.

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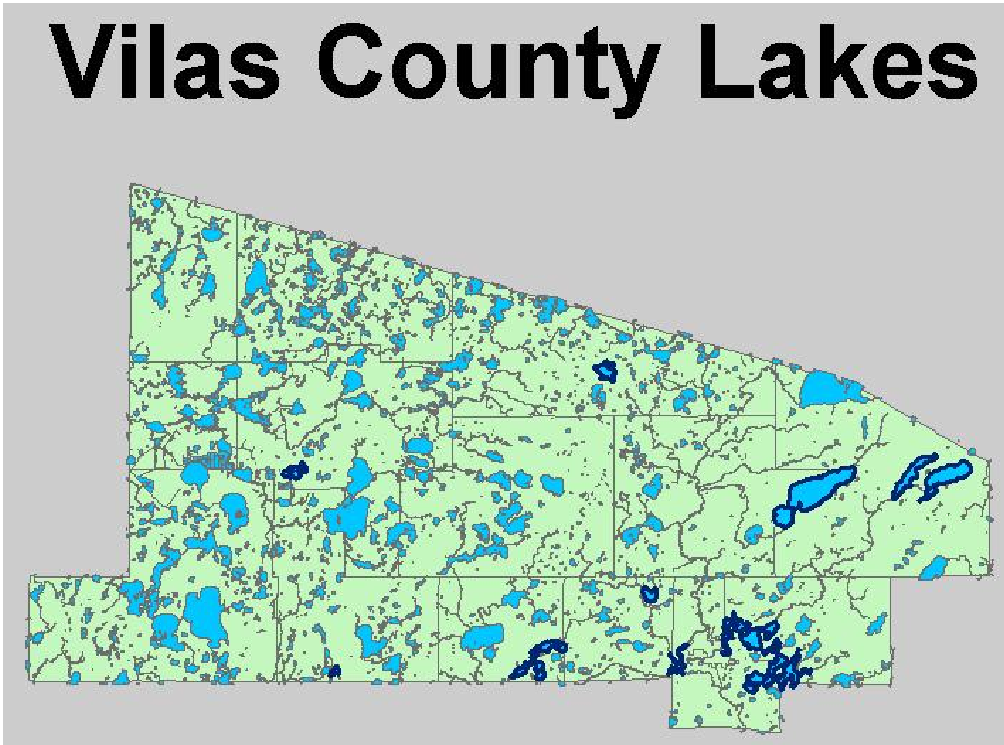
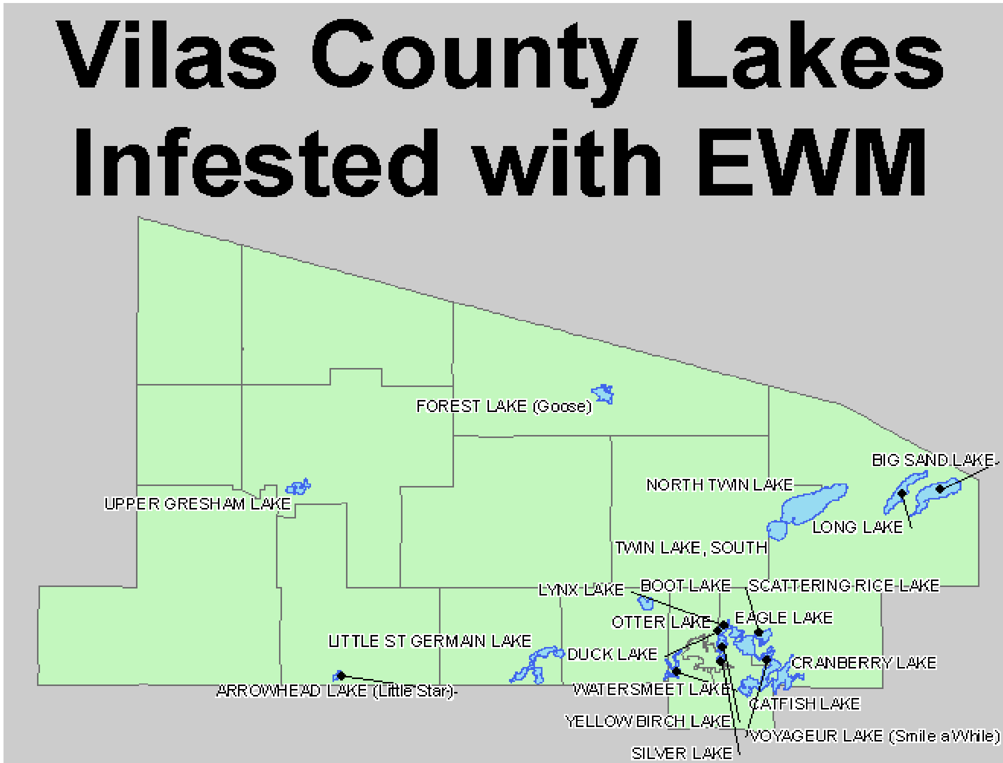
[5] The author thanks Mike Duening for supplying these data.
[6] The author thanks Barb Gibson for supplying these data.
[7] Spatial water data refers to a GIS layer of all lakes, rivers, streams, and other bodies of water in Vilas County.
[8] See Wisconsin Lakes Book at http://www.dnr.state.wi.us/org/water/fhp/lakes/list/#lakebook.
[9] See Listing of Wisconsin Waters with EWM at http://dnr.wi.gov/invasives/fact/milfoil/charts/ewm2006_by_county.pdf.
[10] See Wisconsin Lakes Book (cited in the previous footnote) and Wisconsin Muskellunge Waters: Vilas County at http://www.dnr.state.wi.us/fish/musky/lakes/vilas.html.

The entire panel of data represents 1841 transactions on 172 lakes in Vilas County, including 17 that are affected by EWM.[11] Figure 5 displays the dense collection of lakes found in Vilas County with EWM-infested lakes highlighted in dark shading, along with a more specific mapping of the affected lakes in the data set.

Figure 5. Vilas County Lakes Infested with EWM



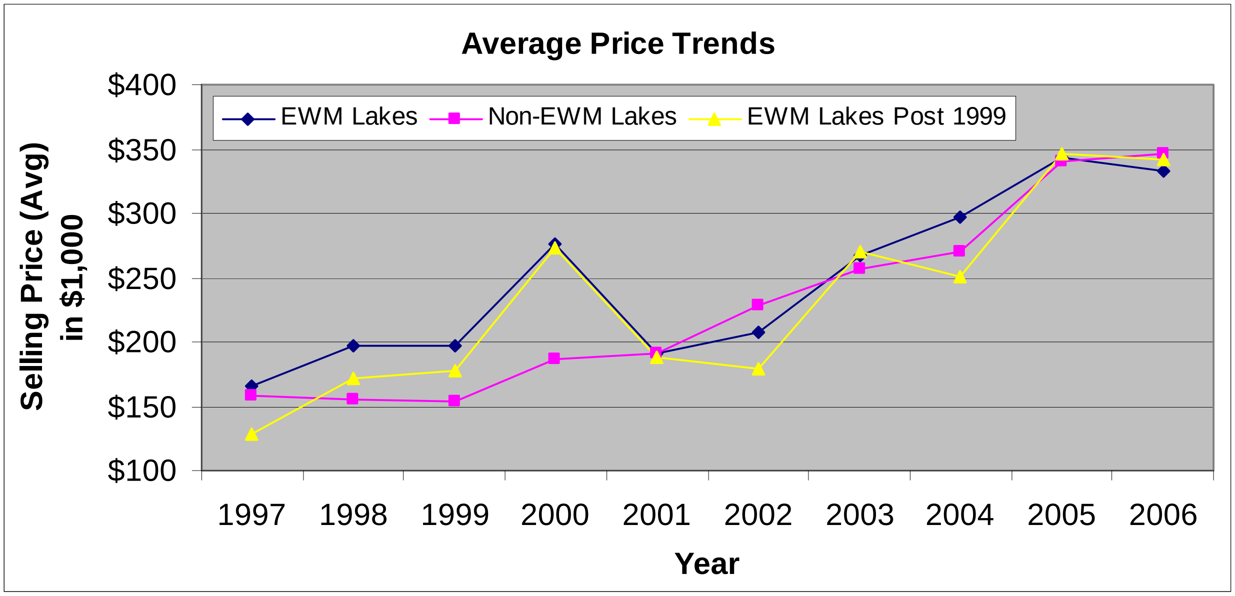
[11] Lakes infested with EWM in the data set include: Arrowhead Lake, Boot Lake, Catfish Lake, Cranberry Lake, Duck Lake, Eagle Lake, Forest Lake, Little Saint Germain Lake, North Twin Lake, Otter Lake, Scattering Rice Lake, Silver Lake, South Twin Lake, Upper Gresham Lake, Voyageur Lake, Watersmeet Lake, and Yellow Birch Lake.



4.2 Descriptive Statistics

Since the purpose of the hedonic model is to analyze the price effect associated with any given characteristic of a transacted property, it is first useful to address the price trends present in the data set. To illustrate this, price trends for transacted properties on non-infested lakes are compared with those on lakes that have become infested with EWM, as seen in Figure 6.

Figure 6. Trend Analysis by Lake Type



Note: All dollar amounts reflect real dollars in the year of the sale.

Two trend lines are used for EWM-infested lakes. The first includes all properties affected by EWM regardless of timing of infestation. The second trend line includes only those properties on lakes that became infested after 1999. Eight out of the seventeen lakes in the data set affected by EWM became infested during 1992-1995, while the other nine lakes were invaded during 2000-2005.

While the average trend lines are relatively close together and similar in pattern over time, one should observe the clear price differential of EWM-infested lakes over those uninfested up until 2000. After 2000, this premium narrows as the non-EWM trend line begins to fluctuate more closely with the other trends, even exceeding them at some points. Given that the majority of affected lakes became infested after 2000, this could indicate the price effect of EWM. It is of particular interest that the lakes affected by EWM sell for a premium for most of the time period, relative to non-affected lakes. The fact that highly demanded lakes contracted EWM may be no fluke, but rather a function of the inherent popularity of these lakes. This is a potentially important issue as this paper moves into econometric estimation.

It may be important to address the extent to which infested lakes are of high demand. A proxy for the level of demand is the average selling price of property on these lakes.

