Measuring the Value of Hg and Acid Pollution in New York State through Property Values

Final Report

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Measuring the Value of Hg and Acid Pollution in New York State through Property Values

Final Report

Prepared for:

New York State Energy Research and Development Authority

Albany, NY

Greg Lampman
Senior Project Manager

Prepared by:

Clarkson University

Potsdam, NY

Martin D. Heintzelman
Thomas M. Holsen
Chuan Tang
Investigators

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    (Clarkson University, Canton, NY). nyserda.ny.gov/publications

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Executive Summary

We conducted a hedonic analysis to investigate how different levels of fish mercury and acidity in lakes will affect property values in a large swath of New York State. The hedonic analysis was based on more than 228,000 property transactions covering 34 counties in New York State from 2004 to 2013, and water quality data for 173 big lakes with sizes greater than 17.3 ha (43 acres)[1] covering the same time period.

As far as we know, this is one of the largest hedonic analyses of water quality ever completed. We believe this comprehensive study area and large sample size provide important spatial and temporal variation to quantify the capitalization effects of environmental concerns caused by atmospheric deposition of mercury and acidity.

Having tested a set of hedonic models of various specifications with fixed effects at various levels (e.g., census block, census block group, census tract, city/town), we found that:

- There is insufficient evidence to reject the null hypothesis that the effect of elevated fish mercury levels on property values is zero.
- The effect of lakes with high pH (i.e., pH >8.5) on property values is not significant while the effect of lake with low pH (i.e., pH < 6) on property values is positive and significant, which runs counter to expectations.
- Proximity to a lake with a fish consumption advisory significantly depreciates property values by three to four percent. This negative effect increases to 15-25 percent for waterfront and near-waterfront properties within one mile from an affected lake.

In general, a house with average real sale price of $128,441 could gain up to $3,853 in value if water quality improvements at the nearest lake are such that it is removed from the advisory list. Furthermore, based on a predicted mean sale price for 968,789 properties in the study region, water quality improvements that allow for a lifting of advisories on nearby lakes could generate a $4,231 premium to nearby properties. This provides an upper bound to the benefits of widespread improvement of water quality in the study region. The aggregated capitalization affects from such an improvement ranges from $30 million to about $4 billion (2004 dollars) in the study region.

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[1]   The size of included lakes is determined based on water quality data availability. More details about the selection will be discussed below.

1   Introduction

There are 17 major watersheds consisting of thousands of lakes, ponds, and reservoirs as well as tens of thousands of miles of rivers and streams in New York State. These waterbodies often serve as drinking water supplies for local communities, and as habitat for aquatic plants and animals. They also support a wide range of human activities, including recreation, tourism, agriculture, fishing, power generation and manufacturing. Unfortunately, those waterbodies are a primary medium through which mercury and acid deposition impact ecosystems due to methylation and acidification in wetlands, lakes, and rivers (Driscoll et al., 2003a; Krabbenhoft and Sunderland 2013).

In New York State, atmospheric deposition of mercury and acid rain rank among the top 10 most prevalent causes/sources of water quality impact (DEC 2015). Within aquatic ecosystems, inorganic mercury is transformed by certain bacteria to a special chemical form, methyl mercury, which is readily bio-magnified through the trophic web, harming higher-level predators and leading to neurological damage in humans (Meili 1997; Harris et al., 2003). Most people and wildlife at high trophic levels are exposed to mercury by the consumption of methyl mercury contaminated fish. Meanwhile, abnormal pH values likewise result in various adverse impacts on aquatic ecosystems. The Adirondack region of New York State has historically received the highest rates of atmospheric inputs of acid deposition in the United States (Driscoll et al., 2001). Most acid-sensitive lakes in New York State are in the Adirondack region and are identified in New York's 1998 (and subsequent) Section 303(d) lists maintained pursuant to the Clean Water Act (DEC 2014). The lake ecosystems are projected to be unable to achieve complete chemical and biological recovery in the future (Zhou et al., 2015). Impaired water quality due to atmospheric deposition of mercury and acid rain not only raises health concerns, but also causes significant economic damage through the loss of valuable ecological services.

In order to address these environmental problems, several regulatory instruments have been proposed and implemented in the United States. The United States acid rain program was enacted in 1990 as part of the 1990 Clean Air Act Amendments (CAAA) and could be titled as the most successful "market-based" environmental policy in the country. According to the EPA, more than 55 percent average reductions have been achieved on wet deposition of sulfate across the eastern United States, over the 1989–1991 and 2009–2011 observation periods (EPA 2016). Though it may take longer than expected for lakes to recover from acidification, significant decreases in acidification based on reductions in sulfur deposition during 1992–2000 have been recorded in the Adirondack region (Driscoll et al., 2003b). The estimated annual economic value under the Post-Clean Air Act scenario in the year 2020 will reach two

trillion dollars, which is mainly the consequence of significant reductions in air pollution related death and illness, protecting the health of ecosystems, and better environmental conditions such as improved agricultural yields and better visibility conditions (DeMocker 2003).

On the other hand, the 1990 Clean Air Act amendments give the EPA broad discretion in crafting regulation to reduce power plant mercury emissions. Under section 112 of the CAAA, Congress identified 189 substances, including mercury as "hazardous air pollutants." Since then, there have been dramatic reductions in mercury emissions from most municipal waste combustors, medical waste incinerators, and a number of other sources (Simonin et al., 2008). However, regulations on controlling emissions of mercury and other common toxic air pollutants from power plants, the largest single source of anthropogenic mercury emission in the United States (EPA 2011) have only recently been adopted. In 2005, the EPA issued the Clean Air Mercury Rule (CAMR), limiting mercury emissions from new and existing utilities. Similar to the acid rain program, this rule also included a cap-and-trade program to reduce mercury emission in the nation within two phases. However, the U.S. Supreme Court vacated this rule three years after its initialization. In 2011, the EPA announced the Mercury and Air Toxics Standards (MATS) aiming at limiting mercury, acid gases, and other toxic pollution from power plants exclusively. The U.S. Supreme Court again overturned MATS last year, declaring that the EPA should take cost into consideration when finding it is "appropriate and necessary" to regulate electric utilities. Eventually, in April 2016, the EPA provided final evidence including a consideration of cost and maintained their determination in promoting MATS: "It is appropriate and necessary to set standards for emissions of air toxics from coal- and oil- fired power plants." Almost at the same time, the U.S. Supreme Court changed its perspective and refused to stay MATS. Therefore, MATS becomes the first standard in the U.S. for mercury emissions from power plants and is expected to lead to an extraordinary nationwide reduction in the near future.

In crafting and evaluating policies to reduce atmospheric deposition of mercury and acidic compounds, policy makers would be well-served to have information on the costs and benefits of these policies. Since waterbodies, as an important part of the ecosystem, are the direct recipient of those adverse depositions and are highly valued by the public (Keeler et al., 2012), measuring the economic values of water quality and related ecosystem services is an important component to quantifying the benefits of mitigating mercury and acidic emissions. Because there is no established market for surface water quality, it is common to use a revealed preference approach, which relies on consumer behavior in related markets to estimate the non-market benefits of improving environmental amenities. Housing markets are a great example of a market where the composite goods prices are associated with their characteristics as

well as the services provided by their locations. With sufficient information on property transactions and the market, the implicit price of one or several environmental amenities surrounding the houses can be estimated.

Specifically, hedonic analysis uses regression techniques to estimate a hedonic price function, which represents the impact of observable property characteristics, including environmental amenities and spatial factors, on the equilibrium prices of parcels. By including observable characteristics, like lot size, square footage, and some information about the buyer, including their mailing address, the method will also be able to estimate how water quality factors impact the values of different types of homes in different ways. This method is firstly proposed by Rosen (1974), which provides the framework for estimating the dollar values of environmental amenities based on property values.

The idea of using the variation in housing prices to reflect the value of water quality can be traced back to the 1960s. A study on 60 artificial lakes in Wisconsin, (David 1968) found that water quality was positively associated with waterfront property values. This relationship between water quality and property values was further explored and analyzed in a nationwide study concerning the potential benefits of water pollution control on property values (Dornbusch and Barrager 1973). Subsequently, more hedonic studies on water quality were performed in the spirit of Rosen's model (Epp and Al-Ani 1979; Leggett and Bockstael 2000; Gibbs et al., 2002; Poor et al., 2007; Phaneuf et al., 2008; Egan et al., 2009; Guignet and Klemick 2015; Tuttle and Heintzelman 2015; Wolf and Klaiber 2016).

In general, a majority of hedonic studies on water quality agree that waterfront property owners capitalize on the water quality of the adjacent lake/river as it increases their property value while degraded water quality depreciates the value. In contrast to many previous hedonic studies, rather than clarity or other more aggregated measures for water quality, this research includes specific measures, which have more important ecosystem and human health implications (Michael et al., 1996; Boyle et al., 1999; Gibbs et al., 2002; Walsh et al., 2011).

The two major objectives of this research are:

- Deploy the hedonic method to establish a link between lake water quality–specifically acidity (i.e., pH) and fish tissue Hg content, and property values–trying to reveal the dollar value of mercury pollution and acidification capitalized into people's decisions in property transactions.
- Use results of hedonic property value analysis together with model forecasts of future environmental conditions under various policy scenarios to estimate future changes in property values from water quality changes.[2]

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[2] Since the actual fish mercury level is not found to affect property values, we perform predictions based on hypothetical policy scenarios to remove fish advisories on lakes. More details about prediction and results will be discussed below.

