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"The Spatial Dynamics of the Economic Impacts of an Aquatic Invasive Species: An Empirical Analysis," by Katherine Y. Zipp, David J. Lewis, Bill Provencher, and M. Jake Vander Zanden

Appendix

A.1 Data

A.1.1 Lake data

Our analysis is based on five counties spanning the NHLD (Forest, Iron, Oneida, Price, and Vilas) that includes 2,407 lakes that are larger than one hectare, of which 453 appear in our boater dataset. Table A6 presents statistics on these lakes. Some features of the lake data are especially relevant to our modeling. First, the years in which invaded lakes in the NHLD were first known to be invaded is made available from the Wisconsin Department of Natural Resources (WDNR)[1]. As of 2012, there were 72 lakes in the NHLD with reported and confirmed milfoil, with the earliest recorded invasion occurring in 1989. The distribution of reported milfoil invasions in the NHLD by year is shown in Figure 1 of the primary text. Our sample of boater data includes trips to 58 of the 72 lakes with milfoil reported as of 2012.

Lakes in the NHLD vary in their ecological suitability for milfoil. Even with a high level of propagule pressure, a lake might never become invaded due to its ecological characteristics. Several studies have shown that alkalinity, conductivity and pH are important factors determining the presence of milfoil (Hutchinson, 1970; Madsen & Sand-Jensen, 1991). The ecological suitability of a lake for milfoil is increasing with alkalinity, conductivity and pH, all of which are highly correlated and indicative of hard-water lakes (Barko and Smart, R.M., 1985; Buchan & Padilla, 2000; Lillie & Barko, 1990; Nichols &

[1] WDNR records are biased downward due to a lag between invasion and discovery, and, because they rely on citizen reports, they are likely skewed towards more popular lakes where citizens are more likely to report invasions. To address this concern we supplemented the WDNR data on invasions by random stratified sampling of lakes based on one or several ecological niche models developed in the ecology literature to predict invasions. Of 457 lakes from across all of Wisconsin, 120 lakes had EWM, and only 16 of those had populations that were previously undetected, indicating that lag between an invasion and its detection and confirmation is relatively low for EWM (Latzka et al. *in prep*). By comparison, three other species (Chinese mystery snail, banded mystery snail, and curly-leaf pondweed) each had over 60 new detections.

Buchan, 1997; C. S. Smith & Barko, 1990). Wisconsin has many soft-water lakes that are low in alkalinity, conductivity and pH and are essentially fishless and would not support populations of milfoil. Data on lake characteristics are available in the Wisconsin Lake Historical Limnological Parameters dataset (Papes & Vander Zanden, 2010).

A.1.2 Boater data

Boater data were collected using an intercept and follow (I&F) sampling procedure in which boaters were intercepted at boat ramps and recruited into a diary program to record their recreational trips to lakes during the 2011 and 2012 boating seasons (April – October). Previous studies of recreation demand that use boater diaries include (Adamowicz, 1994; Bockstael, Mcconnell, & Strand, 1989; Hunt, Boxall, & Boots, 2007; Murdock, 2006; Provencher et al., 2002; Provencher & Bishop, 1997; M. D. Smith, 2005; Timmins & Murdock, 2007). We intercepted 3,010 boaters leaving lakes in the NHLD and asked them a series of "diary" questions regarding the number of trips taken in the previous months, which lakes in the NHLD that they visited in the previous two weeks, and asked them to record each trip they took to a lake in the NHLD from the day they were recruited until the end of the season.

Boaters who returned completed diaries also received an end-of-season (EOS) survey that included questions to identify the lakes in their boating choice set.[2] Respondents visit on average 3.4 lakes (ranging from 1 lake to 36 lakes), report an additional 1.8 choices in the EOS survey (ranging from 0 to

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[2] The appropriate identification of the choice set is critical in discrete-choice models. The inclusion of choices that are irrelevant or unknown to the boater, and the exclusion of relevant choices, are a source of bias in choice models (Haab and Hicks 1997). In our model, the lakes in a boater's choice set include the lakes the respondent reported visiting in the two weeks before intercept, the lakes they recorded visiting in their diary, and the lakes identified in the following two questions in the EOS survey (see (Parsons, 2017) and citations therein for a summary of research-defined versus individual-defined choice sets):

- "Are there any lakes in the NHLD that you have not yet visited, but that you have heard about and would like to visit?"
- "Are there any lakes in the NHLD that you have visited in the past but did not get to this year?".