Table 4. Ranking the Average Selling Price of Lakes

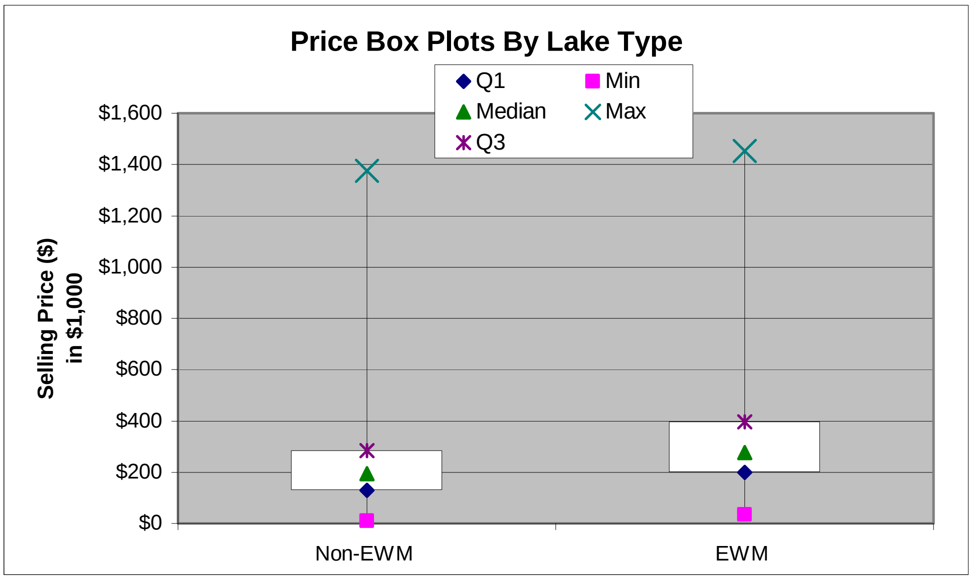
Lake Name	Average Selling Price ($1,000)	Rank (out of 172)	Lake Name	Average Selling Price ($1,000)	Rank (out of 172)
PLUM LAKE	$ 1,108	1	**CRANBERRY LAKE**	**$ 412**	**20**
CRAB LAKE	$ 705	2	**NORTH TWIN LAKE**	**$ 388**	**24**
STONE LAKE	$675	3	**CATFISH LAKE**	**$ 342**	**34**
LONE PINE LAKE	$ 624	4	**YELLOW BIRCH LAKE**	**$ 332**	**38**
HIGH LAKE	$ 589	5	**DUCK LAKE**	**$ 313**	**44**
CLEAR LAKE	$ 588	6	**EAGLE LAKE**	**$ 286**	**58**
BIG LAKE	$ 544	7	**FOREST LAKE (Goose)**	**$ 282**	**62**
FENCE LAKE	$ 522	8	**LITTLE ST GERMAIN LAKE**	**$ 280**	**63**
LITTLE STAR LAKE	$ 506	9	**VOYAGEUR LAKE**	**$ 274**	**67**
MARSHALL LAKE	$ 505	10	**SCATTERING RICE LAKE**	**$ 273**	**68**
TWIN LAKE, SOUTH	**$ 443**	**16**	**OTTER LAKE**	**$ 272**	**69**

Note: EWM-infested lakes denoted in bold. All dollar amounts in 2006 dollars.

Table 4 illustrates the presence of EWM-infested lakes in the upper echelon of the average price rankings. In fact, 12/17 infested lakes are in the top 70 of 172 lakes on this list, using the full 1997-2006 data set. Moreover, when standardizing price by average frontage or lot size, 12/17 EWM lakes appear in the top 58 and 51 respectively of all 172 lakes. As concluded from Figure 6, this indicates the relative price premium for EWM lakes, regardless of the presence of EWM. Naturally, the premium is likely to have changed due to the presence of EWM, and econometric analysis will be offered to further address this question.

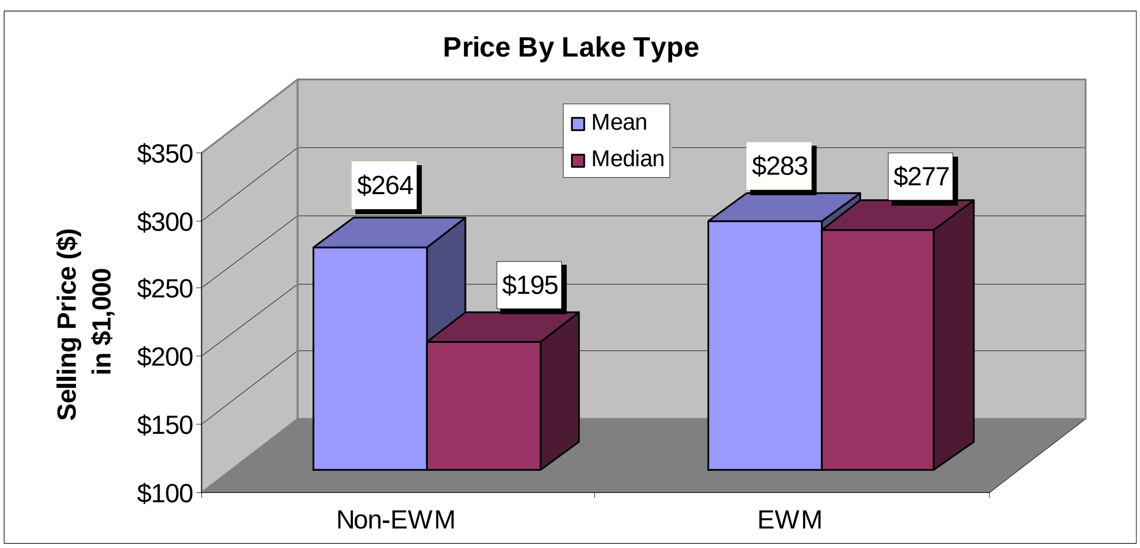
Figures 7 and 8 further illustrate the difference in price between properties on lakes affected by EWM and those that are not. Figure 7 is particularly useful because it demonstrates the distribution of price across each lake type, as summarized by the box plots below. Figure 8 is an abbreviated summary of Figures 6 and 7.

Figure 7. The Distribution of Price by Lake Type



Note: All dollar amounts in 2006 dollars; Q1 and Q3 refer to 1st and 3rd quartiles

Figure 8. Mean and Median Price by Lake Type



Note: All dollar amounts in 2006 dollars

Figure 7 further emphasizes the discrepancy between the selling price on EWM lakes and Non-EWM lakes. Properties on EWM lakes sell for a greater amount at every level of the box plot (minimum, first and third quartiles, median, and maximum). Moreover, Figure 8 demonstrates that the average and median selling prices are greater on EWM lakes. Using a simple difference of means statistic, it can be inferred that this difference is significant at the 90% confidence level, given this sample size and data.

The relative premium for properties on EWM lakes likely existed before these lakes became affected by EWM. After all, an infestation of EWM should not be expected to increase property values (all else equal), only decrease values or have no effect. This implies that the effect of EWM on affected lakes may be a reduction in relative premium between infested and non-infested lakes, rather than a clear discount for properties affected by EWM. This again underscores the inherent popularity of lakes that become infested with EWM relative to other lakes.

Finally, Table 5 offers summary statistics for non-binary variables for both EWM and non-EWM lakes.

Table 5. Summary Statistics

Summary Statistics of Select Variables for EWM Lakes								
	1997		2000		2003		2006	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Price	$166,416	$112,231	$276,417	$220,394	$267,483	$150,716	$327,310	$113,722
Structure	$69,411	$54,596	$105,586	$103,145	$87,710	$67,657	$98,345	$86,658
Lot (acres)	1.43	0.93	1.42	1.04	1.36	1.84	1.77	1.63
Frontage (ft)	189.53	177.90	164.21	97.96	160.08	118.45	186.28	187.40
Lake Area (acres)	497.58	301.87	604.31	420.80	619.85	363.42	960.01	1029.77
Private (%)	91%	21%	98%	2%	97%	11%	100%	1%
Density[1]	25.31	4.85	26.37	2.27	25.82	3.40	25.16	5.80
Water Clarity[2] (ft)	2.58	1.03	2.94	1.05	2.57	1.02	2.22	0.87
Distance (miles)	6.10	5.38	7.00	6.06	6.28	5.05	7.12	4.98
Max Depth (ft)	31.32	15.58	38.93	18.39	33.77	16.27	32.00	19.82
Muskie[3]	2.74	0.99	2.86	0.69	2.85	0.77	2.90	0.59
Pike	1.21	0.42	1.59	0.50	1.31	0.51	1.03	0.70
Walleye	1.79	0.79	1.76	0.58	1.75	0.70	1.75	0.59
Bass	1.21	0.42	1.07	0.26	1.06	0.32	1.10	0.38
Panfish	1.58	0.51	1.90	0.56	1.69	0.55	1.73	0.51
# Transactions	19		29		48		40	

1. Density is measured as the number of parcels per mile of private frontage
2. Water clarity is measured by a secchi disk, where the depth of clarity is determined.
3. The fishery quality variables (Muskie, Pike, Walleye, Bass, and Panfish) are rankings determined by the WI DNR. Muskie ratings range from 0-4, while ratings for other species range from 0-3.

Note: All dollar amounts reflect real dollars in the year of the sale.

Summary Statistics of Select Variables for Non-EWM Lakes								
	1997		2000		2003		2006	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Price	$157,995	$85,717	$185,822	$102,211	$256,416	$181,430	$348,024	$233,218
Structure	$73,115	$63,512	$65,093	$53,413	$85,627	$94,497	$107,608	$100,090
Lot (acres)	2.52	2.89	2.19	3.04	1.90	1.73	2.41	2.92
Frontage (ft)	179.84	102.06	186.03	148.34	190.41	131.61	194.20	133.40
Lake Area (acres)	451.13	371.37	454.87	420.84	395.42	363.67	512.53	691.56
Private (%)	92%	18%	92%	17%	93%	15%	89%	20%
Density[1]	20.61	8.24	21.90	10.07	23.40	8.25	24.73	15.84
Water Clarity[2] (ft)	3.44	1.31	3.26	1.24	3.15	1.11	3.26	1.23
Distance (miles)	14.94	7.47	16.59	8.32	14.95	8.73	13.66	7.76
Max Depth (ft)	42.02	19.92	38.56	19.09	36.62	18.09	36.88	20.03
Muskie[3]	2.49	1.58	2.57	1.48	2.36	1.45	2.39	1.53
Pike	1.09	0.80	1.18	0.89	1.13	0.87	1.14	0.80
Walleye	1.39	0.76	1.32	0.87	1.21	0.83	1.24	0.81
Bass	1.32	0.51	1.31	0.48	1.28	0.53	1.41	0.55
Panfish	1.84	0.79	1.87	0.71	1.86	0.83	1.75	0.79
# Transactions	87		118		173		173	

1. Density is measured as the number of parcels per mile of private frontage
2. Water clarity is measured by a secchi disk, where the depth of clarity is determined.
3. The fishery quality variables (Muskie, Pike, Walleye, Bass, and Panfish) are rankings determined by the WI DNR. Muskie ratings range from 0-4, while ratings for other species range from 0-3.

Note: All dollar amounts reflect real dollars in the year of the sale.

As can be seen from the descriptive statistics above, several variables show expected trends. For example, the price, assessed structure, and density variables trend upward over time, as is expected. Moreover, the remaining variables show a relatively steady set of statistics over time, which would also be expected. In comparing the summary statistics across lake types, we see a discrepancy in several variables. Lot size and frontage are greater, on average, for non-EWM lakes, further emphasizing the price premium that EWM lakes get once price is standardized by either measure. Having less frontage and smaller lots is consistent with the higher density and lower water quality measures seen for the EWM lakes. EWM lakes have a lower average distance to the nearest town because 9/17 infested lakes in the data set are part of the Eagle River Chain, which sits right near the town of Eagle River. Also, higher average muskie and walleye rankings are observed for EWM lakes. These are two popular game fish that attract a lot of boaters. The rest of the variables are pretty constant between lake types.

Chapter Five: Empirical Model One

5.1 Set One of Empirical Models

The following chapters are used to explore the empirical analysis. An explanation of variables is offered, in addition to a discussion of the econometric challenges faced in this research. Parameter estimates are provided using two sets of models: cross-sectional and panel-based estimations. The first set of models includes three cross-sectional estimations, using 457 observations from 2005-2006. These models take on the following general form:

$$(5.1) \quad Price_{it} = \beta_0 + \beta_1 \, Struc\_val_{it} + \beta_2 \, Lot_{it} + \beta_3 \, Front_{it} + \beta_4 \, (Front_{it})^2 + \beta_5 \, Lake\_area_{it} + \beta_6 \, Assoc_{it} + \beta_7 \, Private_{it} + \beta_8 \, Access_{it} + \beta_9 \, Dev\_dens_{it} + \beta_{10} \, Max\_dep_{it} + \beta_{11} \, Prime_{it} + \beta_{12} \, EWM_{it} + \beta_{13} \, EWM_{it} * Treatment_i + \beta_{14} \, Dum\_2006_{it} + \beta_{15} \, Water\_Clarity_{it} + \beta_{16} \, Muskie_{it} + \beta_{17} \, Pike_{it} + \beta_{18} \, Walleye_{it} + \beta_{19} \, Bass_{it} + \beta_{20} \, Panfish_{it} + \beta_{21} \, Dist_{it} + \beta_{22} \, (Dist_{it})^2 + \epsilon_{it}$$

for $i = 1, 2, \ldots, N$ and $\epsilon_{it} \sim N(0, \sigma_i^2)$

where: N is the number of observations and t is the time period.