2　Study Area & Data

2.1　Study Area

The study area of this research covers 34 counties of New York State[3] as shown in Figure 3-1. The reasons for choosing those counties are generally three-fold. First, the lakes in these counties are the ones most heavily impacted by mercury deposition and acid rain in the State. The NYS section 303(d) list of impaired waters is a list of waters that fail to meet certain water criteria, can no longer support appropriate uses, and may require development of a Total Maximum Daily Load (TMDL). Major lakes in our study area can be found on this list as impaired waters. Second, water quality data and transaction data for those counties are relatively comprehensive. In order to achieve sufficient variation in water quality, we need to confine our study area to regions with the most available data. Last, many lakes within the selected counties, especially those in the Adirondack Park and Finger Lakes Region, are important destinations for fishing and recreation in NYS.

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[3]　Those 34 counties include: Albany, Cayuga, Chenango, Clinton, Columbia, Cortland, Essex, Franklin, Fulton, Hamilton, Herkimer, Jefferson, Lewis, Livingston, Madison, Montgomery, Oneida, Onondaga, Ontario, Oswego, Otsego, Rensselaer, Saratoga, Schenectady, Schoharie, Schuyler, Seneca, St. Lawrence, Steuben, Tompkins, Warren, Washington, Wyoming, Yates.

Figure 2-1. Map of Study Area
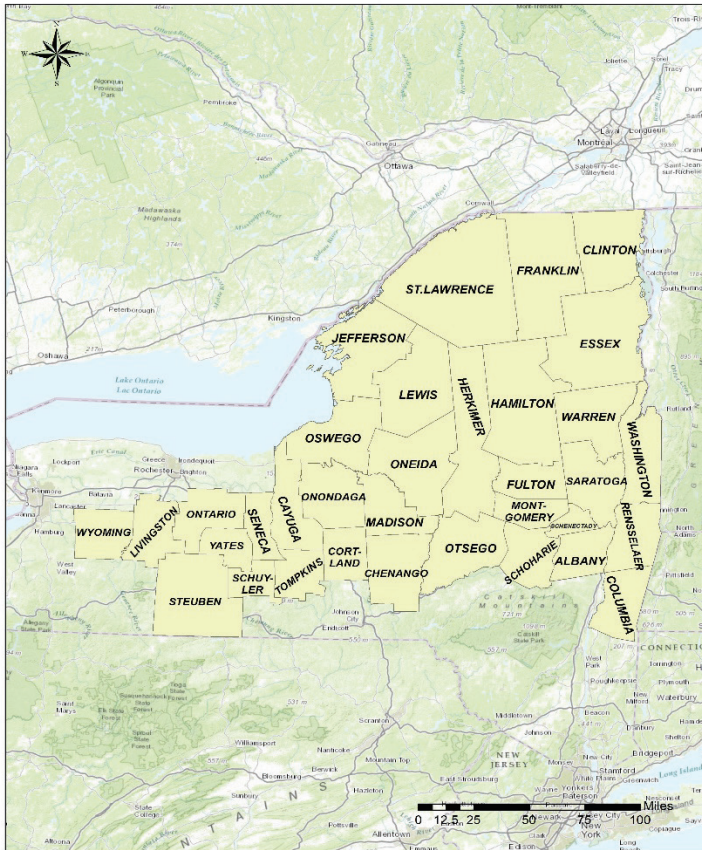
2.2   Transaction Data

We collected and compiled 332,652 real residential property transactions from 2004–2013 in the 34 counties. The New York State Office of Real Property Taxation Services provided the real estate transactions dataset as well as the detailed parcel and property characteristics of all transactions. In the data cleaning stage, transaction observations that have incomplete and abnormal records – such as, number of bedrooms less than one, number of stories less than one, etc. – were cleaned out. Outlier observations, such as sale price lower than $10,000 or living area less than 100 square feet were discarded as well. We also dropped out transactions data with unidentified/incomplete address information. Finally, the transaction dataset contains 218,832 real property sales to be used for hedonic analysis.

We projected each transacted parcel-on-parcel reference shapefile via ArcGIS (v13.1). We measured the Euclidean distance between each parcel centroid to environmental and cultural amenities, including population centers, hospitals, public schools, lakes and others. This spatial information is integrated into the hedonic analysis model to carefully control locational effects on property values. In our analysis, we focused on large lakes that serve for multiple water-based recreational activities such as fishing, boating and swimming. We consider that both waterfront and non-waterfront property owners are likely to care about the water quality of those lakes. We therefore link every parcel in our database to the nearest lake equal to, or larger than, 17 ha (43 acres). This lake size threshold was determined based on the 25th percentile of the size of all lakes with water quality data (either acidity or fish mercury, or both). This cut-off is a balance between taking advantage of as much available water quality data and impeding the noise brought by lakes with unknown information. This way, there are 629 lakes included in the hedonic analysis, with 173 lakes that have water quality information[4]. With this specification, we made an assumption that those specific sized lakes are major water recreation destinations for nearby property owners. The water quality of those lakes would therefore influence consumer decisions related to both recreation and home purchases.

In addition, all transaction data were deflated to the base year 2004 using the quarterly house price index (HPI) constructed by the Federal Housing Finance Agency. Our study area covers seven metropolitan statistical areas (MSA)[5]. If available, we used specific HPI for major MSA otherwise, the HPI for non-metropolitan New York State was used. The log form of deflated sale price was used as the dependent variable in the hedonic model.

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[4]   We also tried setting the lake size threshold to 15 acres (10 percentile) and to 135 acres (50 percentile). The hedonic analysis results are not substantially different from those shown in this report using 43 acres. In this final report, we only report results based on 43 acres threshold. We also excluded water quality data for Lake Champlain and Lake Ontario. We mark those two lakes as data "unknown" in the later hedonic analysis since we consider that water quality of those huge lakes is hard to be described with just a few discrete observations.

[5]   Those seven MSA are: Albany-Schenectady-Troy; Ithaca; Syracuse; Watertown-Fort Drum; Glens Falls; Rochester; Utica-Rome.

2.3   Water Quality Data

2.3.1 Fish Mercury Data

Fish mercury data used in our hedonic analysis mainly comes from the fish mercury database maintained by the Division of Fish, Wildlife and Marine Resources of New York State Department of Environmental Conservation (DEC). The DEC started monitoring the mercury concentration in fish tissue in the late 1960s. Continued monitoring programs have tracked trends in fish mercury levels in NYS since then (Howard Simonin et al., 2008). More recently, several independent mercury monitoring programs are active for research purposes[6]. This database primarily stores contaminant results for samples taken in NYS. There are results from other states as well, mostly from marine waters. Most samples are from fish, but aquatic vertebrates and terrestrial animals are also present. The database contains nearly all analyses done by or for the Division of Fish, Wildlife and Marine Resources' contaminant monitoring program since about 1970 to 2015. In addition, we also include fish mercury monitoring data from 2008 to 2012 by the Adirondack Lakes Survey Cooperation, a non-profit-organization. This monitoring project collected approximately 600 fish samples, covering 36 lakes within the Adirondack region. All fish samples were analyzed for total mercury concentration while a few samples were tested for methyl mercury concentration.

Following the scientific literature on mercury contamination (Simonin et al., 2009; Yu et al., 2011; Wathen et al., 2015), the total mercury concentration in fish tissue was used as the mercury pollution indicator for lakes. Though only methyl mercury poses a threat to human beings, data for methyl mercury in fish body are normally scarce compared to data of total mercury concentration. Fortunately, methyl mercury concentrations in fish muscle are directly proportional to total mercury concentrations, but the ratio varies by abiotic factors of different locations and by fish species (Kannan et al., 1998). It is reported that methyl mercury accounts for 64-100 percent of the total mercury in fish body (Agah et al., 2007; EPA 2011). The usage of total fish mercury directly instead of converting it into methyl mercury in our analysis could be regarded as a worst-case scenario approach to estimate the average fish mercury pollution in a lake.

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[6]   From 2001–2003, DEC led a project investigating the mercury and organic chemicals in fish from the New York City reservoir system. In 2006, DEC reported another project studying the total and methyl-mercury in the Never-sink reservoir watershed. Furthermore, the Biodiversity Research Institute (BRI) has conducted a project assessing mercury concentration in loons and prey fish at 44 lakes in Adirondack region during 2003 to 2004. NYSERDA funded another extensive fish mercury monitoring project during 2003–2007, analyzing 2605 individual fish mercury samples from 131 lakes in New York State.

In total, we initially compiled 26,642 fish mercury data points from these two data sources. We filtered out fish observations with incomplete information, such as missing fish length or if the sampling coordinate is unidentified or incorrect. We also dropped observations where fish mercury is reported to be negative. Since we only focus on lakes in this research, any fish mercury observations from rivers, streams, creeks/brooks, and canals are dropped out as well. Furthermore, we dropped observations which is the only observation for certain species and rename species with few observations (<5) to species alike[7]. Finally, we have 7,563 fish observations covering 207 lakes across the State from 1970 to 2015 in the ready-to-use dataset for fish mercury standardization.

In addition, we introduced fish advisory information into hedonic analysis. According to the EPA: "A fish consumption advisory is a recommendation to limit or avoid eating certain species of fish or shellfish caught from specific water bodies or types of water bodies (e.g., lakes, rivers or coastal waters) due to chemical contamination." Fish advisory thus becomes the direct path from which the general public retrieve information about mercury pollution in the lakes near to them. Incorporating fish advisory information allows us to identify how being proximate to a lake with fish advisory affects property values. More details about this variable and how it works in the hedonic model and predictions will be discussed in next sections.