16 additional lakes), which leads to an average choice set of 6.2 choices (ranging from 2 to 47 choices) when combined with the decision not to go boating.

We combine the I&F survey data and the EOS survey data into a master dataset that contains, for each boater in our sample, (1) the boating trip in which the boater was intercepted by our surveyors, (2) the number of total trips per month for all months prior to the interception date, (3) all boating trips in the previous two weeks before interception (but not any individual boating trips prior to this two week period), (4) all boating trips after interception, along with (5) demographic data and a boater-specific choice set from the EOS survey (see Figure A1).

Our dataset consists of 1,020 boaters in 2011 taking 7,860 trips, 325 boaters in 2012 taking 2,640 trips, and 98 boaters from the 2011 season who continued in the diary program in 2012 taking an addition 1,266 trips in 2012. The final dataset consists of 1,443 boaters taking 11,766 trips to 453 unique lakes over 117,298 choice occasions (respondent-days) across the 2011 and 2012 boating seasons.

We have two types of boaters in our sample – permanent residents of the NHLD (45% of the sample) and vacationers (the remaining 55%). Permanent residents are respondents who have a primary year-round residence (82% of permanent residents in the sample) or primary summer residence in the NHLD (the remaining 18% of permanent residents). Vacationers are respondents who have vacation property/weekend getaway (62% of vacationers in the sample) or a short-term vacation rental in the NHLD (the remaining 38% of vacationers) but whose permanent address is not in the region. The distinction between the two types of boaters is important for properly modeling the decision to go boating in the NHLD. On each day of the season, permanent residents of the NHLD choose a single boating destination $j = 1, \dots, J$ or choose not to go boating ($j = 0$). Therefore we define the trip occasions for a permanent resident as every day from the first trip reported (either in the two weeks prior to interception at a landing or the first diary entry) in season s for boater n, until the last day of the season s (October 30th). We define the trip occasions for boaters vacationing in the NHLD as every day in a Saturday-to-Saturday week with an observed trip to a lake in the NHLD.[3] That is, if a boater classified as a vacationer records a trip to a lake in the NHLD then we assume that the boater was in the region for the whole week (Saturday to Saturday). If there is no recorded trip for a given week then we assume that the boater was not in the NHLD during that week.[4]

The majority (80%) of recreational boating trips in the NHLD occurred in June, July and August, with July being the busiest month, accounting for 35% of all trips. Forty-two percent of all trips occurred on the weekend (Saturday or Sunday). Fifty-four percent of all trips occur within 24 hours of a previous

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[3] The trip decision of vacationers is more complex. In our modeling, we treat the decision process of vacationers as a two-stage process and address only the second stage. The first stage is the decision about whether and where to vacation in the NHLD, and how long to stay. The second stage involves the day-to-day decision about whether to boat, and where to boat, once in the NHLD. Separating these stages, and focusing only on the second, is appropriate under the assumption that the decision to visit, and the length of stay, is independent of the daily trip decisions made after arrival. Of course this is not strictly true, but we argue it's not too far off the mark, for four reasons. First, vacations are likely to be taken in weekly increments because (a) summer vacation rentals are almost exclusively weekly, and (b) the standard work week places a premium on weekly vacations (that is, five work days sandwiched between two weekends lowers the average daily cost of the vacation). Second, the decision to take the vacation, and how long to stay, is a household decision made by the boater and other household members (or, in the case of children, with their welfare in mind) not necessarily interested in boating activities. Third, for vacationers with summer homes in the NHLD, the decision about whether to vacation in the NHLD, and where to locate, is basically predetermined. And fourth, the decision to take a vacation usually involves a commitment that is difficult to break and made weeks if not months in advance[3], substantially weakening the connection between the decision about when to take the vacation, and how long to stay, and the day-to-day decisions about whether and where to boat.