Variables appearing in 5.1 are explored below in Table 6.

Table 6. Description of Variables in Model One

Descriptive Name	Variable Name	Variable Description
Selling price	*Price*	total selling price in real dollars (2006)
Assessed structure value	*Struc_val*	assessed structure value before transaction
Lot size	*Lot*	lot size (in acres)
Frontage	*Front*	frontage (in feet)
Lake area	*Lake_area*	surface area (in acres) of the lake that the property borders
Association	*Assoc*	=1 if the property is on a lake with an association and 0 otherwise
Private frontage	*Private*	proportion of frontage that is privately owned on the lake that the property borders
Public access	*Access*	=1 if the property is on a lake with public access and 0 otherwise
Development density	*Dev_dens*	number of parcels per mile of private frontage on the lake that the property borders
Maximum depth	*Max_dep*	maximum depth (in feet) of the lake that the property borders
EWM prime season	*Prime*	=1 if the transaction takes place between June 1 and September 30 and is on an EWM lake
Eurasian Watermilfoil measures	*EWM*	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*	=1 if the lake the property borders was treated for EWM before the transaction within the same calendar year
Year 2006	*Dum_2006*	= 1 if the transaction took place in 2006
Water clarity	*Water_Clarity*	water clarity measure of the lake that the property borders
Fishery quality indices	*Muskie (and other fish)*	index for quality of muskie fishery (or other fish) on the lake the property borders
Distance to nearest town	*Dist*	distance to nearest town (in miles)

The literature does not provide concrete guidance on the selection of variables or functional form, although a common trend seems to have emerged. The general model above is an attempt to emulate this trend, in which property prices are determined by their structural and lot characteristics, neighborhood characteristics, and spatial attributes. In any hedonic study, it is nearly impossible to account for all potential determinants of property values. As a result, model specification is often determined by data availability. The methodology in this study is no different. However, great care was given to variable selection, and unconventional measures like fishing quality indices were sought out.

5.2 Structural and Lot Variables

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. This however should not be considered a major limitation, since the assessed value should do a reasonable job of capturing all the relevant structural variables seen in other studies (i.e. presence/absence of a garage, number of stories, square feet, etc.). Moreover, it is likely that a number of those individual variables are collinear. Thus, having one summary proxy variable is arguably preferable. Frontage and frontage-squared are included to provide flexibility in functional form, since additional feet of frontage likely bring about diminishing contributions to price. All structural and lot variables are expected to make positive contributions to the dependent variable.

5.3 Neighborhood Variables

Many of the lake-specific variables account for variation in neighborhood characteristics, including lake area, water clarity, fishery quality variables, and maximum depth. The fishery 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. Depth and area are important if EWM is present. A small and shallow lake, for example, will likely be impacted more harshly by EWM because there is less space over which the species can be distributed, and because a shallower lake has a larger littoral zone, in which the EWM can grow and be seen. The littoral zone is the region of a lake in which vegetation growth is possible. This is usually described as a twenty- to thirty-foot-wide ring around the perimeter of the lake, though vegetation can grow all throughout in some lakes. 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. Lastly, two variables account for differences in development, including density and type (public/tribal land vs. private). The signs of many of these variables cannot firmly be hypothesized due to heterogeneous preferences among property owners.

The final variables included as neighborhood characteristics concern the presence/abundance of EWM. As stated above, the first model is estimated using a few different combinations of the EWM 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 EWM 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 lakes surveys only began a state-wide sampling of lakes believed to be infested with EWM in the past couple years. Consequently, abundance data cannot be retrieved from years past. However, the presence/absence measure of EWM has been documented for several years. All of the EWM variables are expected to have a negative impact on selling price.

Any measure of EWM (continuous abundance measure, discrete categories based on abundance, or presence/absence) is interacted with a variable called, *treatment*. The idea here is that properties on lakes with EWM that have been treated will likely suffer a moderated negative price effect, relative to untreated lakes, when comparing to lakes that have no EWM at all. The variable is defined in such a way that requires a treatment to have taken place on a given lake with EWM and before the transaction (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). Thus, to keep this measure simple, the treatment must take place before the transaction, allowing time for capitalization of the treatment into price.

In addition to the EWM variables and treatment, a variable called, *prime*, is included. This incorporates whether or not a transaction took place during the prime months that EWM affects lakes. Naturally, this variable can only take on a value of 1 if the transaction took place on a lake infested with EWM. Generally EWM begins to show in early June, peaking in August, and subsiding by late September. The coefficient on this variable is expected to be negative, since buyers would be exposed to EWM in full bloom if visiting a potential home during these months. If the state of EWM differs greatly between the time the offer is made and when the buyer closes on the property, this difference is assumed to be accounted for at the time of closing.

It is important to note that there is variation in the EWM data, as not all transactions are affected by the presence of EWM. In fact, only 17 out of the 154 lakes represented in the cross-sectional data set are affected by EWM.[12] In terms of observations, about 20% are affected by EWM. Finally, it should be mentioned that defining the EWM variable(s) in terms of time (such

[12] The cross-sectional data, 2005-2006, only cover 154 of the total 172 lakes. All lakes are represented in the panel data set for years 1997-2006.

as number of years present before a given transaction) is not theoretically, or also in this case, econometrically sound. In fact, this sort of definition may not be useful since persistently low EWM populations have been documented, such as the case of Chesapeake Bay where EWM levels remained stagnant for some sixty years before exploding. In other cases, EWM populations have taken little time to take over their host body of water (see Maryland DNR 2008; Smith and Barko 1990; Vermont DEC 2008; and Wisconsin DNR 2007). This lack of determinism in the time-growth relationship was also discussed in a meeting with Wisconsin DNR scientists. Thus, it is important to focus on presence or abundance and not time necessarily. In an initial run of the model, this time-related definition of EWM was inappropriately used and also caused problems with multicollinearity (which will be discussed in a subsequent section), providing further motivation for its redefinition to abundance or presence/absence.

5.4 Spatial Variables

So far this discussion has covered the structural/lot attributes and neighborhood (lake-specific) characteristics. The final variables suggested by previous studies to be determinants of price are spatial variables. Two relevant variables are included here: distance and distance-squared (in miles) to the nearest town. The towns relevant in this data set are Eagle River and Minocqua. Whichever town is nearer to a given observation is used to calculate this measure. These two distance variables are included in an effort to account for some of the spatial variation across observations.

5.5 Other Variables

The last variable seen in the cross-sectional model is called, *dum_2006*. This variable is included to absorb any differences in price due to time, such as market-specific inflation or trends. In this sense, any time-specific characteristics of price will be absorbed by this variable, allowing the unbiased effects of other variables to be observed.

Now that the independent variables have been discussed, we move briefly to the discussion of the dependent variable. The dependent variable in this model, selling price, is the simplest definition used in the hedonic literature. The variable is in real dollars, using 2006 as the base year. Therefore, all results presented in this paper are in terms of 2006 dollars. Other specifications were also used that standardized price, dividing sales price by frontage or acres. While it may seem advantageous to standardize price to avoid heteroskedasticity, the transparency of the existing model is attractive. Moreover, heteroskedasticity is not a major issue for this model and, where present, is accounted for using other means. A more extensive exploration of this issue is covered in a subsequent section.

5.6 Econometric Considerations

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. The third model, a double-log specification, was a variation of this second form, where non-dummy variables would be transformed using the natural log operator. This had potential in terms of model fit and ease of interpretation, but too many continuous variables had 0 and 1 values (i.e. assessed structure value and percentage of private frontage), causing the transformation to be more problematic than helpful. Thus, this model was never estimated. In addition, 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 (Bender, Gronberg, and Hwang 1980; Sakia 1992). 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). Finally, a non-linear specification is estimated, such that:

(5.2) $Price_{it} = \beta_1 \, Struc\_val_{it} + e^{\sum_{j=2}^{K} X_{jit}\beta_j} + \epsilon_{it}$ for i = 1, 2, ..., N in time period t; $\epsilon_{it} \sim N(0, \sigma_i^2)$

where: N is the number of observations and K is the number of parameters.

This specification assumes 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:

(5.3) $\partial Price/\partial X_j = \beta_j * e^{\sum_{j=2}^{K} X_{jit}\beta_j}$ for j = 2, 3, .., K

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, p. 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: one transforming the non-binary independent variables with a constant value of λ, one allowing λ to vary over the independent variables, and others that include transformations of the dependent and independent variables, allowing λ to vary for all parameters in the most flexible case. While the less restrictive model always fits best, the most flexible forms were not chosen due to interpretation problems. For example, the λ 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). 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 McConnell 1988, p. 674). As it turns outs, all specifications have a relatively similar fit, with the linear Box-Cox (constant λ 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. However, results from the non-linear specification are presented with the panel data estimations later in the paper to demonstrate model robustness across specifications.

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. To test for the presence of multicollinearity, two diagnostic tests were used. The first was pair-wise correlation analysis. This simple diagnostic revealed that no two variables had a correlation value of .7 or greater, except for distance & distance–squared and frontage & frontage-squared, which was expected. Second, variance inflation factors (VIF) were calculated for each variable (see Gujarati 2004, p. 350-353).[13] Using Gujarati's rule of thumb, attention is paid to variables where the VIF is greater than 10 (Gujarati 2004, p. 362-363). Once again, the only variables of concern were distance & distance-squared and frontage & frontage-squared, which was expected. Thus, multicollinearity does not seem to be a problem for the models specified above.

[13] Variance inflation factors are calculated by regressing each independent variable on all other independent variables (including a constant), from which VIF = $1/(1-R^2)$.

Next, the above models were tested for the presence of heteroskedasticity. This was done by calculating a Breusch-Pagan test statistic for each model. The test statistics were highly significant. Upon further investigation, it became apparent that a number of variables were likely the cause for this heteroskedasticity. Instead of trying to formulate the nature of the present heteroskedasticity (multiplicative, exponential, etc.) and estimating with GLS, a far simpler solution was discovered. Gujarati (2004) stresses the problems that outliers can cause, including heteroskedasticity (p. 390). With this in mind, outlier observations were quickly identified. Using the mean and standard deviation of the dependent variable, observations outside of two standard deviations from the mean were eliminated. This was done for both the 2005-2006 data and the full panel. While it is never preferred to omit observations, doing so in this case helps to alleviate the problem of heteroskedasticity. For the cross-sectional estimations, 23 observations were omitted.[14] The threshold of two standard deviations was chosen because this was the first point where heteroskedasticity seemed to disappear. To be sure that the problem of inefficiency does not arise, White's robust standard errors are used in addition to the elimination of outliers. These robust errors allow for reliable statistical inference tests to be carried out.

[14] In later estimations when the full panel data set (1841 observations) is used, 92 observations 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.

Chapter Six: Results of Cross-sectional Estimation

Three cross-sectional models were estimated using the general specification set forth above in equation 5.1. Each model differs from another only in the specification of the EWM variables. The first model uses a continuous relative frequency measure; the second model uses three dummy variables based off relative frequency (two are aggregated into one category—medium/high), while the third uses a presence/absence dummy variable. All three models use ordinary least squares for estimation and are used to demonstrate the consequences of ignoring the endogeneity of the EWM variables. The results for these models are summarized into Table 7 below.