2.3.2 Fish Mercury Standardization

Since fish mercury data are derived from different monitoring programs, there are differences in the characteristics of fish samples collected over time and across different lakes which presents a challenge in comparing pollution levels across lakes. Without standardizing raw fish mercury data, the actual mercury pollution level of different lakes may be falsely interpreted due to variations in sample characteristics, such as species, size, age, etc. (Wente 2004). For example, a larger fish (e.g., Walleye) caught in Lake A may contain higher mercury than a smaller fish (e.g., yellow perch) taken from Lake B. However, based on those two fish samples, it would be inappropriate to conclude that Lake A is more polluted than Lake B since the higher mercury concentration of the larger fish could be the consequence of its higher trophic

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[7]   We dropped the only observation whose species named as "PNTL" and re-classify five observations whose species are "MUSK (Musky)" and "TML (Tiger Muskelluge)" as "NOP (Northern Pike)."

status or longevity. Environmental scientists have proposed various methods (Somers and Jackson 1993; Parks et al., 1994; Meili 1997; Tremblay et al., 1998; Sonesten 2003; Wente 2004; Money et al., 2011) and applied them in numerous regional or nationwide fish mercury related studies (Lockhart et al., 2004; Kamman et al., 2005; Driscoll et al., 2007; Evers et al., 2007; Melwani et al., 2009; Simonin et al., 2009; Gandhi et al., 2014; Åkerblom et al., 2014; Wathen et al., 2015).

Each standardization method has its own advantages and disadvantages in interpreting fish mercury monitoring data. Surprisingly, there has been minimal effort to systematically evaluate the relative performance of these methods. Since accuracy of comparable fish mercury levels will dictate the results of hedonic analysis, we choose four widely used standardization methods to process our data. We then applied hedonic analysis based on the results of those four standardization methods to test the sensitivity of those different methods in hedonic analysis. More details about the standardization methods are discussed in Methods section.

2.3.3 Lake Acidity Data

Similar to many other hedonic analyses (Epp and Al-Ani 1979; Netusil et al., 2014; Tuttle and Heintzelman 2015), pH is used as an indicator for the acidity level of lakes in this study. It is the most frequently measured water chemical parameter and reduced pH is one of the most important impacts of acidic deposition on watersheds(Driscoll et al., 2003a). There are many water quality monitoring programs in NYS that track acidity. In order to maintain the consistency and integrity of our dataset, we only employ data from programs that have the most comprehensive and complete monitoring data over time. For our hedonic analysis, we include pH data from three different monitoring programs: (1) the New York Citizens Statewide Lake Assessment Program (CSLAP) conducted by DEC, (2) Adirondack Long Term Monitoring (ALTM) program administered by the Adirondack Lake Survey Corporation and the Temporally Integrated Monitoring of Ecosystems (TIME) conducted by the EPA since 1991 as part of EPA Environmental Monitoring and Assessment Program. We used the arithmetic mean of monthly observed pH to indicate the average yearly acidity level of a lake. In summary, we obtained 3,173 yearly acidity observations for 232 lakes from 1986–2012 within our study area. Table 2-1 is a summary of data sources for this research.

Table 2-1. Summary of Data Sources

	Data Description	Time Frame	Source
1	Fixed effect (e.g., census block/block group/tract, town city) Reference Shapefile	2015	U.S. Census Bureau
2	Amenities Reference Shapefile (e.g., Public facilities, population centers, etc.)	various	New York State GIS Clearinghouse
3	Water Body Reference Shapefile	2012	National Hydrologic Database (NHDplus)
4	Parcel Shapefile	2012-2013	Individual counties
5	Parcel Sale Data & Characteristics	2004-2013	NYSORPTS
	Fish Tissue Mercury Data	1970-2015	Division of Fish, Wildlife and Marine Resources(NYSDEC)
			Adirondack Lakes Survey Cooperation
6	Acidity Data	1986-2012	NYSDEC
			Adirondack Lake Survey Corporation
			U.S. EPA
7	Fish Advisory Reference Shapefile and Other Information	2010	U.S. EPA Office of Water (OW)
			New York State Department of Health (NYSDOH)

3   Methods

3.1   Hedonic Analysis Model

3.1.1   Empirical Model

The hedonic method generally involves two stages. The first stage is to estimate the hedonic price function by regressing house prices on attributes using an econometric model, then the marginal implicit prices of the attributes can be recovered from the estimated coefficients. The second stage aims to derive the demand function for attributes based on the results of first stage. Most hedonic studies, including this one, focus on the first stage hedonic estimation due to its well-defined framework and the challenges associated with estimating the second stage with confidence.

The general form of the hedonic model applied in this study is:

Equation 1. $\ln(Price) = f(S, L, E)$

where *Price* is the real transaction price, *S* is the structural characteristics, *L* is the locational characteristics, and *E* indicates environmental characteristics.

Given that the form of the econometric model was not explicitly defined in Rosen's paper, like other studies, we employ a standard semi-log specification for our regression model (Kuminoff et al., 2010). When constructing the econometric model, several potential econometric challenges and issues that may lead to biased estimates need to be addressed. These challenges include arbitrary functional form, omitted variable bias, endogeneity, spatial dependence and autocorrelation, heteroscedasticity, and multicollinearity. In hedonic studies on water issues, the most discussed common problem is omitted variable bias (Tuttle and Heintzelman 2015). Econometricians may fail to include important characteristics that are correlated to other independent variables and important to home buyers, which then bias the remaining estimated coefficients. The "emitter effect" described by (Leggett and Bockstael 2000) is an example of this problem. In the case where home owners live near pollution emitters and variables indicating the proximity to those emitters are missing, the seemingly correct and significant impacts of water quality on house values suggested by regression results may actually be the consequence of other nuisance, such as noise or odors, brought by pollution emitters.

Knowing that omitted variables bias exists in our model since it is impossible to have information on all house price related characteristics, therefore we used spatial fixed effects to absorb the price effects of spatially clustered omitted variables. We incorporated a variety of fixed effect levels into our hedonic model in order to balance the competing goals of reducing omitted variables bias (done by using smaller scale fixed effects) and maintaining sufficient variation in our variables of interest to allow for proper identification. The introduction of fixed effects is important in terms of ensuring the accuracy of model estimation. In addition, in order to dampen the spatial autocorrelation and heteroscedasticity, we allow the clustering of error terms for parcels within each fixed effects group, but enforce the error terms to be independent across the groups.

The specific model applied in this study can be written as:

Equation 2. $\quad \ln(Price)_{ijt} = \beta_0 + \beta_1 S_{ij} + \beta_2 X_t + \beta_3 L_j + \beta_4 pH_{it} + \beta_5 FishHg_{it} + \eta_{jt} + \epsilon_{it}$

where $\ln(Price)_{ijt}$ represents the price of the property i in the fixed effects group j at time t; S_{ij} stands for characteristics (e.g., number of bedrooms, living space, etc.) of property i in group j; X_t represents a set of time series dummy variables for the month and year of sale; L_j is the fixed group effects(e.g., census block, census block group, etc.); pH_{it} and $FishHg_{it}$ are categorical variables for t year average pH (i.e., High, Normal, Low, Unknown) and for average fish mercury level (Unsafe, Safe, Unknown) in the nearest large lake connected to property i, therefore, β_4 and β_5 are parameters we are interested in; lastly, η_{jt} and ϵ_{it} are fixed effects group error and individual error respectively.

3.1.2 Specification of Variables

3.1.2.1 Fish Mercury

Average people's perceptions of water quality are general rather than quantitative. Therefore, it may not be appropriate to use continuous scientific measures in hedonic analysis and estimate the implicit price for water quality based on a continuous scale. We transformed the continuous water quality data into categorical variables. The 0.3 parts per million (ppm) human health criterion for methyl mercury in fish tissue established by the EPA and the U.S. Food and Drug Administration (FDA) is the maximum advisable concentration of methyl mercury in fish body to protect consumers (Driscoll, C.T. et al., 2007). We follow these criteria and sort the yearly average fish mercury data into three categories: *safe* (lesser or equal to 0.3 ppm), *unsafe* (greater than 0.3), and *unknown* (all lakes that have not been sampled). The *safe* level was used as the reference level in hedonic model (the omitted category). In the following section, fish mercury levels of a lake mean the yearly average fish mercury level of that lake.

3.1.2.2 Acidity

The lake acidity level was captured using the annual average pH of lakes. Though pH readings could not be observed by home owners and lake users directly, abnormal pH values could noticeably affect the ecosystem, reducing species diversity and abundance of aquatic life (Driscoll et al., 2003a). Scientifically, pH is a numeric scale for acidity. In natural conditions, a lake's pH measure falling between 6.5 and 8 is considered normal. Lakes with pH values that are either too low or too high are all regarded as impaired. This unique characteristic of pH suggests that it is inappropriate to use continuous pH readings in hedonic models due to the ambiguity in interpretation. As a result, most existing studies transform continuous pH readings into dummy variables distinguishing acid-stressed lakes from others (i.e., dummy variable equals to zero if pH was 5.5 or lower, otherwise equal to one) (Epp and Al-Ani 1979). In our dataset, the annual pH values range from 4.21 to 9.31. Lakes with pH lower than 6.5 were coded as *Low* and those with pH greater than 8 are coded as *High*, otherwise, as *Normal* (>= 6.5 and <=8). Lakes without pH readings are marked as *Unknown*. Therefore, in the following section, the pH level of a lake means the yearly average pH level of that lake.