We rely on the understanding that vacations are typically week-long not only to justify abstracting the day-to-day trip decision from the first-stage decision to take a decision, but to identify *when* the boater is in the NHLD. Though the diary data records boating trips within the NHLD, unfortunately it does not record data on the dates of visitation to the NHLD.

[4] These two assumptions could be violated if vacationers often take trips to the NHLD that last less than one week (single-day trips or weekend trips) or if vacationers often take trips to the NHLD and do not go boating while in the region. Only seventeen percent of trips taken by vacationers are the only trip taken in a given week, providing empirical support for assuming that vacationers are not making single-day trips. However, when vacationers only take one trip per week seventy-nine percent of these trips are taken on a Friday, Saturday or Sunday, indicating that vacationers may be taking weekend trips instead of week-long trips. If vacationers are taking shorter trips than we assume, then our models will underpredict the probability of going boating in the NHLD for these boaters and, thus, underpredict the propagule pressure from these vacationers. On the other hand, if vacationers take week-long trips to the NHLD and do not go on any boating trips, then our models will overpredict the probability of going boating in the NHLD for these boaters and, thus, overpredict the propagule pressure from these vacationers.

boating trip. Fifty-seven percent of all consecutive trips are made to two different lakes. Fourteen percent of all consecutive trips to two different lakes are from a lake invaded with milfoil to a lake that is not invaded with milfoil. See Table A8 for summary statistics by type of boater.

Consistent with previous literature (Timar & Phaneuf, 2009),we calculate the physical distance from each boater's residence to each lake in their choice set as a proxy for travel cost. The decision to go boating on a given lake depends on the travel cost required to visit each site in a boater's choice set. The travel cost consists of the driving costs, which are generally assumed to be proportional to the distance the boater must travel to the site, and the opportunity cost of travel time, which is assumed to be proportional to distance and wage rates. Money-metric utility, while necessary for welfare analysis, is not necessary for our estimation purposes, therefore we do not scale the distance traveled by driving costs. Our use of distance as a proxy for travel cost imposes an implicit assumption that the opportunity cost of time is the same for all boaters. We measure the distance traveled from the centroid of the zip code the boater reported staying the night before the trip to all lake destinations in their choice set. The average one-way distance traveled to lake destinations is 14.6 miles for permanent residents and 11.9 miles for vacationers.

A.1.3 Intercept and follow sampling considerations

Our population is people who go boating in the NHLD between April 1 and October 31 (anglers, jet skiers, sailors, canoers/kayakers). This population of boaters has a set of characteristics such as age, gender, income, employment, targeted fish type and most importantly preferences over which lakes to visit and the total number of trips to take per season. We do not have a random sample from this population, but rather we have a choice-based sample at the intercept sites with a panel of diary entries after the initial interception. There are two questions that arise when using an I&F sample to draw inference on recreation behavior for a population of boaters. First, can we estimate consistent maximum likelihood parameters with the I&F sample? Second, can we predict behavior in the population with the I&F sample and the maximum likelihood parameters?

To estimate consistent maximum likelihood parameters we need to understand the data-generating process (DGP) of the I&F sample. The DGP of the intercept trips is not a random sample from the population of boaters taking trips to the intercept site. Rather the DGP of the intercept trip is conditional on the individual boater being intercepted at the interview site which is a function of the number of trips the respondent takes to each site and the number of individuals interviewed at each site (e.g. see (Haab & Mcconnell, 2002) sec. 8.7 for a general discussion). On the other hand, the DGP of the diary entries and the trips in the previous two weeks from the intercept survey are a random sample from the sample of boaters who are intercepted. The trip behavior reported in the diary entries and the two weeks prior to being intercepted can therefore be modeled with a typical travel cost random utility model. Therefore, we can drop the interception trip from the I&F sample and get consistent (although inefficient) maximum likelihood estimates (McFadden, 1996).