Table 7. Cross-Sectional Estimation Results

	Model 1		**Model 2**		**Model 3**	
R^2	.7445		.7529		.7460	
Adj-R^2	.7316		.7392		.7331	
	Coef.	**Robust Std. Err.**	**Coef.**	**Robust Std. Err.**	**Coef.**	**Robust Std. Err.**
Constant	-103235.60**	58656.591	-131502.400*	58445.511	-105339.600**	58522.000
Struc_val	1.601*	0.090	1.604*	0.089	1.590*	0.089
Lot	7778.311**	4181.888	8159.484*	4141.870	7892.881**	4154.148
Front	584.021*	126.138	567.881*	123.452	596.593*	125.599
$Front^2$	-0.533*	0.125	-0.530*	0.125	-0.539*	0.124
Lake_area	9.074	10.802	12.912	10.584	8.662	10.828
Assoc	-7886.761	11266.801	-10625.180	11549.109	-9800.712	11396.177
Private	1083.478	36115.933	4359.930	43599.300	10926.030	42023.192
Access	13616.310	17916.197	21047.090	18144.043	16692.670	17949.108
Dev_dens	447.697	418.408	526.798	438.998	436.959	416.151
Max_dep	788.128	486.499	968.887*	489.337	707.029	468.231
Prime	518.953	17298.433	9844.470	20090.755	17318.92	21120.634
EWM_rel_freq	2701.739	2196.536	--	--	--	--
*Freq * treat*	24372.150*	4994.293	--	--	--	--
EWM_low	--	--	-55701.150*	18817.956	--	--
EWM_medhigh	--	--	52865.610**	27391.508	--	--
*Low * treat*	--	--	182821.600*	46877.333	--	--
*Medhigh * treat*	--	--	106356.100*	26522.718	--	--
Impact	--	--	--	--	-20678.31	18462.777
*Impact * treat*	--	--	--	--	133706.900*	31167.110
Dum_2006	-10563.710	10157.413	-12893.420	10072.984	-10874.580	10163.159
Water_Clarity	9338.464	6309.773	9986.444	6320.534	9493.68	6287.205

Muskie	17888.400*	5807.922		14462.230*	5761.845		17608.930*	5754.552
Pike	15387.660*	7157.051		13928.460*	6929.582		12807.900**	7076.188
Walleye	6626.333	9332.863		7103.535	9866.021		12683.970	9536.820
Bass	-5297.832	8277.863		-9147.773	8392.452		-6032.913	8264.264
Panfish	975.294	6966.386		3353.409	7134.913		1777.784	7111.136
Dist	6503.151*	2676.194		9911.214*	2715.401		5422.353*	2533.810
$Dist^2$	-209.936*	82.979		-304.420*	85.034		-186.771*	79.817
Moran's I	0.217*	0.037		0.190*	0.038		0.214*	0.037

Note: n = 457 for all models
All dollar amounts in 2006 dollars
*** indicates significance at the 95% level, ** indicates significance at the 90% level**

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. Alternatively, the coefficients could have been multiplied by the mean of the corresponding independent variable (or other point of evaluation) and divided by mean selling price so that the interpretation could be done in terms of elasticities. The coefficients appear to be somewhat unstable across the above models. This model instability is resolved in later modeling, where alternative econometric techniques are used to address the issues of endogeneity and spatial autocorrelation (to be discussed in a subsequent section).

Several non-EWM variables are significant at the 95% confidence level across estimations in Table 7, including the assessed structure value, frontage, frontage-squared, muskie, pike, distance, and distance-squared variables. Moreover, the lot size variable is significant at the 90% level. Of the significant variables, those with unexpected signs across all three models include distance and distance-squared. The results indicate that property values increase at a diminishing rate with distance from the nearest town, which is opposite of the standard Mills bid-rent model (Mills 1981). However, many of these homes are cottages/second homes or otherwise meant to be secluded, so isolation may be a desired good.

The emphasis of these results should be placed only on the EWM variables, as these estimations are rife with unaccounted econometric problems. The discussion of the EWM variables below serves to motivate these problems. Therefore, concerns about the unexpected signs of non-EWM variables, the statistical insignificance of variables, or the lack of model robustness across specifications are unnecessary at this point and will only be addressed after subsequent estimations, once the econometric issues described below are accounted for.

The EWM-variables differ across the above cross-sectional models, but in each case, illustrate a central challenge of this research—the endogeneity of EWM. Before discussing the results of the model, the intuition of this concept should be explained. It was established in a prior section that EWM is most commonly transported in Vilas County by recreational boaters, mostly unintentionally. With this in mind, we expect recreational boaters to visit lakes that are most popular. In general, property values in a place with desired amenities will be bid up, and so we would expect lakes that are most popular to have higher property values. Accordingly, the argument can be extended to claim that lakes with a higher probability of getting EWM or already having EWM have higher property values relative to less-popular lakes.

In some instances, the popularity of the lake is observable, such as with the fishing indices used in this study. The quality of fisheries drives a lot of recreation and hence, lake popularity. However, lake popularity is also likely to be a function of variables that are unobserved. An unobserved attribute that drives popularity may have to do with a lake's natural beauty or scenic views. Such characteristics cannot reliably be measured and in general, data do not exist for such amenities. To the extent that the attractiveness of a lake is unobserved to the analyst, EWM will be correlated with the error term in the hedonic model and OLS estimation will produce coefficient estimates that are positively biased.

Looking first at Model 1 in Table 7, a continuous measure of relative frequency is used to gauge the effect of EWM. The coefficient on this variable represents the change in price from an additional percentage of EWM, relative to all other species in the lake. The estimated coefficient is positive, but statistically insignificant, indicating that marginal additions of EWM have no effect on price. 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 intuitive sense, indicating that a lake treated for EWM sells for a statistically significant premium (of greater than $27,000 at the lowest level of abundance) relative to lakes that are not infested.[15] In other words, the model says it is beneficial to a property owner to have EWM in the lake *and* to treat it, than to not have EWM at all. The coefficient on the f*req*treat* variable is expected to be positive given that this is the differential for infested lakes that are treated, relative to infested lakes that are untreated. However, the magnitude of this interaction coefficient dominates the coefficient on the *EWM_rel_freq* variable leading to the non-intuitive conclusion made above—properties on treated, infested lakes sell for a statistically significant premium relative to those on uninfested lakes.

Moving onto Models 2 and 3 in Table 7 above, we reach a similar conclusion. Model 2 uses two dummy variables to indicate if a lake has low abundance levels of EWM (≤3% relative

[15] This is derived using the summation of coefficients on the *EWM_rel_freq* and *freq* treat* variables, since $\partial Price/\partial EWM = \beta_{EWM\_rel\_freq} + \beta_{freq*treat}$ (assuming a minimal level of abundance—1%). The second piece is turned on or off depending if the lake has been treated. The variance is calculated for this statistic, allowing the analyst to determine that the statistic is significant at the 95% confidence level. This same methodology is applied to the other models in Table 7 to get at the relative premium of treated, infested lakes relative to uninfested waters.

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 EWM suffers a negative price effect of $55,700, relative to uninfested lakes. However, the medium/high coefficient indicates a fixed price premium of $52,800, relative to uninfested lakes (significant at the 90% confidence level). Once these variables are interacted with the treatment variable, the issue of endogeneity is again made apparent. As in Model 1, a statistically significant premium is associated with treated, infested lakes as compared to those free of EWM. This time, however, the premiums are huge—over $127,000 for low-level treated lakes and over $159,000 for the medium/high-level treated lakes.

Model 3 aggregates the dummy variables seen in Model 2 into one presence/absence measure and the same results are found. A statistically insignificant price effect is found for properties on lakes with EWM. However, once these lakes are treated, a statically significant premium is associated with properties on these lakes, relative to properties on uninfested waters. Properties on a treated lake with EWM should not be getting a price premium over an uninfested lake. Based on anecdotal evidence and basic knowledge about the effects of EWM (not to mention the costs of treatment), it is difficult to imagine individuals who prefer that EWM be present on their lake, treated or not. The purpose of this cross-sectional analysis is to illustrate the presence of the endogeneity issue, despite often being overlooked in the hedonic literature.

Further indications of the endogeneity of EWM were presented in Figures 6, 7, and 8, along with Table 4. Recall, Figure 6 demonstrates a premium for properties on EWM lakes through the early 2000s, while Table 4 shows that properties on 12 of the 17 lakes with EWM (in the data set) sold in the upper echelon of selling price of all properties. Furthermore, Figures 7 and 8 serve as further evidence that properties on infested lakes sell for more, relative to properties on uninfested lakes at all statistical categories (mean, median, 1st quartile, etc.).

A reasonable explanation for the results seen across the OLS models and in the figures and tables from the descriptive statistics section is that EWM is endogenous, or correlated with unobserved lake characteristics. In other words, properties on lakes with EWM may have sold for a premium before the lake became infested with EWM, due to the lake's natural beauty or other unobserved factors. Leggett and Bockstael (2000) argue that the potential for endogeneity in hedonic analyses of environmental quality due to unobserved attributes is often overlooked, but is critical to address if the effect of interest is to be properly identified. Small (1974) even refers to this set of unobserved attributes as "unmeasured neighborhood characteristics" (p. 105). This description is quite fitting in this discussion, as each lake serves as a natural neighborhood. This will be helpful for later estimations.

The following section explores the issue of endogeneity a bit further, but mostly as it relates to the issue of spatial autocorrelation. The issue of spatial autocorrelation is motivated, in part, using the Moran's I statistics presented in Table 7 above. Given the presence of both econometric challenges in this study, difference-in difference analysis is coupled with a random or fixed effects estimation. We turn now to a section that motivates this modeling approach.

Chapter Seven: Empirical Model Two

7.1 Further Econometric Issues

Due to the spatial nature of this problem, in particular, the unobserved lake specific effects, spatial autocorrelation is expected to be an issue for this model. In other words, observations that lie on the same lakes are expected to have similar errors, due to unobserved characteristics of the lake. It is important to account for this clustering of errors across space to avoid inefficiency of the standard errors. To test for the presence of spatial autocorrelation, the Moran's I statistic is generated. The statistic is calculated as follows:

$$(7.1) \qquad I = \frac{e_s' W e_s}{e_s' e_s}$$

(Anselin and Bera 1998, p. 265).

This statistic is relatively easy to compute because it uses the errors from the restricted model, e_s (CRM residuals), 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, and so W is defined this way. Intuitively, one would expect the error terms to be correlated within a lake because many of the lake characteristics are shared. Using this definition, the weight matrix was built and a Moran's I statistic was calculated for each model in Table 7. The null hypothesis associated with this test is that no spatial dependence exists. Based on the statistics shown in Table 7, the null was rejected at the 99% confidence level in all cases. This confirmed the presence of spatial autocorrelation. Estimating these models with OLS would be inappropriate as inefficiency in the standard errors arises.

To incorporate the spatial correlation of errors into the model, two approaches are used; either a lake-specific fixed effect or random effect is estimated. A random effects model estimates a lake-specific error term that is meant to deal with the efficiency losses associated with autocorrelation. The key assumption made in a random effects model is that these lake-specific error terms are uncorrelated with any observed independent variables. As argued above, this may be too strong of an assumption, given the endogeneity of EWM. Therefore, a fixed effects model is also estimated where time-invariant characteristics, observed or unobserved, are accounted for by the fixed effect. This should relieve the inefficiency issue associated with autocorrelation and also accommodate the potential for correlation between independent variables and the fixed effects. Due to this key difference, the fixed effects would still yield consistent estimates, whereas the random effects specification would lead to bias if correlation exists between any independent variable and the lake-specific unobservables. Since this study is not particularly interested in the marginal willingness-to-pay for time-invariant characteristics, such as lake area or maximum depth, the fixed effects specification simplifies estimation and allows for identification of the EWM-effect on property values.