In addition, for all sampled lakes, pH and fish mercury data measured in the same year of sale are used. When water quality measurements corresponding to the year of sale are not available, the measurement taken closest to the time of sale is used instead. Water quality variables for lakes not sampled are marked as unknown. We match the transaction data with water quality data in this way based on the assumption that water quality, especially yearly average lake pH and fish mercury, fluctuate slightly year by year. In fact, it may take many years for a lake which has already been polluted to recover, by itself, to a healthy state. Once polluted, some lakes will never be able to recover to its healthy state.

3.1.2.3 Fish Advisory

We incorporate fish advisory information in the hedonic analysis by using a dummy variable to identify whether a lake in our study area has been designated with a fish advisory. Specifically, lakes with an active individual fish advisory are coded as one while all others without advisories are coded zero. We identified the location of fish advisory events following the instructions of the EPA Office of Water (OW)[8]. There are 60 lakes that have been assigned fish advisories due to mercury pollution exclusively.

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[8] The Fish Consumption Advisories and Fish Tissue Sampling Stations NHDPlus Indexed Datasets. The detailed dataset and shapefile are available for downloading using the EPA "Clip N Ship Application": https://edg.epa.gov/clipship/. The specific information on fish advisory can be found on "EPA NLFA Technical Advisories Search" website: https://fishadviFsoryonline.epa.gov/Advisories.aspx

However, in the hedonic model we incorporate fish advisory information regardless of the type of pollutants (e.g., PCBs, Chlordane, Dioxin, etc.) and fish species based on the assumption that the effects of various fish advisories have a similar impact on property values[9]. In total, according to the shapefile provided by the OW, there are 556 lakes among our 629 lakes (area greater than 17 ha) that have active individual fish advisories. We believe incorporating this variable into the hedonic analysis model is important and necessary since it allows us to identify how assigning a fish advisory to a lake affects property values nearby. In addition, a fish advisory is the direct information obtained and understood by property owners and could be influential in the house purchasing process.

3.1.2.4 Locational Variables

The locational characteristics of each parcel include distance between the centroid of each parcel to the nearest facilities, including a public hospital, school, university, bus/rail station and population center. We also include the size of the lake in our model. As to measuring the effects provided by nearest lake, a non-linear function of distance to the nearest waterbody to proxy for the ecosystem service effects was proposed and applied in hedonic analysis (Phaneuf et al., 2008). We follow the same convention to describe the fact that the amenity effect is diminishing as distance becomes larger. The variable *lakeproxy* is created by using the function below:

Equation 3. $\quad \textbf{lakeproxy} = \textbf{max}\left[1 - \left(\frac{d}{d_{max}}\right)^{\frac{1}{2}}, 0\right]$

where d is distance between parcel to included lake and d_{max} is the threshold point indicating the amenity effect diminishes to zero. Though setting the value for d_{max} is somewhat arbitrary, we set d_{max} to one mile in our application based on the finding of previous study (Walsh 2009). This variable is between zero and one and is convex.

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[9] We first incorporated fish advisory information due to mercury exclusively and found that it was not significantly related to property values.

It is worth noting that there are more than 4,000 waterbodies (e.g., lakes, ponds, reservoir, etc) identified within the study area, most of which are quite small and do not have water quality data. As previously mentioned, we linked each parcel in our database to the nearest lake equal to, or bigger than, 17 ha (43 acres). However, one concern remains in using this approach: households presumably care about the water quality of those waterbodies in addition to the larger ones which we are able to measure. We partially control for this situation by creating a dummy variable, *lake_tag*, indicating the existence of at least one small lake between the parcel and the nearest threshold lake.

3.1.2.5 House Structural Variables

House structural characteristics include the number of bedrooms, kitchens, full and half bathrooms, and fireplaces. Other amenities, such as a finished basement, the capacity of basement and garage, and central air-conditioning are also included. Age of building and log form of square foot of living area are also considered. In addition, all included parcels are classified into seven groups: mobile, residential multi-purpose, residential, rural residence with acreage, seasonal residence, estate, and other. Each parcel is also graded on condition into five levels: bad (E), fair (D), average (C), good (B) and excellent (A), as defined by assessment records.

3.2   Fish Mercury Standardization

In the final ready-to-use fish mercury dataset, there are 7,563 observations of 23 species covering 207 lakes and 45 years (1970–2015). The objective of standardization is to find the most accurate and comparable fish mercury level for each sampling event (i.e., combination of sampling site and year). We deployed four different methods to standardize the fish mercury data with consideration of heterogeneity in fish length, species, sampling sites, and time. After standardization, the annual arithmetic average of fish mercury concentration was calculated as fish mercury level for each lake. We conducted hedonic analysis based on standardized fish mercury level derived by those four models individually to check the sensitivity of hedonic analysis. Results of those analyses will be discussed thoroughly in next section.

Specifically, those four standardization methods are: Analysis of Covariance (ANCOVA) (Kamman et al., 2005); Mixed-effect model (Eagles-Smith et al., 2016); National Descriptive Model for Mercury in Fish (NDMMF)(Wente 2004) and Empirical Fish Mercury Transfer Function suggested by the United Nations Economic Commission for Europe (CLRTAP 2004). All analysis in this part was completed by R statistical program (R Development Core Team 2008).

3.2.1 ANCOVA Model (Fixed-Effect Model)

Analysis of Covariance (ANCOVA) is an appealing approach integrating not only information of fish characteristics but factors vary substantially during different sampling events (i.e., sampling site and sampling year) as well. Since the model focuses on all main effect of all variables, it is also called Fixed Effect model[10]. The ANCOVA model we used is shown as below:

Equation 4. $\quad \log(FishHg)_{ijt} = \beta_0 + \beta_1 \log(Length)_i + \beta_2 Species_i + \beta_3 Site_j + \beta_4 Year_t + \epsilon_{it}$

where *Length* is continuous variable while Species is categorical variable indicating species; *Site* and *Year* are dummy variables indicating sampling site and year, ϵ_{it} is the error term. The estimate mean fish mercury value based on yellow perch of 234 mm (i.e., median length of pooled observations) for each sampling event were used for hedonic analysis.

3.2.2 Mixed-Effect Model

Though fish length was found to be strongly correlated with fish mercury concentration (R.S. Thorpe 1976; Gewurtz et al., 2011), a bivariate model that uses fish length as the only explanatory variable (Simonin et al., 2009) completely pools the entire dataset and ignores any variations in average fish mercury level between species and sampling events. On the other hand, the ANCOVA model focuses on the main effect of each explanatory variable. It does not pool the data entirely and therefore bias the results for species or sampling events with few observations. Mixed-effect model, however, provides a more flexible approach to describe data by partial pooling the entire dataset: when observations are scarce in certain groups (e.g., species group), the model will get more smooth estimates similar to the overall mean level; when observations are rich in other groups, the model will generate estimates close to the group mean level.

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[10] There are lots of discrepancies in describing "fixed effect" and "random effect". We avoid using those terms in this report for reducing ambiguity.

Similar to (Eagles-Smith et al., 2016), the mixed-effect model used here takes fish length as the single fixed covariate, and sampling site, species, and an interaction term of species and length as random effects. In order to account for the variations of sampling years, we also include year as another random effect term in this model. The model was run using the *lme4* package of R (Bates et al., 2014). The estimate mean fish mercury value based on yellow perch of 234 mm for each sampling event were used for hedonic analysis.

3.2.3 National Descriptive Model for Mercury in Fish (NDMMF)

The National Descriptive Model for Mercury in Fish was firstly proposed in (Wente 2004) and officially recommended by USGS. It takes the spatial and temporal trends of fish mercury level into consideration and has a parsimonious specification. Wente (2004) described that this model fit the fish mercury data from National Listing of Fish and Wildlife Advisories database very well with a pseudo-R squared of 0.82. It is also found that this model performs well on standardizing and predicting fish mercury of yellow perch and walleye in Ontario Lake, Canada (DeLong 2012). The specific form of model is shown as:

$$\ln(C_{ijk} + 1) = \sum_{k=1}^{m} \alpha_k \times \ln(Length_k + 1) + \sum_{j=1}^{n} (\beta_j \times Event_j) + \varepsilon_{ijk}$$

$$Length_k = \begin{cases} Length_{ijk} & \text{if } k = k_l \\ 0 & \text{if } k \neq k_l \end{cases}$$

$$Event_j = \begin{cases} 1 & \text{if } j = j_l \\ 0 & \text{if } j = j_1 \end{cases}_3$$

Equation 5.

where C_{ijk} is the fish mercury concentration from i^{th} sample of the jth sampling event (i.e., a collection of samples from a specific site and date) for the kth species and cut combination (e.g., skin-off fillet); α_k is a set of parameters relating variation in fish mercury concentration to fish length for each of m species and cut combinations of fish[11]; $Length_{ijk}$ is the length of the ith sample of the jth sampling event

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[11]   It is worth mentioning that the α_k term only indicates m species in our model rather than species and cut combination since, in our fish mercury dataset, the fish cut is unknown. We assume that all fish samples are prepared using identical fish cut.

for the kth species; β_j is a set of parameters describing variation in fish mercury concentration among each of n sampling events; ε_{ijk} is an error term for the ith sample of the jth sampling event for the kth species; k_l is the value of k for the lth observation; and j_l is the value of j for the lth observation. The estimate mean fish mercury values based on yellow perch of 234 mm for each sampling event were used for hedonic analysis.