However, to use the consistent maximum likelihood estimates to predict population behavior (such as the population number of trips from invaded lakes to uninvaded lakes), we need a representative sample of the population. I&F samples are not representative samples because they are biased toward explanatory variables that induce more frequent visits to the intercept sites (Ben-akiva, 1997). This is typical sample selection bias – the boater characteristics in the sample of intercepted boaters will be different than the boater characteristics in the population. Specifically, boaters in the sample will take more trips on average (and have characteristics associated with higher avidity) and they will (potentially) have a higher proportion of their trips to the intercept sites (the lakes that are associated with higher avidity will be overrepresented in the sample).

Given the typical assumption in RUMs of conditional independence, we assume that trips are independent (conditional on the included explanatory variables) and so the choice of the intercept lake does not affect the decision of what other lakes to visit for the rest of the season. This means that the sample of boaters that we interview take more trips on average than the population, but the sample proportion of trips to each lake is proportional to the population proportion. This bias would cause an upward bias in the absolute probabilities of invasion and the welfare estimates but the relative probabilities of invasion would be valid. To correct this bias we need data on the average number of boating trips by our population of boaters.

Data on the average number of boating trips to the NHLD are not available. However, (Kovski, 2015) estimates a single-site recreation demand model of trips to any lake in the NHLD (the NHLD is the so-called "single site") using a Poisson count specification that corrects for on-site sampling bias with sample demographic data to yield unbiased predictions of the sample number of trips taken to the NHLD (see (Englin & Shonkwiler, 1995; Shaw, 1988) for development of the on-site corrected model). The single-site recreation demand model provides the expected demand for recreation trips to the NHLD over a single boating season as a function of travel costs and boater demographic characteristics. (Kovski, 2015) then uses the estimated on-site corrected single-site recreation demand model and applies population means of the demographic data to predict expected trip rates for the general population. The results from this thesis are an estimated 854,954 trips (95% Confidence Interval of 731,019 to 978,872 trips) to any lake in the NHLD during one summer season. We use the estimated number of total recreation trips to the NHLD by the population in (Kovski, 2015) to weight the number of trips by our sample to ultimately generate unbiased estimates of the number of trips to *each lake* in our sample.

A.2 Simulations of the effects of milfoil invasions on economic welfare using a fully coupled model and an uncoupled model

We simulate the effects of milfoil invasions on the economic welfare loss of lake users. Here we focus on shoreline property owners and visiting recreational boaters. The simulations aim to ask the following questions. First, given the state of milfoil invasions across the lake system in 1998, how much economic welfare would be lost over a 15 year period if a lake were invaded with milfoil in 1998? The welfare loss associated with an invasion of lake j in 1998 is the economic welfare of the entire lake system with lake j invaded minus the economic welfare of the lake system with lake j protected from invasion during each of the 15 years. We use the boater recreation demand model to simulate the spread of milfoil associated with lake j being invaded. Our simulations calculate welfare losses from milfoil invasions one lake at a time – that is, our thought experiment asks how much total economic welfare loss arises from lake j being invaded with 100% certainty in 1998, and we calculate welfare losses for each of the J lakes in the system one at a time. Second, given the more advanced state of milfoil invasion across the lake system in 2013, we ask the same question regarding economic welfare loss for each lake over a 15 year period starting in 2013. Since fewer lakes were invaded in 1998 than in 2013, there is potential for significantly more spillover losses in 1998 as there are more potential 'victims'.

Our simulations are defined by our econometrically estimated recreational boater model which defines the spread of invasive milfoil across the system. An important issue is whether the natural system (measured here as a lake's milfoil status) is coupled back to the human system (measured here as boater decisions of which lakes to visit). Fully coupling the system requires a functional relationship between a lake's milfoil status and the indirect utility function of boaters when deciding whether to visit that lake. The recreational boater model uses lake fixed effects to capture all observable and unobservable factors that make a lake attractive for boaters and which are constant across boaters and over the two boating seasons in our data. A lake's milfoil status is included in each fixed effect, and disentangling the effects of milfoil apart from other lake features (e.g. lake size, fishing quality, etc.) on the fixed effect would require either significant temporal variation in milfoil invasions within lakes, or an excluded instrument that is correlated with a lake's milfoil status but uncorrelated with the lake's attractiveness to boaters. Our data provide neither the temporal variation in lake milfoil status nor an excluded instrument.