In addition to spatial autocorrelation, the other econometric issue central to this study, endogeneity, has already been established based on the cross-sectional results presented above. This problem is related to the issue of spatial autocorrelation as exogenous variables may be correlated with the error term, particularly the unobserved characteristics of each lake. To deal with some of the endogeneity bias, this study uses a difference-in-difference methodology as motivated by several recent studies (Tu 2005; Schwartz et al. 2006; Hallstrom and Smith 2005; and Galster, Tatian, and Pettit 2004). A difference-in-difference specification looks at the change in premium that is present both before and after infestation for properties on lakes with

EWM relative to those on uninfested lakes. If one can assume that any unobserved characteristics related to a lake's attractiveness remain constant within the sample period, then difference-in-difference can help control for these unobserved characteristics and ensure proper identification of EWM. Thus, the identification issue is resolved, in part, by the difference-in-difference methodology.

In summary, the issues of endogeneity and spatial autocorrelation are dealt with using a spatial difference-in-difference specification. This approach is simple enough to be estimated using linear regression techniques and yet, simultaneously accounts for both the bias and inefficiency associated with unobserved, spatially-correlated neighborhood effects.

7.2 Set Two of Empirical Models

The second set of models is estimated using the entire panel data set from 1997-2006, resulting in a total of 1841 observations, spanning 172 lakes. The panel-based models take one of two general forms:

1) Random effects specification

Theoretical Model

(7.2) $Y_{it} = \alpha + X'_{it}\beta + \mu_{j(i)} + \varepsilon_{it}$, where $\mu_{j(i)}$ is the jth lake-specific random error associated with observation i in time period t.

$E[\varepsilon_{it} \mid X_{it}] = E[\mu_{j(i)} \mid X_{it}] = 0$

$\eta_{it} = \mu_{j(i)} + \varepsilon_{it} \qquad \epsilon_{it} \sim N(0, \sigma_{\epsilon i}^2) \qquad \mu_{j(i)} \sim N(0, \sigma_\mu^2) \qquad \eta_{it} \sim N(0, \sigma_{\epsilon i}^2 + \sigma_\mu^2)$

Empirical Model

(7.3) $Price_{it} = \beta_0 + \beta_1\, Struc\_val_{it} + \beta_2\, Lot_{it} + \beta_3\, Front_{it} + \beta_4\, (Front_{it})^2 + \beta_5\, Lake\_area_{it} + \beta_6\, Assoc_{it} + \beta_7\, Private_{it} + \beta_8\, Access_{it} + \beta_9\, Zone\_100\_any_{it} + \beta_{10}\, Zone\_200\_300_{it} + \beta_{11}\, Aft\_100\_any_{it} + \beta_{12}\, Aft\_200\_300_{it} + \beta_{13}\, Max\_dep_{it} + \beta_{14}\, Prime_{it} +$

$\beta_{15}\, Impact_{it} + \beta_{16}\, Before_{it} + \beta_{17}\, Time_{it} + \beta_{18}\, Water\_Clarity_{it} + \beta_{19}\, Muskie_{it} +$

$\beta_{20}\, Pike_{it} + \beta_{21}\, Walleye_{it} + \beta_{22}\, Bass_{it} + \beta_{23}\, Panfish_{it} + \beta_{24}\, Dist_{it} + \beta_{25}\, (Dist_{it})^2 + \mu_{j(i)}$

$+ \epsilon_{it}$ for j = 1, 2, …, 172 (total lakes)

2) Fixed effects specification

Theoretical Model

(7.4) $Y_{it} = X'_{it}\beta + D'_{j(i)}\alpha + \varepsilon_{it}$, where $D_{j(i)} = [d_1\ d_2 \ldots d_n]$ is a matrix of dummy variables associated with lake j(i) where parcel i is located, α is a j x 1 vector of fixed effects coefficients, and $\epsilon_{it} \sim N(0, \sigma_i^2)$

Empirical Model

(7.5) $Price_{it} = \beta_1\, Struc\_val_{it} + \beta_2\, Lot_{it} + \beta_3\, Front_{it} + \beta_4\, (Front_{it})^2 + \beta_5\, Aft\_100\_any_{it} +$

$\beta_6\, Aft\_200\_300_{it} + \beta_7\, Prime_{it} + \beta_8\, Before_{it} + \beta_9\, Time_{it} + \sum_{j=1}^{172} a_j D_{j(i)} + \epsilon_{it}$

New variables appearing in 7.3 or 7.5 are explored below in Table 8.

Table 8. Description of Additional Variables in Panel-based Models

Descriptive Name	Variable Name	Variable Description
Lake that changes zoning from 100ft to other amount	*Zone_100_any*	= 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
Lake that changes zoning from 200ft to 300ft	*Zone_200_300*	= 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
After zoning change from 100ft to other amount	*Aft_100_any*	= 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
After zoning change from 200ft to 300ft	*Aft_200_300*	= 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
EWM lake	*Impact*	= 1 if the property is on an EWM-infested lake as of 2006 and 0 otherwise
Before EWM	*Before*	= 1 if the property is on an EWM-infested lake AND the transaction occurs before infestation
Time	*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.
Fixed effect	D_j	= 1 to designate which lake the property borders

As shown above in the theoretical setup for the random effects model, the error term for observation i is additive between a general error term and a group-specific error term. Conversely, the fixed effects appear as independent variables. The fixed effects are not present in the error term, so correlation can still exist between the fixed effects and independent variables without violating the assumption, $E[\epsilon_{it} \mid X_{1t}, X_{2t}, \ldots, X_{Kt}] = 0$. This assumption is violated in the case of the random effects if correlation exists between X_{it} and η_{it}, which seems to be the case based on the thorough body of evidence established in the preceding sections concerning the endogeneity of EWM. The issue of violating this assumption is explored in a subsequent results section, but for now it is important to remember the purpose of using a fixed or random effects model; due to the spatial nature of the problem, these effects soak up any unobserved (and observed in the fixed effects case) spatial heterogeneity that is clustered within neighborhoods. For the purposes of this study, these neighborhoods are defined as within a lake.

The fixed effects specification has far fewer variables than the random effects model. This is because any time-invariant characteristic, such as lake area, maximum depth, or distance to nearest town is absorbed by the fixed effect and thus, cannot also be included individually in the model if multicollinearity is to be avoided (Allison 2005, p. 3-4). This also includes the constant term. If a variable varies within a lake or over time, such as the *before* variable, lot size, or frontage, the variable appears in the model. In general, the fixed effects absorb both observed and unobserved characteristics that are time-invariant.

Both models outlined above use a difference-in-difference specification. In particular, nine lakes became infested with EWM after 1999.[16] In light of this, difference-in-difference can be used to identify an unbiased estimate of the effect of EWM on these lakes. Given the above specifications, the coefficient on *impact* (β_{15} in the random effects model, equation 7.3) will specify the premium/discount that properties on lakes with EWM sell for, relative to those on non-infested lakes. Because the *impact* variable is time-invariant, this variable is swallowed up into the fixed effect in that model. The additive result of *impact* and *before* ($\beta_{15} + \beta_{16}$ in the random effects model) will specify the premium/discount that properties on lakes with EWM sell for before infestation, relative to properties on non-infested lakes.[17] Finally, the difference-in-

[16] Lakes infested with EWM 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.

[17] Recall from Table 8 that the *before* variable is an interaction of *impact* and a variable that designates whether or not the transaction takes place before the infestation. Therefore the partial derivative with respect to *impact* is $\partial Price/\partial Impact = \beta_{15} + \beta_{16}$ in the random effects model. The second component of this effect, β_{16}, is turned on or off depending if the transaction took place before or after an infestation.

difference component follows from this; the before infestation premium ($\beta_{15} + \beta_{16}$) minus the after infestation premium (β_{15}) is simply β_{16}. Therefore, the addition of β_{16} allows the researcher to back out the difference in premium of now-infested lakes, before they became infested.

A few differences in variables and data are apparent between the cross-sectional models and the panel-based models. Most simply, the EWM variables that appeared in part as continuous abundance measures in the cross-sectional models are purely presence/absence indicators in the panel data models. This is primarily because abundance data are unavailable for years prior to 2005. Given that EWM is nearly impossible to remove once present and expensive to manage, and because the time-growth relationship for EWM is so uncertain, the mere presence of EWM is likely the greatest concern of lakefront property owners, as opposed to the level of infestation at any given time. In this sense, the presence/absence measure used above is appropriate.

Moreover, empirical analysis provides some support for this claim. Table 9 presents the regression results for a simple OLS estimation that regresses 2006 abundance levels of EWM on a few primary determinants thereof. This is done for the 17 lakes in Vilas County, for which data are available. Abundance is measured in terms relative frequency and the independent variables are the same as those described in above sections.

Table 9. Abundance Regressions

	Model 1			**Model 2**			**Model 3**	
R^2	.6220			.6144			.618	
Adj-R^2	.4502			.4859			.491	
	Coef.	**Std. Err.**		**Coef.**	**Std. Err.**		**Coef.**	**Std. Err.**
Constant	3.750	5.952		6.078**	3.268		2.213	3.751
Area	0.001	0.002		0.001	0.002		0.001	0.002
Depth	-0.166	0.111		-0.122**	0.060		-0.183**	0.095
Water clarity	0.894	1.902		--	--		1.262	1.502
Years_since_ Invasion	0.054	1.080		-0.312	0.867		0.450*	0.201
Years_since_ invasion_sqaured	0.022	0.065		0.040	0.052		--	--

Note: n = 17 for all models
*** indicates significance at the 95% level, ** indicates significance at the 90% level**

In general, the first two models in Table 9 reveal no significant determinants of abundance, with *depth* as perhaps the lone exception. However, when *Years_since_invasion* is included without a quadratic term, the coefficient is statistically significant, as seen in Model 3 in Table 9. Across all specifications most coefficients are not significant and even vary in sign. Unfortunately these models are based off very few observations, given the limited amount of abundance data available. Moreover, the adjusted-R^2 figures reveal that none of the models are a particularly strong fit for the data. The assumption about linear growth must be imposed in order to gain statistical significance in the *Year_since_invasion* coefficient, as seen in Model 3 above. This may be too strong of an assumption.

Table 10 below further demonstrates the spurious relationship between time and growth of EWM.

Table 10. Abundance and Time Since Invasion

Lake	Abundance (%)	Years Since Invasion
Little St. Germain	0.01	3
Forest	0.01	5
North Twin	0.27	5
Arrowhead	0.43	1
Upper Gresham	0.77	5
Cranberry	1.2	5
Catfish	2.4	11
South Twin	2.43	5
Duck	3.3	14
Otter	3.3	14
Silver	3.38	1
Voyageur	4.9	12
Eagle	6	14
Yellow Birch	6.4	14
Boot	6.6	6
Scattering Rice	11.11	14
Watersmeet	14.5	14

Table 10 reveals that time and growth are not as strongly correlated as one might expect. Certainly the table above reveals some positive relationship, but determinism is clearly lacking. Due to this lack of determinism, the risk of an invasion resulting in a severe infestation is not clear to property owners. With this uncertainty, property owners are likely to act most conservatively by capitalizing the full price-effect of EWM into property values almost immediately after an invasion, instead of being moderated over time. For example, say a property owner is looking for property on two similar lakes, except one just became infested EWM, while the other is uninfested. The lake with EWM could explode into a severe infestation the following year, or it could take several years for the species to become a significant nuisance. With this uncertainty, the average risk-averse property buyer will be forced to assume the worst case-scenario and differentiate the properties using the full price effect associated with EWM. Therefore, there seems to be strong evidence for using the presence/absence measures used in the panel data estimations. Once additional abundance data become available in the future, refined estimates could be derived based off abundance levels. However, the preceding discussion justifies why measures that proxy for unavailable abundance data, such as time since invasion, may not be overly useful.