3.2.4 Empirical Fish Mercury Transfer Function

Besides regression-based standardization methods, some research applied empirical transforming model to convert fish mercury with heterogeneous sampling characteristics into one comparable species (Meili 1997; Depew et al., 2013; Åkerblom et al., 2014). One example is introduced by the United Nations Economic Commission for Europe (CLRTAP 2004):

Equation 6. $$Hg_{std} = \frac{Hg_{obs}}{\left(f_{HgY} + f_{HgW}W^{\frac{2}{3}}\right)}$$

where Hg_{std} is the standardized mercury concentration, Hg_{obs} is the observed mercury concentration; f_{HgY} is a parameter representing the concentration ratio between newly hatched young fish and 1-kg pike, and f_{HgW} is a species-specific empirical coefficient; W is the wet weight of fish sample. According to (Åkerblom et al., 2014), parameters were set to default values: f_{HgY} to 0.13 and f_{HgY} 0.87 for pike, 1.65 for perch, and 1 for other species. Therefore, observed individual Hg concentrations were standardized correspondently to a 1-kg pike in the same lake[12].

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[12]   We were unable to transfer individual fish mercury to yellow perch due to insufficient information for transfer parameters. However, the 1-kg pike standardized results make no difference from other standardize methods in hedonic analysis: there effects of fish mercury level on property values is nominal.

4 Hedonic Analysis Results and Discussion

4.1 Sensitivity Analysis of hedonic analysis

We deployed several validation approaches and statistics for the performance test. The Coefficient of Determination (R squared, denoted as R^2 or r^2) of a regression model will be used to measure how well data will fit the regression model. For a regression model, the R square indicates the ratio of variance explained by the model to the total variation in the dependent variable. Mean Absolute Error (MAE) represents the average absolute deviation of predicted values with respect to the observed ones. It is an unambiguous measure of average error magnitude. Generally, the smaller MAE is, the better a standardizing method performs. Root Mean Square Error (RMSE) is used for measuring the quantity of accuracy of this regression model. Similarly, the smaller RMSE is, the better a standardizing method performs. The Akaike information criterion (AIC) (Arlot et al., 2010) is a measure of the relative quality of the full and reduced forms of a regression model for a given set of data. Among a set of candidate models for the data, the most preferred model is the one with lowest AIC value. Different from r square, AIC rewards goodness of fit, but penalizes the number of variables included in the model. In addition, Bayesian Information Criterion (BIC) is based, in part, on the likelihood function and used in similar convention as AIC. Table 4-1 shows a summary of statistical performance of those four methods.

Table 4-1. Summary of Statistical Performance of Four Fish Standardization Methods

	Methods	Adj. R square	AIC	BIC	RMSE	MAE
1	VA(Fixed-Effect)	0.8618	7075	8926	0.6683	0.4824
2	Mixed-Effect	NA	-10195	-10146	0.0947	0.0700
3	NDMMF	0.9961	6581	9069	0.1869	0.1097
4	Transfer Function	NA	NA	NA	0.3489	0.2318

  * NA indicates statistics are not available.

Four models are all used to describe our fish mercury data with consideration of temporal and spatial trends. Those statistics illustrate how well those models not only describe a real dataset, but also, predict new observations. According to Table 4-1, it is easy to conclude that the mixed-effect model is superior among those four methods in terms of relative low RMSE and MAE, and low AIC and BIC. Therefore, in the further hedonic analysis with various fixed-effect scenarios, we only used the fish mercury standardized by mixed-effect model. However, for the sensitivity analysis, we conducted hedonic analysis based on fish mercury calibrated by all four models individually and evaluate the differences in estimating the effect of fish mercury on property values.

Table 4-2. Hedonic Analysis Results Based on Four Fish Mercury Standardization Methods

	(1)	(2)	(3)	(4)
	Mixed-Effect	**ANOVA**	**NDMMF**	**Transfer Function**
Lakeproxy	0.683***	0.683***	0.683***	0.686***
	(0.0317)	(0.0317)	(0.0317)	(0.0318)
Fish Advisory	-0.0294**	-0.0295**	-0.0292**	-0.0225
	(0.0147)	(0.0147)	(0.0147)	(0.0148)
Lake_tag	0.0168**	0.0168**	0.0168**	0.0168**
	(0.00771)	(0.00770)	(0.00770)	(0.00771)
Fish Hg (Unknown)	-0.0222	-0.0220	-0.0236*	0.00814
	(0.0137)	(0.0136)	(0.0136)	(0.0121)
Unsafe Fish Hg (>0.3 ppm)	-0.00390	-0.00234	-0.0138	0.00466
	(0.0239)	(0.0241)	(0.0241)	(0.00758)
Constant	7.542***	7.542***	7.545***	7.511***
	(0.271)	(0.270)	(0.271)	(0.273)
FE-groups	2668	2668	2668	2668
Year/Monthly FE	YES	YES	YES	YES
R-squared	0.403	0.403	0.403	0.403
Observations	218832	218832	218832	218832

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Standard errors (SEs) in parentheses. SEs have been clustered at the FE levels respectively

Fixed-effect level: census block group

Table 4-2 shows the regression results for major variables based on those four standardization models. The full regression results are available in the appendix. The hedonic analysis was performed using census block group as fixed-effect level. Disproxy and Lake_tag are both positive significant across four models, these consistent results indicate that the closer a property is to a lake, the higher the value, and a smaller lake within the distance to the interested big lake also is of value to homeowners, which proves our hypothesis. As to the estimation on fish mercury categorical variables, the regression results are consistent showing that, *ceteris paribus*, unsafe fish mercury levels of lakes have nominal effects on property values compared to lakes with safe fish mercury levels (<=0.3 ppm). The estimation for mercury unknown category is also insignificant except for model 3 (NDMMF). The sensitivity test confirms that the four standardization methods do not significantly alter the results of hedonic analysis. This is reasonable since we used categorical variables rather than using continuous variables for fish mercury directly. The standard error of each standardization method are considered trivial in determining the category that a lake should be assigned to.

4.2 Hedonic Analysis

We performed hedonic analysis using basic OLS model with fixed effect on different levels: census block, census block group, census tract, and city-town group. The standardized mercury data prepared by the mixed effect model and acidity data were used for those hedonic analysis. Table 4-3 is a summary of primary variables of hedonic analysis. Full regression results can be found in the appendix.

Table 4-3. Results of Hedonic Analysis

	(1)	(2)	(3)	(4)	(5)
	OLS	FE-Block	FE-Block Group	FE-Tract	FE-City Town
Lakeproxy	0.582***	0.695***	0.682***	0.625***	0.558***
	(0.00677)	(0.0456)	(0.0318)	(0.0370)	(0.0410)
Fish Advisory	0.139***	0.0239	-0.0293**	-0.0373*	-0.0227
	(0.00360)	(0.0223)	(0.0148)	(0.0212)	(0.0288)
Lake_Tag	0.0514***	0.00419	0.0168**	0.0195**	0.0295***
	(0.00554)	(0.00639)	(0.00772)	(0.00822)	(0.00999)
Fish Hg (Unknown)	-0.0225***	0.00683	-0.0181	0.00497	0.00359
	(0.00249)	(0.0131)	(0.0148)	(0.0209)	(0.0243)
Unsafe Fish Hg (>0.3 ppm)	-0.371***	0.00989	-0.00591	-0.0263	-0.0168
	(0.00472)	(0.0136)	(0.0222)	(0.0260)	(0.0285)
Lake pH (High)	-0.0961***	0.0301	0.0154	0.0103	-0.00456
	(0.0180)	(0.0228)	(0.0242)	(0.0282)	(0.0365)
Lake pH (Low)	0.548***	0.329	0.424***	0.246***	0.209***
	(0.0645)	(0.233)	(0.0522)	(0.0381)	(0.0373)
Lake pH (Unknown)	-0.0000348	-0.0273*	-0.0131	-0.0206	-0.0232
	(0.00267)	(0.0147)	(0.0137)	(0.0172)	(0.0198)
Constant	8.576***	7.004***	7.557***	7.502***	7.114***
	(0.0324)	(0.390)	(0.265)	(0.352)	(0.394)
FE-groups		49218	2668	877	602
Year/Monthly FE	YES	YES	YES	YES	YES
R-squared	0.555	0.331	0.403	0.428	0.446
Observations	218833	218830	218832	218832	218833

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Standard errors (SEs) in parentheses. SEs have been clustered at the FE levels respectively

As mentioned above, the two variables we are especially interested in are fish Hg and lake pH. In the OLS model, *ceteris paribus,* a lake with unknown or with unsafe fish mercury levels pose significant negative impacts on property values compared to lakes with safe fish mercury level (<=0.3 ppm). As to estimation of effects of acidity, all else equal, a lake with high pH or with unknown pH levels negatively affects property values compared to lakes with pH levels in normal range. In contrast, it is surprising to observe that lakes with low pH levels add premium to property value rather than depreciate it as lakes with high pH level do. These results based on a much wider geographical area differ from previous research focused on the Adirondack region exclusively (Tuttle and Heintzelman 2015). However, this result is explainable. Though lake acidification directly impacts the ecosystem (Driscoll et al., 2003a; Driscoll et al., 2003b) to a certain extent, lake water stressed by acidification becomes clear and may deliver a false implication to property owners about the water quality.