To couple the natural back to the human system, we use a stated preference experiment that we conducted from the end-of-season survey given to each boater. This stated preference experiment asked each boater about their willingness-to-pay to prevent their favorite lake from being invaded by milfoil, and full design and estimation information from the experiment is published in (Lewis, Provencher, & Beardmore, 2015). The primary result from this study (Lewis et al., 2015) is that boaters in our region are willing-to-pay $98 per year to prevent their favorite lake from being invaded by milfoil. Because the stated preference respondents take an average of 9 trips per year, the per-trip welfare loss from a milfoil invasion is $10.89. This dollar estimate of welfare loss provides us with an experimentally based avenue for coupling the natural to the human system. Because the boater recreation model uses distance as a proxy for travel cost, we convert the $10.89/trip annual welfare loss into an equivalent additional roundtrip distance that a boater would have to travel to an invaded lake using the AAA cost per mile of $0.60/mile. Thus, if lake j becomes invaded in our simulation, we increase each boaters distance to lake j by $10.89/$0.60 = 18.15 miles round-trip (or about 9 miles one-way). Thus using the marginal effects for distance from the recreational boater model, a milfoil invasion on a lake would reduce the average probability of visiting that lake by 11%.

Coupling the natural system to the human system is extremely expensive computationally. Thus, we consider both a model with trip feedback and a model without trip feedback. In the model without trip feedback, boaters are assumed not to change their boating trips to a lake if it becomes invaded by milfoil. This model without trip feedback would be consistent with an assumption that milfoil invasions impart losses for recreational boaters that are independent of their usage of the lake (a non-use value), while the model with trip feedback would be consistent with an assumption that milfoil invasions impart losses that are completely dependent on their usage of the lake (a use value). Given our approach for coupling the natural system to the human system, our simulation to estimate the economic welfare loss from a milfoil invasion in two time periods – with the initial invasion state in 1998 and in 2013[5] -- is described formally as follows.

1. Draw a lake j^T. The baseline represents the scenario that the subject lake j^T becomes invaded in season s^T, where $s^T = 1998$ or 2013. The counterfactual is that lake j^T is not invaded in any season, $s_P \in [1998, 2013]$ or $s_F \in [2013, 2028]$.
2. For each simulation run, in season, s^T, determine the propagule pressure, given the invasion status of lake j^T and all other lakes in the system. In 1998, there were 10 invaded lakes and in 2013, there were 58 invaded lakes in our sample of 453 lakes and in the baseline scenario the subject lake j^T is invaded.
    a. In the case without trip feedback, boater trip behavior is not dependent on milfoil invasion. Therefore, we use the RUM to simulate 100 transition matrices of consecutive trip decisions from origin lakes to destination lakes. We draw from the distribution of this transition matrix to simulate the number of trips between each lake in our sample. Given the trips between lakes, the invasion status of the lake system, and the

[5] To test the out-of-sample forecasting ability, we run our model from 2013-2016 and compare the predicted number of invaded lakes with the actual number of invaded lakes. As of the end of the 2016 season, there were 64 verified lakes in our sample with milfoil. Starting with the 58 lakes that were actually invaded in 2012, our model predicts that there will be on average 64.08 lakes invaded by 2016 (with a range of 59 – 69 invaded lakes) over 100 simulations.

assumption that 3% of boaters going to invaded lakes become carriers, we predict the propagule pressure to each lake.

b. In the case with trip feedback, boater trip behavior is dependent on milfoil invasion. Therefore, we simulate the RUM for each day of season s^T, given the invasion status of the lake system. Lakes with milfoil become less attractive to boaters equivalent to an additional 9 miles that they have to travel one-way to an invaded lake. Given the trips between lakes, the invasion status of the lake system and the assumption that 3% of boaters going to invaded lakes become carriers, we predict the propagule pressure to each lake.