Another difference between the cross-sectional and panel-based models is seen in the density/zoning variable. Whereas in the cross-sectional models, a continuous measure of density was used, dummies indicating before and after changes in zoning are used in panel estimations. First, given the positive sign of density in the cross-sectional models, the potential for endogeneity may exist. This concern arises because past surveys of lakefront property owners in the study region have shown a distinct preference for less density (or stricter zoning). Density can be correlated with similar unobserved attractive features of a lake as with EWM. Second, expectations about density are captured through zoning, so a similar consideration for development density is made in this specification as was in the cross-sectional models. Finally, many lakes in the data set underwent a change related to zoning in May, 1999. At this time, the Vilas County Shoreland Zoning Ordinance went into effect, as discussed in Chapter 2.

The above specification is a difference-in-difference approach used with respect to zoning to see how the premium/discount of affected lakes differs after the zoning change, relative to unaffected lakes and within affected lakes over time. Similar to the EWM variables, β_9 (in the random effects model, equation 7.3) represents the premium/discount that properties on lakes that undergo a change from 100ft to some stricter level sell for relative to properties on lakes that remain unchanged in zoning restriction. Likewise, β_{10} represents this relative premium for properties on lakes that change from 200ft to 300ft. Both of these effects are present in the fixed effect for that model. $\beta_9 + \beta_{11}$ (or $\beta_{10} + \beta_{12}$) represents the difference in premium between properties on affected lakes and those on unaffected lakes after the change in zoning.[18] Finally, β_{10} and β_{12} (β_5 and β_6 in the fixed effects model, equation 7.5) represent the difference in premium/discount for affected lakes after the zoning change, relative to before—this is the difference-in-difference component. Most simply, the *aft_100_any* and *aft_200_300* coefficients show the price effect on properties affected by a change in zoning, *after* the change. Not all lakes underwent a change in zoning, as some lakes were zoned 200ft before the Lakes Classification Ordinance went into effect and ended up 200ft under the new classification. This fact makes the difference-in-difference analysis feasible.

The time variables used above, accounting for the year a given transaction takes place (or the average change in price over the study period), are used to absorb any time-related effects on price. As discussed above with the *dum_2006* variable in model one, the inclusion of these variables allows for the absorption of market-specific inflation or trend effects. In this sense, the marginal effects of other variables are properly identified. Moreover, all results are reported in 2006 dollars.

Also, notice a treatment variable is not interacted with the *impact* or *before* variables. This is because observations that are included in the *before* variable border lakes that are yet to be infested with EWM as of the transaction date. Thus, the lakes would not be considered for treatment and therefore were not treated. Moreover, treatment data are not reliably available for years prior to 2005. This is in part because large-scale treatment records prior to 2005 are difficult to locate and decipher; additionally, many treatments in the study region go undocumented since many lakefront property owners choose to remove EWM from their own

[18] See previous footnote. The same logic set forth with regard to the *impact* and *before* variables applies to the zoning variables—*zone_100_any* & *aft_100_any* and z*one_200_300* & *aft_200_300*. In this case, however, the change of interest is *after* the change, not before, as was the case with the EWM difference-in-difference analysis.

beaches. Any variable that does not account for these numerous small-scale treatments would be a poor measure.

One additional item to note with the specifications above is the variation in year of invasion. These 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 EWM invasions is highly unlikely. Again, this is due to the variation of years in which invasions took place.

Finally, with respect to the EWM variables, the effect associated with the presence of EWM should be further emphasized. Take the case of zoning first as a counter example. Zoning laws are put in place over time and expectations about the laws are captured in real estate values well before the laws actually go into effect. In that sense, identification of a change in zoning effect can be a challenging task due to expectations. On the contrary, lake owners are unlikely to believe that their lake will be affected by EWM if the species is not already present. While this study has argued that EWM is more likely to show up in lakes highly popular for recreational activities, particularly boating, the vast majority of "popular" lakes in Vilas County are still free of EWM. Therefore, the effects associated with an invasion are unlikely to be diluted by any previous expectations about such an event, as these expectations are unlikely to exist.

Chapter Eight: Further Results

8.1 Estimation Results

We turn now to the results for the panel-based estimation. Tables 11 and 12 summarize the results, one table for each time variable specification. In Table 11, time influences are accounted for using a dummy for each transaction year, while a time trend variable is used in Table 12. Results for the fixed effects model are presented in the linear (equation 7.5) and non-linear form (NLLS—see equation 5.2), as mentioned would be done in an earlier section. Random effects estimations correspond to equation 7.3.

Table 11. Estimation Results for Set Two of Models with Year Dummies

	Fixed Effects			**NLLS Fixed Effects**			**Random Effects**	
R^2	.8183			.8296			.7381	
	Coef.	**Robust Std. Err.**		**Coef.**	**Robust Std. Err.**		**Coef.**	**Robust Std. Err.**
Constant	--	--		--	--		-143363.900*	45512.349
Struc_val	1.519*	0.055		1.513*	0.027		1.530*	0.052
Lot	5006.164*	1468.083		1.293*	0.155		5560.049*	1506.788
Front	235.263*	38.316		3.466*	0.275		225.957*	37.042
Front^2	-0.034	0.025		-2.363*	0.343		-0.031	0.024
Lake_area	--	--		--	--		22.063	16.972
Assoc	--	--		--	--		-3843.854	10115.405
Private	--	--		--	--		16458.540	29924.618
Access	--	--		--	--		25746.500*	12144.575
Zone_100_any	--	--		--	--		40853.890*	15019.813
Zone_200_300	--	--		--	--		44149.670*	18243.665
Aft_100_any	-38626.530*	8778.757		-0.216*	0.079		-37383.910*	7870.297
Aft_200_300	-59163.000*	15248.196		-0.202	0.470		-44463.950*	15767.358
Max_dep	--	--		--	--		612.373	395.079
Prime	8772.964	10830.820		-0.006	0.060		9713.950	10445.108
Before	28294.200**	14891.684		0.210*	0.093		19684.830	13670.021
Impact	--	--		--	--		5859.234	20204.255
Dum_1998	10095.200	10095.200		0.124	0.096		10802.680	8927.835
Dum_1999	54634.800*	11015.081		0.392*	0.095		53067.200*	10088.821
Dum_2000	63306.830*	12972.711		0.542*	0.095		61345.160*	11911.682
Dum_2001	60896.670*	11533.460		0.477*	0.094		59118.830*	10463.510
Dum_2002	79208.170*	12454.115		0.645*	0.091		77758.050*	11384.780
Dum_2003	95634.540*	12517.610		0.729*	0.088		93254.930*	11789.498

Dum_2004	109544.100*	12664.058		0.830*	0.089		107961.700*	11722.226
Dum_2005	128563.200*	12882.084		0.968*	0.088		127456.900*	11911.860
Dum_2006	128854.000*	13380.478		0.952*	0.087		120722.600*	12523.091
Water_Clarity	--	--		--	--		6456.105	5083.547
Muskie	--	--		--	--		8843.965**	4754.820
Pike	--	--		--	--		2452.120	6452.947
Walleye	--	--		--	--		9504.168	8410.768
Bass	--	--		--	--		-3164.745	7718.890
Panfish	--	--		--	--		243.968	6099.200
Dist	--	--		--	--		4500.164**	2356.107
$Dist^2$	--	--		--	--		-135.404*	65.413

Note: n = 1841 for Fixed Effects and Random Effects models; n = 1708 for NLLS Fixed Effects Model
172 fixed effects not displayed for space (106 for the NLLS model)
All dollar amounts in 2006 dollars
*** indicates significance at the 95% level, ** indicates significance at the 90% level**

Table 12. Estimation Results for Set Two of Models with Year Trend Variable

	Fixed Effects			NLLS Fixed Effects			Random Effects	
R^2	.8165			.8273			.7356	
	Coef.	**Robust Std. Err.**		**Coef.**	**Robust Std. Err.**		**Coef.**	**Robust Std. Err.**
Constant	--	--		--	--		-132668.700*	47381.679
Struc_val	1.517*	0.056		1.512*	0.027		1.525*	0.053
Lot	4928.066*	1416.111		1.277*	0.154		5427.885*	1463.042
Front	241.142*	38.769		3.573*	0.273		233.144*	37.483
$Front^2$	-0.036	0.025		-2.511*	0.341		-0.034	0.025
Lake_area	--	--		--	--		23.161	18.237
Assoc	--	--		--	--		-3840.594	10973.126
Private	--	--		--	--		20628.030	31735.431
Access	--	--		--	--		25942.580*	13036.472
Zone_100_any	--	--		--	--		28290.330**	15804.654
Zone_200_300	--	--		--	--		34632.260**	17851.680
Aft_100_any	-23783.320*	6814.705		-0.117**	0.068		-23024.640*	6360.398
Aft_200_300	-44400.530*	14276.698		-0.073	0.456		-32032.840*	14300.375
Max_dep	--	--		--	--		583.120	422.551
Prime	9471.351	10641.967		-0.024	0.059		9703.883	10323.280
Before	29518.130**	15294.368		0.201*	0.092		21593.460	14113.373
Impact	--	--		--	--		4867.683	22125.832
Trend	13537.410*	937.494		0.096*	0.005		13079.100*	870.200
Water_Clarity	--	--		--	--		5837.465	5306.786
Muskie	--	--		--	--		8545.269**	5116.928
Pike	--	--		--	--		1652.916	6887.150
Walleye	--	--		--	--		10255.490	8996.044
Bass	--	--		--	--		-2648.911	8277.847

Panfish	--	--		--	--		580.105	7251.313
Dist	--	--		--	--		4374.912**	2528.851
Dist^2	--	--		--	--		-130.913**	70.007

Note: n = 1841 for Fixed Effects and Random Effects models; n = 1708 for NLLS Fixed Effects Model
172 fixed effects not displayed for space (106 for the NLLS model)
All dollar amounts in 2006 dollars
*** indicates significance at the 95% level, ** indicates significance at the 90% level**

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 specifications, indicating a certain degree of model robustness. This robustness was also observed when tinkering with other specifications for the density/zoning variables. Although these results are not presented, the stability of coefficients over a variety of model specifications provides strong evidence that the results seen above are quite robust and insensitive to small changes in model formulation. The coefficients of the non-EWM variables are incredibly stable across the linear fixed effects and random effects specifications. For example, the coefficients on the assessed structure value, lot size, frontage, frontage-squared, prime, and time variables are nearly identical and of the same order of statistical significance.

This 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. The zoning variables are the lone exceptions in this comparison. 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 out of the total 1841. Given the functional form of this model, $Price_{it} = \beta_1 \, Struc\_val_{it} + e^{\sum_{j=2}^{K} X_{jit}\beta_j} + \epsilon_{it}$ (see equation 5.2 for other information), the

Gauss-Newton algorithm used to solve out the non-linear specification is very sensitive to large values of independent variables. Furthermore, a fixed effect with fewer than five transactions is too similar to a column of zeros for the purposes of the algorithm; hence, the reduction in observations for the non-linear model. Since the magnitudes cannot be compared with the linear models directly, they are of little concern. Instead, the signs of the coefficients and levels of significance should be compared across models, and they reveal a relatively consistent and robust model, regardless of specification.

In addition, results are presented in Table 13 below for three NLLS fixed effect models (equation 5.2) that vary based on the number of lakes included in each estimation. NLLS Fixed Effects 1, shown below in Table 13, is the same model as presented in Table 11. The other two models below have the same specification, but include lakes with 10 transactions or greater and 15 transactions or greater respectively. The reason for comparing these models is to gauge the possibility of an incidental parameters problem (see Greene 2003, p. 697). This is a potential problem for non-linear fixed effects models with short panels, but not for the linear specifications. Essentially, the concern is whether the vector of coefficients is consistent. Since some fixed effects are estimated with as few as five transactions, concern for inconsistency is not unfounded. With so few observations on some lakes, the analyst may not be able to rely on asymptotic results to show consistency of the fixed effects. Moreover, this lack of consistency may spill over into the estimated parameters associated with non-fixed effect variables.