Results generated by the OLS model meet our expectations on impacts of pH level and fish mercury, however, those estimations by the OLS model are not reliable due to omitted variable bias and other challenges as previously mentioned. Those econometric challenges become more severe, especially considering the sizable dataset and wide geographical area this research focuses on. Therefore, results from hedonic models with fixed effects are more useful and meaningful. Except for models with census block fixed effects, other three fixed effect models agree with OLS's results on low pH level: positively impacting the property values. However, lakes with high pH level pose nominal effects on property values. In addition, all four hedonic models with fixed effects on different levels indicate that*, ceteris paribus,* impacts of elevated fish mercury in a lakes on property values are very small, or none. These results could indicate the inability of property owners or buyers to observe fish mercury level prevent them capitalizing on their property value. On the other hand, fish advisory is the vehicle designed for delivering the negative impacts of elevated mercury pollution to the general public. In New York State, the DEC provides comprehensive fish advisory information covering the State. The general public can view and acquire that information for free. Attainable information may therefore influence the decisions made by home owns and potential buyers during the transaction process. As expected, models 2 and 3 both show that being close to a lake assigned a fish advisory significantly depreciates property values
by about three to four percent.

In addition, the *Lakeproxy* variable is included to indicate the amenity effect brought by lakes based on distance. All five models show consistent results that being closer to the lake implies a positive amenity added to property value. This result agrees with previous research (Phaneuf et al., 2008). Not surprisingly, *Lake_tag* variable is significant in the OLS model and three models, which proves our hypothesis that smaller lakes also are of value to homeowners.

Table 4-4. Results of Hedonic Analysis (Transaction within one mile from interested lakes)

	(1)	(2)	(3)	(4)	(5)
	OLS	FE-Block	FE-Block Group	FE-Tract	FE-City Town
Disproxy	0.681***	0.755***	0.826***	0.745***	0.691***
	(0.0120)	(0.0522)	(0.0395)	(0.0470)	(0.0571)
Fish Advisory	0.0565***	-0.00389	-0.146**	-0.252**	-0.219**
	(0.0131)	(0.0766)	(0.0699)	(0.108)	(0.106)
Lake Tag	0.0436***	0.00280	0.0132*	0.0147*	0.0231***
	(0.00652)	(0.00652)	(0.00749)	(0.00771)	(0.00865)
Fish Hg (Unknown)	-0.0165**	0.0316	-0.108**	-0.0778	-0.0664
	(0.00644)	(0.0364)	(0.0464)	(0.0525)	(0.0630)
Fish Hg (>0.3 ppm)	-0.246***	0.00695	0.00323	-0.0340	-0.000726
	(0.0111)	(0.0176)	(0.0321)	(0.0380)	(0.0478)
Lake pH (High)	-0.163***	0.0367	0.0631	0.0204	0.0136
	(0.0570)	(0.0521)	(0.0525)	(0.0579)	(0.0396)
Lake pH (Low)	0.374***	0.434	0.339***	0.0268	0.106
	(0.0780)	(0.286)	(0.0513)	(0.0664)	(0.0828)
Lake pH (Unknown)	-0.0610***	-0.0712	-0.0263	-0.0483	-0.0206
	(0.00726)	(0.0482)	(0.0345)	(0.0500)	(0.0638)
Constant	8.549***	5.078***	5.969***	7.139***	8.541***
	(0.0890)	(1.341)	(1.107)	(1.377)	(1.406)
FE-groups		9006	849	389	362
Year/Monthly FE	YES	YES	YES	YES	YES
R-squared	0.541	0.356	0.422	0.440	0.437
Observations	38151	38151	38151	38151	38151

*   p<0.10, ** p<0.05, *** p<0.01

Standard errors (SEs) in parentheses. SEs have been clustered at the FE levels respectively

We also conducted hedonic analysis based on transaction observations within one mile from interested lakes. Water quality would be more influential to properties located near to lakes. Hedonic analysis with properties close to lakes only further confirms people's value on amenities provided by a lake. Table 4-4 is a summary of primary variables of hedonic analysis on transaction within one mile from lakes. Full regression results can be found in the appendix. The overall observations for this hedonic analysis shrink to 38 thousand. In general, results in table 4-4 are consistent with those reported in Table 4-3. More interestingly, three of four fixed effect models indicate that a lake with a fish advisory depreciated waterfront and near-waterfront properties by about 15-25 percent. Our findings by hedonic analysis are robust based on different scales of observations.

5 Property Values Prediction

5.1 Fish Advisory and Hypothetical Policy Scenarios

In the process of designing policy to mitigate mercury pollution, fish mercury levels of a lake are measurable and meaningful parameters. However, the nominal impacts of raw fish mercury levels a lake has on property values suggested by our hedonic analysis dampens the possibility to predict the changes of property values based on this parameter. Therefore, we performed the property values prediction based on several hypothetical policy scenarios trying to mitigate mercury pollution and to rescind fish advisory.

Since 1993, the EPA began to compile information from states, U.S. territories, Native American tribes, and local governments about fish consumption advisories and safe eating guidelines, making that information available to the public annually. The 2011 National Fish Advisory (NLFA) database integrates fish advisory information on approximately 17.7 million lake acres and 1.36 million river miles, representing 42.3 percent of the nation's total lake acreage and 36 percent of the nation's total river miles[13]. Till today, all states in the United States have their own fish consumption advisories in place to protect the public from the potential health risks of consuming fish caught in local waters (EPA 2013). However, due to the variability among states and tribes in the scope and extent of monitoring and information provided, there is no federal fish advisory in place.

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[13] More detail information about the 2011 NLFA database and background could be found on the EPA website: https://www.epa.gov/choose-fish-and-shellfish-wisely/fish-and-shellfish-advisories-and-safe-eating-guidelines

Figure 5-1. Percentage of total lake acres and river miles under advisory from 1993 to 2011 (U.S. EPA 2013)
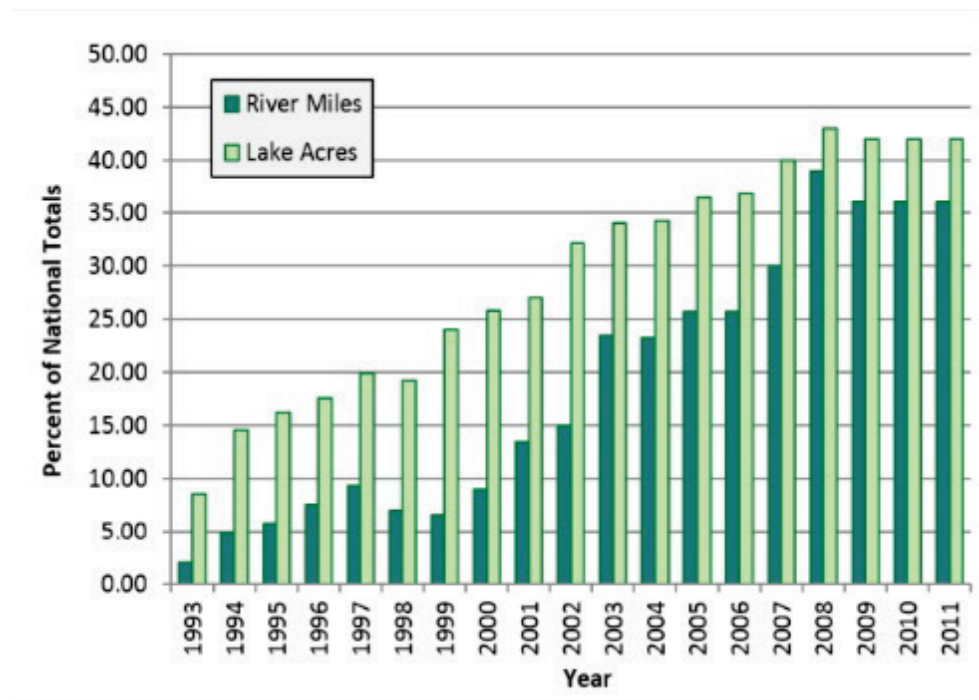

Figure 5-1 illustrates the changes in coverage of fish advisory on lake acres and river miles from 1993 to 2011. However, it is important to note that the increase of pollution levels or frequency of contamination may not necessarily account for the increase of coverage rate of fish advisory. The observed increasing results may occur primarily from increased sampling of previously untested waters. The NLFA database covers 34 different chemical contaminants, five bio-accumulative chemical contaminants: mercury, polychlorinated biphenyls (PCBs), chlordane, dioxins, and dichlorodiphenyltrichloroethane (DDT), which are the most frequent contaminants involved in the latest NLFA. Specifically, 81 percent of all fish advisories in effect were issued, at least in part, because of mercury. There are 50 states, one U.S. territory, and three Native American tribes had mercury advisories in effect. In 2014, the FDA and the EPA released an updated nationwide mercury advice on fish consumption for pregnant woman and children, which will replace the fish advice issued in 2004 once it's finalized.

The fish consumption advisory in New York State is provided by the Department of Health (DOH). Starting in 1977, the DOH releases fish advisory annually. There are at least 10 different printing materials on fish advisory available on DOH website, ranging from general information to specific regional fish advice. Consumers can view data on the DOH website, or acquire information directly from the DOH. Material is also available in the major tourism centers and locations where fishing licenses are

purchased. Specific fish advisories for certain waterbodies and species of nine regions in the New York States are published: St. Lawrence Valley, Adirondacks, Western, Finger lakes, Leatherstocking/central, Catskill, Hudson Valley, NY City, and Long Island. Generally, the DOH issues two types of fish advisory:

- General advice: people can eat up to four, one-half pound meals a month (which should be spaced out to about a meal a week) of fish from New York State fresh waters and some marine waters near the mouth of the Hudson River. This general advice is aiming to reduce the risk of consuming unhealthy levels of chemicals or other contaminants.
- Specific Advice: stricter advice on certain fish species of certain waterbodies due to specific contaminants (e.g., mercury, PCBs, etc.).