3. In season s^T, given the invasion status of all lakes in the system, the trips to each lake, and the number of shoreline properties around each lake, we predict the welfare loss to each lake as follows.

   a. The own lake effect is the welfare loss to property owners around the subject lake j^T and boaters who visit the subject lake j^T when lake j^T is invaded in the baseline case. The own lake effect is zero in the counterfactual case because j^T is protected from invasion.

$$WL_{own}^T = \$1400 * shoreline\ properties_{j^T} + \$10.89 * trips_{j^T}$$

   b. The spillover effect is the welfare loss to lakes that experience a higher probability of invasion given that lake j^T is invaded in the baseline case. The spillover effect is measured as the difference between the total welfare loss in the baseline case minus the total welfare loss in the counterfactual case minus the own lake effect.

$$WL_{spillover}^T = WL_{base}^T - WL_{counter}^T - WL_{own}^T$$

4. In season, s^T, given the propagule pressure, we predict the lakes invaded in the next season, s^{T+1}, using the hazard model. The hazard model predicts the probability that a lake becomes invaded, given that it has not become invaded yet, based on the ecological characteristics of the lake, a trend[6], and propagule pressure. We draw a random uniform number between 0 and 1, r_j, for each lake j and if the probability of invasion for lake j is greater than r_j then lake j becomes invaded that simulation.
5. Repeat steps 2-4 for each season $s_P \in [1998, 2013]$ or $s_F \in [2013, 2028]$.
6. Repeat steps 2-5 for 100 simulations.
7. Repeat steps 1-6 for each lake in the simulation.

[6] The trend in the hazard model for predicting invasion probabilities represents increased awareness and education about the transportation of invasion species over time, including the Wisconsin Administrative Code Chapter NR 40 (2009) that prohibits the transport, possession, transfer and introduction of invasive species including milfoil. In the end-of-the-season survey we asked boaters their familiarity with milfoil and 87% were somewhat to very familiar. Given the wide familiarity with milfoil and the difficulty with out-of-sample simulations, we hold the trend constant at the 2013 level for the simulations from 2013-2028.

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Table A1: Summary of variables used in the RUM estimation

	Description	Permanent residents	Vacationers
Distance	the distance from the centroid of the zip code where respondent n spent the night before the trip to the centroid of lake j	16.84 (20.19)	14.15 (18.94)
Weekday	an indicator variable that equals one if day t is a weekday and the respondent took a trip ($j \neq 0$)	0.63 (0.48)	0.62 (0.49)
Holiday	an indicator variable that equals one if day t is a holiday (Memorial Day, the Fourth of July or Labor Day) and the respondent took a trip ($j \neq 0$)	0.014 (0.12)	0.019 (0.14)
Trend	the number of days since the first trip of the season (April 1)	105.00 (65.36)	100.38 (52.97)
Trend^2	the square of $trend$ to capture the nonlinear trend in boating activity, with the height of boating activity in July	15,296.8 (13,730.03)	12,881.66 (10,198)
Walleye abundance = common	an indicator variable that equals one if respondent n targeted walleye on day t and lake j has a walleye rating of abundant or common	0.60 (0.49)	0.55 (0.50)
Walleye abundance = uncommon	an indicator variable that equals one if respondent n targeted walleye on day t and lake j has a walleye rating of present or not present	0.36 (0.48)	0.12 (0.33)
Bag limits = 3	an indicator variable that equals one if respondent n targeted walleye on day t and lake j has bag limit of 3 walleye per day	0.031 (0.17)	0.023 (0.15)
Bag limits = 5	an indicator variable that equals one if respondent n targeted walleye on day t and lake j has bag limit of 5 walleye per day	0.81 (0.031)	0.65 (0.48)

Note: Standard deviation in parentheses.

Table A2: Coefficient results from the model of boater behavior for permanent residents in the NHLD

	Non-consecutive trips			**Consecutive trips**		
	Coef.	Std. Err.	P>|z|	Coef.	Std. Err.	P>|z|
Distance (miles)	-6.428	0.644	0.000	-10.052	0.929	0.000
Weekday	-0.318	0.057	0.000	-0.526	0.078	0.000
Holiday	0.152	0.199	0.446	0.447	0.234	0.056
Trend	12.413	0.664	0.000	-0.328	1.102	0.766
Trend^2	-12.178	0.606	0.000	-1.646	1.003	0.101
Walleye = common * targeted walleye	-0.333	0.089	0.000	-0.291	0.110	0.008
Bag limit = 5 * targeted walleye	-6.275	0.106	0.000	-4.856	0.188	0.000
Bag limit = 3 * targeted walleye	-6.927	0.224	0.000	-5.836	0.332	0.000