Table 13. Estimation Results for NLLS Models with Year Dummies

	NLLS Fixed Effects 1			**NLLS Fixed Effects 2**			**NLLS Fixed Effects 3**	
R^2	.8296			.8201			.8210	
	Coef.	**Robust Std. Err.**		**Coef.**	**Robust Std. Err.**		**Coef.**	**Robust Std. Err.**
Struc_val	1.513*	0.027		1.517*	0.028		1.523*	0.031
Lot	1.293*	0.155		1.286*	0.162		0.737*	0.130
Front	3.466*	0.275		2.774*	0.304		2.509*	0.342
Front^2	-2.363*	0.343		-1.807*	0.357		-1.544*	0.384
Aft_100_any	-0.216*	0.079		-0.200*	0.082		-0.167**	0.088
Aft_200_300	-0.202	0.470		0.382	1.819		0.403	1.919
Prime	-0.006	0.060		0.011	0.061		0.026	0.068
Before	0.210*	0.093		0.211*	0.094		0.270*	0.110
Dum_1998	0.124	0.096		0.152	0.103		0.108	0.115
Dum_1999	0.392*	0.095		0.389*	0.104		0.348*	0.116
Dum_2000	0.542*	0.095		0.562*	0.105		0.523*	0.118
Dum_2001	0.477*	0.094		0.465*	0.103		0.422*	0.115
Dum_2002	0.645*	0.091		0.633*	0.101		0.617*	0.113
Dum_2003	0.729*	0.088		0.720*	0.099		0.645*	0.111
Dum_2004	0.830*	0.089		0.843*	0.099		0.788*	0.111
Dum_2005	0.968*	0.088		0.996*	0.098		0.920*	0.109
Dum_2006	0.952*	0.087		0.935*	0.098		0.929*	0.110

Note: n = 1708, 1476, and 1149 respectively for NLLS Fixed Effects Models
Fixed effects (106, 70, and 43 respectively) are not displayed for space
All dollar amounts in 2006 dollars
*** indicates significance at the 95% level, ** indicates significance at the 90% level**

In examining the above models, one will notice the relative consistency across many variables, though not all. The most important consistent parameter to notice is the price effect associated with EWM. The coefficients and levels of significance are nearly identical across all three models, indicating a consistent price effect associated with EWM regardless of specification. This price effect is presented in greater depth later in this chapter. The coefficients on the zoning variables, however, are unstable across specifications, both in sign and significance. The zoning variables (density variable in the cross-sectional models) are included to control for any variation in density or changes in zoning. However, the results associated with these variables should not be taken as reliable price effect estimates, given the variability throughout estimations. In any case, the relative consistency across the NLLS models, particularly in the *before* coefficient, provides further indications of robustness in the EWM effect and within NLLS models.

Given the robustness of these models, only the results from Table 11 will be discussed in depth, primarily because the R^2 measure is slightly higher. The conclusions derived from these results would apply to the results seen in Table 12 as well. 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. 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. This provides some empirical evidence for their inclusion in addition to the theoretical argument made for them previously. Given the significance of the distance and fishery-quality variables in the cross-sectional estimations, it should not be surprising that these fixed effects are statistically significant here.

As in the cross-sectional results, several non-EWM variables are significant at the 95% confidence level in both the fixed and random effects models, including the assessed structure value, lot size, frontage, the zoning variables, and time-related variables. In addition, the access, muskie, distance, and distance-squared coefficients are significant in the random effects model at the 90% confidence level of greater. Of the significant variables, variables with unexpected signs only appear in the random effects model and include distance, distance-squared, and the after-change zoning variables. The intuition for the distance variables appearing opposite to the Mills bid-rent model was discussed above in the cross-sectional results. Due to the desire for seclusion, as many properties are second homes or cottages, the coefficients are reasonable.

Along with this seclusion assumption, however, come the unexpected signs of the after-change zoning variables. Essentially, these variables indicate a negative price effect from stricter zoning (resulting from the 1999 Vilas County Shoreland Zoning Ordinance), regardless of the exact change. Given the fact that many lakefront property owners have expressed a desire for less density, which can be encouraged via stricter zoning, these price effects are puzzling. Perhaps residents actually desire the ability to subdivide and develop further more than they desire the preservation of amenities. However, the zoning parameter estimates are not robust across model specifications, so it is difficult to draw strong conclusions regarding their price effect.[19]

One variable of particular interest across all estimations is the positive and statistically significant *muskie* coefficient. In the latest runs from the random effects model, this variable is estimated to have a price effect of over $8,500 for each increasing class of the fishery.[20] This variable is intriguing for a few reasons. First, fishing quality variables generally do not appear in the hedonic literature. Based on these results, it may be necessary to incorporate measures of fishing quality for a unique species like muskie. Second, the coefficient on *muskie* may be

[19] See Spalatro and Provencher (2001) and Papenfus and Provencher (2005) for a more detailed analysis of zoning policies.
[20] Recall that this variable is based on a 0-4 scale, indicating the quality of fishery (4 is a trophy water).

biased upward due to the same endogeneity factors that drove the bias of EWM. In other words, a lake may be popular because it has muskie, but additional stocking of muskie may take place because the lake is popular. However, the other fishing quality variables do not seem to indicate the same potential for this bias. Nonetheless, this is an area for additional work. Lastly, given that EWM is known to affect large prey fish populations, the value of muskie may be another important cost associated with EWM. In particular, if muskie populations begin to decline in the long-term as a result of EWM, an additional cost of EWM has been introduced.

In terms of the EWM variables, *impact* and *before*, we see intriguing results indeed. Looking at the random effects model, we see from the *impact* coefficient that no statistically significant premium exists for properties affected by EWM 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 greater than $28,000. Moreover, the additive sum of *impact* and *before* in the random effects model isn't significant, but the magnitude is quite large, in the area of $25,500. Thinking back to Figure 6, we see this story in the simple trend analysis. Properties on infested lakes sell for a premium prior to invasion, which starts to erode in the early 2000s as invasions occur.

It was argued above that any correlation between the EWM variable and the error term in the random effects model would render the results inconsistent. Based on the empirical evidence presented in the tables above, 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 44% greater in magnitude than in the random effects model.[21] The coefficient is also statistically

[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 concerning statistical significance.

insignificant in the latter case. These results are consistent with the extensive body of evidence presented throughout this paper concerning the correlation between the presence of EWM and unobserved characteristics related to the level of a lake's attractiveness. In fact, the bias appears in other variables that may be correlated to a lake's attractiveness. Take for example, the coefficient estimate on the access variable. The estimate suggests that lakefront property owners are willing to pay over $25,500 for public access on their lake. Given that most lakefront owners are able to access their own lake without the use of a public boat ramp, the magnitude of this coefficient seems far too large.[22] What is likely at work here is the issue of endogeneity and the associated bias that goes along with it. Lakes with public boat launches are more likely to be popular, given the possibility for many visitors, and more popular or attractive lakes have higher property values. Since many lake characteristics related to attractiveness or popularity are unobserved or difficult to quantify, there is potential for bias.

In summary, the fixed effects model should be given preference over the random effects specification. The assumption about the error term being uncorrelated with any independent variable in the random effects model is strong. This assumption is relaxed in the fixed effects model. Coupled with a difference-in-difference approach, the fixed effects model seems to resolve the issues of bias and inefficiency brought about by endogeneity and spatial autocorrelation, allowing for identification of the EWM-effect.

8.2 Landscape Results

Using the results from the fixed effects model, broader conclusions can be made concerning the willingness-to-pay to prevent an EWM infestation. The results from the linear

[22] In addition, the increased boating traffic associated with the presence of a public boat ramp would likely not provide lakefront property owners additional benefits, but rather decrease property values (assuming residents can access the lake without the ramp).

fixed effects model in Table 11 indicate that lakefront property owners are willing to pay, on average, greater than $28,000 more for a property on a lake free of EWM, all else equal. Since the price of land is a stream of rents in perpetuity, we can calculate the annual WTP using the following formula:

Total WTP * Discount Rate = Annual WTP.

Using a 5% discount rate, the annual WTP is approximately $1400. Using these figures, the aggregate cost of EWM (or willingness-to-pay to avoid infestations) can be calculated. Of the twenty lakes infested with EWM, there were 2637 parcels as of 2006. Multiplying the average WTP by the number of affected parcels, we arrive at an aggregate cost of EWM, as presented in Table 14.

Table 14. Aggregate Cost of EWM to Lakefront Property Owners in Vilas County, WI

	Cost of EWM (in millions of $)
Aggregate Cost:	$73.84
Annual Cost:	$3.69

Note: All dollar amounts in 2006 dollars

If the preceding numbers seem somewhat perverse, given the aggregation, the average aggregate cost for one infested lake can also be presented—$3.75 million total or $187,600 annually.[23] In other words, these figures represent the marginal cost associated with one additional infested lake, on average, in Vilas County. Recalling that the State of Wisconsin allocates approximately $4 million dollars annually for the management of all AIS across the entire state, one can conclude that the costs are enormous relative to what is currently being spent.

[23] This is calculated using the average number of parcels on an EWM lake, multiplied by the WTP figures given above.

Conclusions about the willingness-to-pay for EWM can only be made at the margin in a hedonic pricing model because the marginal rate of substitution between any two property characteristics changes as the relative amounts of the goods change. In standard economic theory, the consumer is willing to give up less and less of one good to obtain additional units of another; this is the concept of diminishing marginal utility. Therefore, the marginal WTP measures derived in a hedonic model represent the WTP for additional units of a given implicit good, holding all other characteristics at their equilibrium levels. A non-marginal change in one attribute causes a change in consumption level for all other attributes (holding observed price constant), implying a shift in the entire hedonic price function has occurred. In the present context, aggregation of WTP over all twenty lakes may induce a shift in the hedonic price function; therefore the marginal impact from one additional lake is offered. To derive the WTP for non-marginal changes in environmental quality, one would have to estimate 'second stage' inverse demand curves for each attribute, a non-trivial task.

The models presented in this section reveal a consistent price effect associated with the presence of EWM on property values. The results of the two linear fixed effects specifications (see Tables 11 and 12) indicate price effects of \$28,294.20 and \$29,518.13 respectively (both significant at just under the 95% confidence level). In addition to these estimates, the price effects found in the non-linear specifications are presented below. These price effects are presented in Table 15 and derived using the difference in predicted price between impacted lakes before and after infestation:

(8.1)

$$\widehat{Price}\ (before\ infestation) - \widehat{Price}\ (after) =$$

$$\left(\beta_1 \overline{Struc\_Val} + e^{\sum_{j=2}^{K} \bar{X}_j \beta_j (\overline{Before}=1)}\right) - \left(\beta_1 \overline{Struc\_Val} + e^{\sum_{j=2}^{K} \bar{X}_j \beta_j (\overline{Before}=0)}\right) for\ j = 2,3,\ldots,K$$

Variances associated with these statistics were generated using the delta method (see Greene 2003, p. 70). These statistics are calculated using observations on EWM lakes in 2006, along with the mean value of the independent variables from this year. They are calculated for each non-linear model appearing in Table 13.