Fish advisories in NYS are designed for two groups of population: (1) men over 15 and women over 50, and (2) women under 50 and children under 15. For example, the Adirondack region has both types of fish advisories. People in the first group are supposed to eat up to four meals per month of yellow perch in lakes without specific advisory, while people in the second group are additionally instructed to not eat any yellow perch greater than 10 inches.

There are about 1.9 million regular anglers in NYS with more than 1.9 billion dollars spent on fishing by New York residents in 2011(U.S. Fish and Wildlife Service and U.S. Census Bureau 2011). Whether or not an advisory is assigned to a lake could effectively protect populations most impacted by water pollution including: recreational fishers and their families, some Native American populations, and individuals who fish to nutritional needs (subsistence fishers) (Driscoll, C.T. et al., 2007). Although fish consumption is a recommendation rather than a regulation issued to help protect public health, it could be an important policy indicator to measure the effectiveness of the pollution mitigation program, especially for mercury pollution. The effectiveness of pollution mitigation could be validated when lakes are remitted from a previously assigned fish advisory. Based on this, we hypothesize policy scenarios when certain percentages of lakes with existing individual specific fish advisories are purged from the fish advisory list.

Specifically, the property value prediction was conducted:

- With hedonic analysis results, we first conducted predictions based on overall information from 970,000 properties within our study region to identify the dollar cost of being close to a lake with individual fish advisory list. The property dataset used for prediction include all properties, with or without real sale price, identified on the ArcGIS within the study area.
- Further property value predictions were conducted based on several hypothetical scenarios when 1, 3, 5, 10, 15, 20, 30, 50, and 75 percent of lakes are removed from current fish advisory list.

5.2   Prediction Results and Discussion

Property value predictions were conducted based on the same hedonic analysis model with a census block group fixed effect shown in Table 4-3 (model 3) but with variables of fish mercury levels and pH levels out. Information on 968,789 properties in the study area were used for price prediction in total. Table 5-1 shows the results for the dollar cost of being close to a lake with an individual fish advisory in terms observed transaction and predicted real property values of overall properties within study region. Since we deflated the sale price to 2004 levels in the hedonic model, all results provided here indicate dollar value in 2004.

Table 5-1. Prediction of Property Values Impact

	Observations	Impact of being close to fish advisory lake	Mean Property Value Impact($/2004)	Median Property Value Impact($/2004)	Aggregated price restoration ($/2004) from rescinding all fish advisory
Real Price	218,833	-3%	-3853	-3164	
Predicted Price	968,789		-4231	-3708	~ 4 Billion

Percentages are calculated using Halvorsen and Palmquist's (1980) equation, $g = \exp(c) - 1$, where c is the coefficient derived from the regression and g is the relative percentage effect on the price.

Property value impact calculations use mean value of full dataset of real sale price $128,441. The median property values for the full dataset is $105,459 of 2004 dollar. The mean value of 968,789 predicted sale price is $141,039. The median property values for the predicted sale price is $123,626 of 2004 dollar.

The overall price restoration from rescinding fish advisory was calculated based on mean property value impact of predicted sale price.

This table suggests that, all else equal, a house with an average real sale price of $128,441 could restore up to $3,853 if the nearest lake is removed from the individual fish advisory list. Similarly, according to the predicted mean sale price of 968,789 properties, rescinding a lake's fish advisory could generate

$4,231 premium to a property nearby[14]. Therefore, the overall price restoration from rescinding all existing fish advisories could aggregate about four billion dollars in property values within our study region. It is pointed out that changes in the predicted value of property is an estimate of windfall gain the property owner could recover by selling the property to an individual with a higher expectation for the amenity (Leggett and Bockstael 2000). However, considering the broad region and total number of lakes involved in our analysis, an improvement in the fish mercury concentration would affect a large number of properties and the hedonic price function may shift, causing errors in welfare estimation. The calculated increase of property value ($4,231) according to the predicted mean sale price on the property dataset provides an upper bound to the benefits of widespread, non-marginal effects of rescinding the existing fish advisory of a lake (Bartik 1988; Leggett and Bockstael 2000).

As mentioned above, the hypothetical policy scenario was constructed based on the percentage of lakes with existing fish advisory are removed from fish advisories list. In total, nine hypothetical scenarios when established: 1, 3, 5, 10, 15, 20, 30, 50, and 75 percent of the 556 lakes identified as having individual fish advisory lakes are removed from current fish advisory list. We make no further assumptions on which specific lakes are going to be removed under those scenarios. In order to obtain the uncertainty of our prediction and thus validate the prediction results, we applied a "bootstrapping" technique to randomly pick certain lakes as those to remit from existing fish advisory list. Each prediction was run with randomly picked lakes for 1,000 times and the mean predicted sale price under that scenario was summarized. Figure 5-2 shows the prediction results under all hypothetical scenarios.

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[14]   There is about a $600 difference in the mean property value impact between calculated by real sale price and by predicted sale price. On one hand, due to the temporal range of real transactions we used in fitting hedonic price model, we can only predict the overall sale price based on the assumption that all properties were sold in 2013. This therefore, causes prediction overestimates on the property sale price a little bit. Other specification problems existing in the hedonic model also contribute to this overestimation. But, we consider this prediction as the best efficient estimate of real property values.

Figure 5-2. Predicted average property value (in 2004 dollars) based on different scenarios that certain percentage of lakes are remitted from fish advisory list

Predictions were run 1000 times based on randomly-pick lakes remitted from fish advisory list.
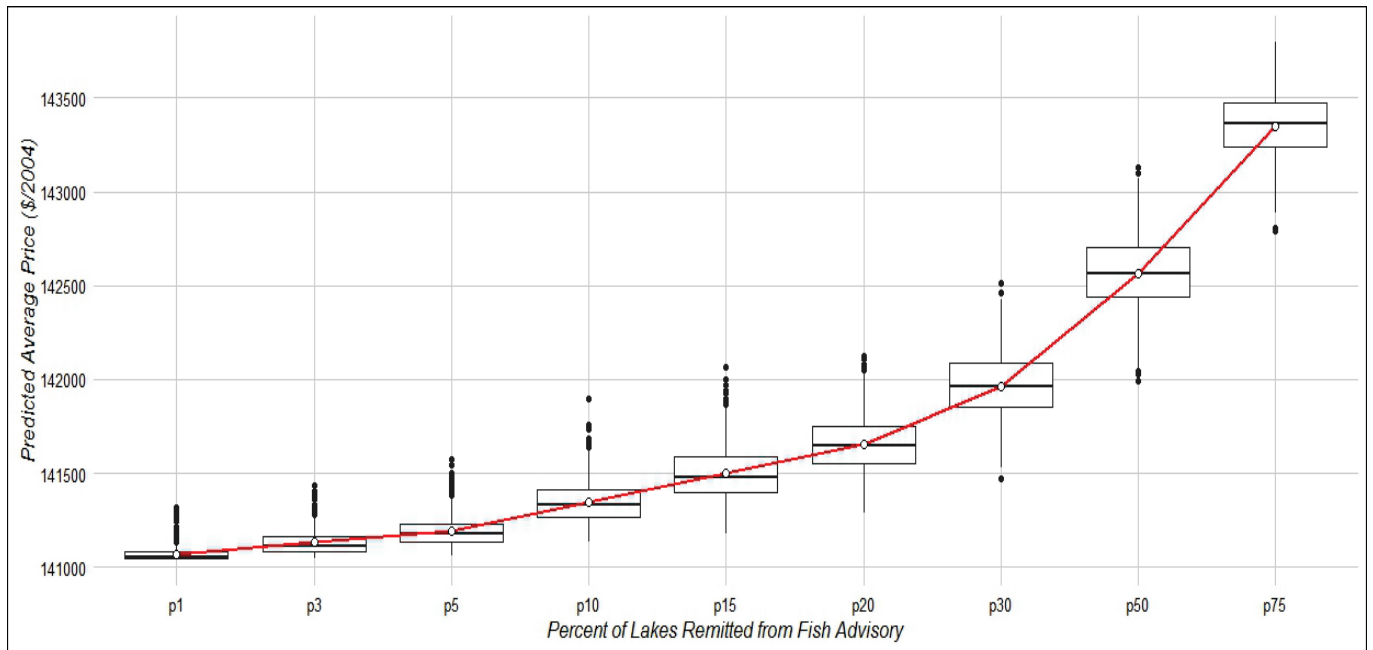
The boxplot describes the 1,000 times of predictions for each scenario. The red line connects the mean predicted property value under each scenario and illustrates the trend of increase of mean property value as the percentage of lakes remitting from the fish advisory list rises. For example, when there is only one percent of lakes removed from the fish advisory list, the mean property value was slightly higher than $141,000, while the mean property value increased by $1,000 dollars if 30 percent of lakes were absent from the existing advisory list. The aggregated property value restoration under these two levels are 30 million[15] and 898 million respectively. This graph also confirms the previously calculated $4,231 stands for the upper bound to the benefits of removing all lakes from the existing advisory list.

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[15]   The aggregated property value restoration under one percent scenario was calculated by subtracting the predicted mean property value at default level ($141,039) from the predicted mean property value under one percent scenario ($131,070), and then multiply the number of total property in study region (968,789).