Table A3: Coefficient results from the model of boater behavior for vacationers in the NHLD

	Non-consecutive trips			**Consecutive trips**		
	Coef.	Std. Err.	P>|z|	Coef.	Std. Err.	P>|z|
Distance (miles)	-3.465	0.484	0.000	-6.419	0.467	0.000
Weekday	-1.271	0.071	0.000	-0.450	0.077	0.000
Holiday	0.629	0.235	0.007	-0.381	0.212	0.072
Trend	0.996	0.904	0.271	6.359	1.055	0.000
Trend^2	-1.853	0.845	0.028	-7.168	0.981	0.000
Walleye = uncommon * targeted walleye	-8.571	0.340	0.000	-6.939	0.313	0.000
Walleye = common * targeted walleye	-7.502	0.307	0.000	-5.854	0.289	0.000
Bag limit = 5 * targeted walleye	1.226	0.267	0.000	0.537	0.196	0.006

Table A4: Coefficient results from the discrete hazard model of milfoil establishment

Probability of invasion	Coef.	Std. Err.	P>|z|
Intercept	-4.640	1.945	0.0170*
Propagule pressure	0.0497	0.0197	0.0117*
Propagule pressure * trend	-0.00162	0.00140	0.245
Alkalinity	0.0182	0.00689	0.00816**
Secchi	-0.419	0.145	0.00973**
Maximum depth (ft)	0.0159	0.00831	0.0552+
pH	-0.0473	0.265	0.859
Forest	-0.915	0.845	0.279
Lake area (ft^2)	-1.649E-09	6.627E-10	0.0128*
Trend	0.214	0.0962	0.0259*
Trend^2	-0.00809	0.00407	0.0467*

Table A5: Robustness of Economic Impacts to Selection of the Discount Rate

	1998-2013			2013-2028		
Discount rate	**Own lake effect**	**Spillover effect**	**Spillover percentage**	**Own lake effect**	**Spillover effect**	**Spillover percentage**
0%	$1,484,418	$713,541	20%	$1,498,197	$42,231	3%
3%	$1,203,800	$505,817	18%	$1,204,393	$28,715	2.5%
5%	$1,058,852	$431,242	18%	$1,059,339	$24,158	2.5%

Table A6: Characteristics of Lakes Selected for the Coupled Model

Lake	Shoreline properties	Average number of trips per year
Big Arbor Vitae	69	19,608
Little Arbor Vitae	20	7,704
Rhinelander Flowage	792	506
Dam Lake	200	4,435
Minocqua	832	36,885
Squash	165	735
Twin, South	14	8,301
Forest	118	2,794
Average across all 453 lakes	52	1,892

Table A7: A comparison of lake characteristics for lakes in our sample that had milfoil by 2013 and lakes that never had milfoil

	Sample lakes with milfoil	**Sample lakes without milfoil**
Number of observations	58	395
Propagule pressure	12.37 (23.74)	2.69 (8.13)
Alkalinity	37.48 (22.97)	26.25 (20.88)
Secchi	2.26 (1.03)	2.95 (1.55)
Maximum depth (ft)	32.16 (19.07)	30.13 (18.89)
pH	7.33 (0.66)	7.09 (0.71)
Forest	0.50 (0.15)	0.57 (0.18)
Lake area (ft^2)	5.06E08 (2.04E08)	5.72E08 (1.94E08)

Notes: Standard deviations in parentheses. See (Papes & Vander Zanden, 2010) for a description of the data.

Table A8: Summary statistics by boater type

	Permanent residents	Vacationers
Number of boaters	645	798
Number of trips to lakes	5,497	6,269
Number of choice occasions	98,397	18,901
Average choices in choice set	7.2	6.3
Consecutive trips	2480	3817

Figure A1: An illustration of the intercept and follow (I&F) sampling procedure used to collect data