Table 15. Discrete Price Effect of EWM Results across NLLS Models[24]

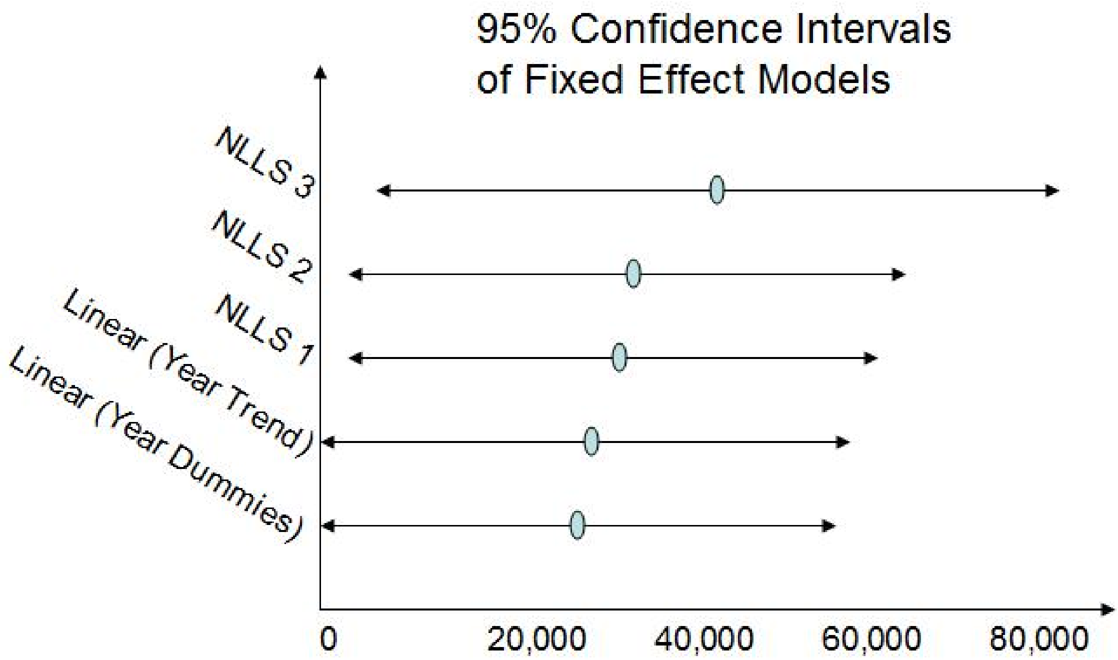
	NLLS Fixed Effects 1	**NLLS Fixed Effects 2**	**NLLS Fixed Effects 3**
Price Effect	-32,087.824*	-32,838.395*	-45,600.499*
Std. Error	15,220.284	15,674.587	20,441.940

Note: All dollar amounts in 2006 dollars
*** indicates significance at the 95% level, ** indicates significance at the 90% level**

Even in the non-linear case, the price effect associated with EWM is very consistent. In fact, 95% confidence intervals around all five estimates (two from the linear models and three from the non-linear models) are intersecting, indicating that no estimate is statistically different from another. These are presented in Figure 9.

[24] The price effects across all EWM lakes range from -$13,750 (Silver Lake) to -$48,400 (Catfish Lake). The difference between these price effects is significant at the 90% confidence level. In general, all lake-specific price effects are significant at the 90% confidence level (or greater) and most do not differ statistically.

Figure 9. Confidence Intervals around Fixed Effects Estimates



Thus, the estimates for EWM are robust across specifications, regardless of functional form. The $28,000 amount used to calculate the aggregate WTP figures above is the most conservative average price effect of these estimates. Using this most conservative estimate, the price effect associated with the presence of EWM is predicted by the model to be just over 13% of total land values and 7.7% of total property values.

Chapter Nine: Conclusions and Future Research

9.1 Conclusions

In general, the findings of this paper reveal that EWM has a negative effect on lakefront property values—greater than $28,000, or a 13% (7.7%) decrease in land values (property values). This analysis reveals that properties on lakes with EWM sold for a premium relative to properties on uninfested lakes, before the lakes were invaded by EWM. After infestation, this premium narrowed significantly, perhaps disappearing entirely, as evidenced by the statistically insignificant *impact* coefficients in the above models. Using the identification strategy outlined in this research—a spatial difference-in-difference specification—the negative price effect associated with the presence of EWM was identified. The estimates produced in this research should be treated as lower-bound estimates since these are only the costs borne by lakefront property owners. EWM also affects non-lakefront property owners (tourists, nearby residents), ecosystem goods and services not capitalized into lakefront property values, etc. Furthermore, the aggregate WTP figures derived in this study were based on the most conservative estimate of the EWM price effect.

Broadly speaking, this study has been an attempt to empirically analyze the economics of invasive species. As such, the present study contributes to a line of literature relatively light on this subject matter. Government agencies are spending immense resources to manage and avoid infestations, but operate largely without reliable estimates concerning the costs of invasions. Estimates that are available are generally not derived from a rigorous economic framework. In that sense, the results presented in this study provide evidence of the potential benefits from avoiding future infestations of EWM, one of the most widespread aquatic invasive species in North America.

In terms of methodology, this study has used the familiar hedonic pricing framework, but incorporates a variety of existing econometric techniques to specifically address the issues of endogeneity and spatial autocorrelation. Since individual lakes serve as natural neighborhoods, controlling for spatial autocorrelation can be achieved conveniently, using fixed or random effects specifications. However, if any unobserved spatial heterogeneity is correlated with the independent variables—perhaps the environmental quality variable of interest—the fixed effects model should be given preference over the random effects approach to avoid bias. Furthermore, a difference-in-difference approach is used to further difference out unobserved heterogeneity that may be biasing parameter estimates of interest, allowing an unbiased effect from the change in environmental quality to be identified.

Given the presence of endogeneity and spatial autocorrelation throughout the hedonic pricing literature, this study has broader implications for dealing with these challenges. The issue of unobserved spatial heterogeneity is generally treated as an inefficiency issue, while this study demonstrates the potential for bias when such characteristics are correlated with variables in the model. Furthermore, this study mitigates bias associated with endogeneity without having to rely on instruments. Instead, the techniques described in this research are simple enough to be estimated using linear regression techniques and yet, are effective in relieving the bias and inefficiency associated with the econometric issues arising from unobserved neighborhood effects.

The fixed effects approach used here works best with clearly defined neighborhoods. This study has a particularly intuitive definition of neighborhoods, as lakes provide "natural neighborhoods." The challenge of defining neighborhoods will be faced for less fragmented landscapes. This has been an ongoing difficulty for many studies attempting to estimate a model with spatially correlated errors. 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 (or random effect), as used in this study. This research offers a demonstration of the potential of fixed effects, given that lakes serve as natural neighborhoods. Nonetheless, this methodology has more general applicability.

9.2 Future Research

This study is moving in two directions. The first is already underway. To validate the results of the revealed preference model, a contingent valuation approach is currently being pursued through a survey of lakefront property owners in the study region. The sample is composed of nearly 1500 lakefront property owners and will focus on the issues of EWM management or EWM prevention, depending if the lake of the sampled individual is infested or not. The survey asks about a wide range of values that property owners might be willing to pay to control or prevent EWM. These WTP questions are framed in a referendum style where the respondent is asked how likely he/she would vote "Yes" to support a management or prevention program given a certain cost. A second cost is also offered to the respondent, adjusted up or down depending on their response to the first amount, to get at multiple amounts with one respondent. These values will be useful for comparing with revealed preference estimates found in this research.

The other potential direction for this research concerns changes in quality of muskie fisheries within the study region. As explored above in the results, the *muskie* coefficient is positive and significant across all estimations, averaging a magnitude of around $8,500 in latter estimations. This amount indicates the additional benefit to property owners from a muskie fishery improving to a higher class level (classes range from 0-4). From a resource management perspective, understanding the value of muskie would provide guidance for management activities that would help support their populations. Fishing quality has not been a traditional focus of hedonic modeling, yet reliable data are available for this study region from the Wisconsin DNR. In a recent survey sent to Vilas County lakefront property owners, one question gave respondents the option to indicate what changes they would most like to make to improve their lake (Provencher 2005). The top response, checked by nearly 50% of respondents, was to "improve fishing quality." Clearly this issue has potential for resource management.

Wisconsin's Muskellunge Management Team (WMMT) has existed within the Wisconsin DNR since the late 1970s, working to manage muskie fisheries. This has been done by setting minimum length requirements, setting daily bag limits, limiting the open season, stocking lakes, carrying out restoration activities, monitoring populations, and implementing education activities (Wisconsin DNR 2008c; Wisconsin DNR 2008d; Wisconsin DNR 2008e). Stocking is a particularly important activity to sustain the increasingly popular sport of muskie fishing, since natural production has always been relatively low. At present, muskie are stocked in 180 waters throughout the state, usually adding 1 fingerling (11"+) per acre, depending on need (Wisconsin DNR 2008d, p. 13). Muskie waters are divided into four categories that describe the reproductive capacity of the fishery and thus, the need for stocking, if any (see Table 16).

Table 16. Reproductive Status of Muskie Waters

Category	Description	# of waters
Category 0	Reproductive status unknown	151
Category 1	Sustained through natural reproduction; no stocking	140
Category 2	Natural reproduction, but some stocking may occur	364
Category 3	Stocking is required to maintain the fishery	149

(Wisconsin DNR 2008d, p. 3-4)

Of the twenty lakes infested with EWM in Vilas County, 13 are stocked at present, while stocking was suspended in two additional infested lakes—Big Sand Lake and Boot Lakes (for up to 10 years)—to see if natural reproduction could sustain the fishery; otherwise stocking will continue (Wisconsin DNR 2008d, p. 22-23).[25] Thus, 75% of the lakes with EWM in Vilas County have actively supported muskie fisheries. Stocking has varied widely over the top muskie fisheries, including EWM-infested lakes, with few trends emerging.

A foundation for a model that evaluates changes in muskie quality has been established in this study. Additional considerations would likely need to be made, particularly if muskie quality is endogenous, which is possible if more attractive lakes are more aggressively stocked. The muskie issue is not independent of EWM. In fact, of the lakes in Vilas County infested with EWM, many are trophy muskie waters:

As seen in Table 17 below, only two of the twenty lakes infested with EWM have sub-prime muskie fisheries. Since EWM is spread by recreational boaters, many of which belong to fishermen, EWM is likely to find its way into waters with high quality muskie fisheries, given the species' popularity. While the effects of EWM on muskie are not entirely clear, severe infestations of EWM have been known to hurt bass and muskie populations by limiting their ability to prey on smaller fish (ESPN 2008). Regardless of how EWM affects muskie populations, the effect of EWM on fishing is perhaps most important. A dense stand of EWM can all but eliminate the possibility of fishing. In this sense, severe EWM infestations may cause losses in muskie benefits in the long-run.

[25] The following EWM-infested lakes are currently stocked with muskie: Arrowhead, Catfish, Cranberry, Duck, Eagle, Lynx, Otter, Scattering Rice, Voyageur, Watersmeet, Yellow Birch, Little St. Germain, and Upper Gresham Lake.

Table 17. Muskie Quality of EWM-infested Waters

Lake Name	Muskie Class
Arrowhead Lake	A2
Big Sand Lake	A1
Boot Lake	A1
Catfish Lake	A2
Cranberry Lake	A2
Duck Lake	A2
Eagle Lake	A2
Forest Lake	--
Little St. Germain Lake	A2
Long Lake	A1
Lynx Lake	A2
North Twin Lake	A2
Otter Lake	A2
Scattering Rice Lake	A2
Silver Lake	C
South Twin Lake	A2
Upper Gresham Lake	A2
Voyageur Lake	A2
Watersmeet Lake	A2
Yellow Birch Lake	A2

Note: A1—Trophy muskie waters
A2—Action muskie fisheries with best overall numbers
B—Good muskie fishing
C—Fishable muskie populations
None—No muskie present
(Wisconsin DNR 2008b).

Based on the regression results presented in this paper, muskie appears to offer a significant benefit to property owners. This benefit may be at stake if EWM affects muskie populations or if the ability to fish is severely limited. Thus, the presence of EWM may depress property values in the short-run by the amount presented in this paper. In the long-term, however, as EWM becomes more established and potentially limits the ability of muskie to flourish (or at least limits the ability of people to fish muskie), EWM could depress property values even further if muskie benefits disappear. Therefore, understanding the benefits associated with muskie may be important for communicating additional losses that may be brought about due to the presence of EWM.

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