6 Conclusion

Based on more than 228,000 transaction observations covering 34 counties in the northern part of NYS 2004 to 2013, and water quality data of 173 big lakes (greater than 17ha) from 2004–2013, we conducted a hedonic analysis to investigate how different levels of fish mercury and acidity in lakes will impact the local economy as measured through the property value metric. Incorporating fixed effects on different levels, the hedonic analysis was performed on pooled transaction data and on transaction data within one mile from interested lakes respectively. The results of the hedonic analysis are consistent and indicate that, all else equal, lakes with elevated fish mercury levels or high pH levels pose very little impacts on property values, while lakes with low pH levels add premium to property values.

Surprisingly, we found that, *ceteris paribus*, a lake with an individual fish advisory depreciates the property values nearby by approximately three to four percent of average property values in study region. This negative impact ascents to about 15-25 percent of average value of waterfront and near-waterfront properties within a one-mile radius from the lake.

In general, a house with an average real sale price of $128,441 could restore up to $3,853 if the nearest lake is removed from the individual fish advisory list. Furthermore, based on the predicted mean sale price of 968,789 properties in study region, rescinding fish advisory of a lake could generate $4,231 premium to a property nearby. This provides an upper bound to the benefits of a widespread, non-marginal effect of rescinding the existing fish advisory of a lake. We also performed property value prediction based on several hypothetical policy scenarios when certain lakes were going to be removed from the existing fish advisory list. Figure 5-2 could be used for estimating average price restoration in New York State in terms of rescinding fish advisory of lakes through mitigating local pollutions and toxic emissions.

7   References

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Appendix A

Table A-1. Results of Full Hedonic Analysis

	(1)	(2)	(3)	(4)	(5)
	OLS	FE-Block	FE-Block Group	FE-Tract	FE-City Town
N of kitchens	-0.341***	-0.169***	-0.221***	-0.243***	-0.283***
	(0.00361)	(0.00514)	(0.00564)	(0.00738)	(0.0142)
N of full baths	0.164***	0.0824***	0.112***	0.117***	0.119***
	(0.00235)	(0.00242)	(0.00275)	(0.00341)	(0.00441)
N of bedrooms	-0.0189***	-0.00264*	-0.00871***	-0.00893***	-0.0159***
	(0.00135)	(0.00158)	(0.00180)	(0.00220)	(0.00377)
N of fireplaces	0.139***	0.0603***	0.0806***	0.0894***	0.104***
	(0.00197)	(0.00245)	(0.00264)	(0.00324)	(0.00491)
Bsmnt_Garage_Cap	0.0227***	-0.00662***	-0.00533**	-0.00518	-0.00284
	(0.00260)	(0.00230)	(0.00250)	(0.00319)	(0.00386)
N of half baths	0.107***	0.0554***	0.0679***	0.0698***	0.0723***
	(0.00232)	(0.00222)	(0.00267)	(0.00326)	(0.00509)
Finished basement	-0.00000575	-0.0000310***	-0.0000169***	-0.0000105	-0.0000111
	(0.00000500)	(0.00000512)	(0.00000568)	(0.00000682)	(0.0000113)
Building Age	-0.00323***	-0.00553***	-0.00261***	-0.00277***	-0.00279***
	(0.0000281)	(0.000133)	(0.0000528)	(0.0000690)	(0.0000978)
Building Age^2	-0.000000532***	0.0000190***	-0.000000429***	-0.000000453***	-0.000000459***
	(1.29e-08)	(0.000000738)	(1.36e-08)	(1.56e-08)	(1.92e-08)
Log(living area/ft^2)	0.481***	0.460***	0.497***	0.504***	0.508***
	(0.00444)	(0.00554)	(0.00624)	(0.00746)	(0.0102)
Log(dis_Hosp)	0.0390***	-0.0161	-0.0198*	-0.0147	-0.0228*
	(0.00124)	(0.0162)	(0.0106)	(0.0111)	(0.0131)
Log(dis_POP)	0.0284***	0.0487***	0.0576***	0.0520***	0.0453***
	(0.00122)	(0.00837)	(0.00489)	(0.00539)	(0.00806)
Log(dis_Sch)	0.0284***	0.0188***	0.00499	-0.00147	-0.00578
	(0.00135)	(0.00605)	(0.00413)	(0.00498)	(0.00654)
Log(dis_Univ)	-0.0699***	-0.0217	-0.0476***	-0.0493***	-0.0618***
	(0.00130)	(0.0175)	(0.0151)	(0.0162)	(0.0196)
Log(Dis_Bus)	0.0147***	0.0942***	0.0607***	0.0463**	0.0712***
	(0.00134)	(0.0307)	(0.0184)	(0.0184)	(0.0233)
Log(Dis_Rail)	0.00822***	0.0163	0.0225**	0.0152*	0.0409***
	(0.00108)	(0.0152)	(0.00900)	(0.00913)	(0.0136)
Log(Dis_POI)	-0.0864***	0.0107	-0.0170	0.0117	0.0323
	(0.00105)	(0.0376)	(0.0274)	(0.0369)	(0.0316)

Table A-1 continued

	(1)	(2)	(3)	(4)	(5)
	OLS	FE-Block	FE-Block Group	FE-Tract	FE-City Town
Disproxy	0.582***	0.695***	0.682***	0.625***	0.558***
	(0.00677)	(0.0456)	(0.0318)	(0.0370)	(0.0410)
Lake Area (Km^2)	-0.0000135***	0.00000867	0.00000550	-1.87e-08	0.00000818***
	(0.000000743)	(0.00000573)	(0.00000348)	(0.00000573)	(0.00000309)
Fish Advisory	0.139***	0.0239	-0.0293**	-0.0373*	-0.0227
	(0.00360)	(0.0223)	(0.0148)	(0.0212)	(0.0288)
Central AC	0.0874***	0.0251***	0.0289***	0.0272***	0.0300***
	(0.00312)	(0.00262)	(0.00339)	(0.00447)	(0.00919)
Grade A	0.399***	0.239***	0.333***	0.342***	0.345***
	(0.0158)	(0.0229)	(0.0220)	(0.0277)	(0.0348)
Grade B	0.187***	0.132***	0.170***	0.181***	0.181***
	(0.00404)	(0.00471)	(0.00563)	(0.00752)	(0.00989)
Grade D	-0.259***	-0.207***	-0.242***	-0.245***	-0.250***
	(0.00346)	(0.00524)	(0.00590)	(0.00773)	(0.0111)
Grade E	-0.610***	-0.530***	-0.600***	-0.611***	-0.614***
	(0.0224)	(0.0449)	(0.0400)	(0.0426)	(0.0408)
Estate	0.0462	0.388***	0.322***	0.291**	0.272***
	(0.0753)	(0.115)	(0.112)	(0.121)	(0.103)
Mobile Home	-0.663***	-0.540***	-0.594***	-0.612***	-0.601***
	(0.0193)	(0.0356)	(0.0358)	(0.0369)	(0.0396)
Residential	-0.0392	-0.114***	-0.123***	-0.119***	-0.0784***
	(0.0238)	(0.0293)	(0.0251)	(0.0266)	(0.0301)
Residential Multi-Purpose	-0.113***	0.199***	0.206***	0.205***	0.198***
	(0.00825)	(0.0258)	(0.0254)	(0.0275)	(0.0275)
Rural Residence with acre	0.262***	0.269***	0.307***	0.299***	0.296***
	(0.00634)	(0.0107)	(0.00925)	(0.0112)	(0.0116)
Seasonal Residence	0.103***	0.00674	0.112***	0.145***	0.163***
	(0.00789)	(0.0128)	(0.0190)	(0.0268)	(0.0261)
Lake Tag	0.0514***	0.00419	0.0168**	0.0195**	0.0295***
	(0.00554)	(0.00639)	(0.00772)	(0.00822)	(0.00999)
Within ADK	0.207***	0.0985*	0.0437	0.0676	0.139*
	(0.00493)	(0.0541)	(0.0507)	(0.0477)	(0.0820)

	(1)	(2)	(3)	(4)	(5)
	OLS	FE-Block	FE-Block Group	FE-Tract	FE-City Town
Fish Hg (Unknown)	-0.0225***	0.00683	-0.0181	0.00497	0.00359
	(0.00249)	(0.0131)	(0.0148)	(0.0209)	(0.0243)
Fish Hg (>0.3 ppm)	-0.371***	0.00989	-0.00591	-0.0263	-0.0168
	(0.00472)	(0.0136)	(0.0222)	(0.0260)	(0.0285)
Lake pH (High)	-0.0961***	0.0301	0.0154	0.0103	-0.00456
	(0.0180)	(0.0228)	(0.0242)	(0.0282)	(0.0365)
Lake pH (Low)	0.548***	0.329	0.424***	0.246***	0.209***
	(0.0645)	(0.233)	(0.0522)	(0.0381)	(0.0373)
Lake pH(Unknown)	-0.0000348	-0.0273*	-0.0131	-0.0206	-0.0232
	(0.00267)	(0.0147)	(0.0137)	(0.0172)	(0.0198)
Constant	8.576***	7.004***	7.557***	7.502***	7.114***
	(0.0324)	(0.390)	(0.265)	(0.352)	(0.394)
FE-groups		49218	2668	877	602
Year/Monthly FE	YES	YES	YES	YES	YES
R-squared	0.555	0.331	0.403	0.428	0.446
Observations	218833	218830	218832	218832	218833

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