Mercury Pollution, Information, and Property Values

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Abstract

In the State of New York, atmospheric deposition of mercury ranks among the 10 most prevalent causes of adverse impacts on water quality. This paper examines the impacts of mercury pollution by exploring the relationship between property values and fish consumption advisory (FCA) designation on New York lakes. We find that New York State property values within one mile of an FCA-designated lake decrease by 6% to 7% on average. This negative impact decreases as the distance between properties and lakes increases. Regressions using samples derived with Mahalanobis metric matching find an even larger FCA effect, ranging from 7% to 10%. Our results can serve as a partial indication of the benefits of the Mercury and Air Toxics Standards (MATS), which includes the first mercury emission standard in the United States.

Keywords: Mercury, Fish Consumption Advisory, Mercury and Air Toxics Standards, Water Quality, Hedonic Analysis, Property Value, Mahalanobis Matching

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1. Introduction

Mercury was identified as one of 189 hazardous air pollutants by the 1990 Clean Air Act Amendments (CAAA). However, unlike acid rain, for example—for which regulatory measures were immediately enacted—it has taken much longer to successfully regulate mercury emissions in the United States.[1] It was not until 2016 that the United States had its first mercury emissions standard for power plants as part of the Mercury and Air Toxics Standards (MATS), which is expected to trigger a substantial reduction in nationwide mercury emissions. The U.S. EPA estimates that MATS will prevent as many as 11,000 premature deaths, 4,700 heart attacks, and 130,000 asthma attacks each year (U.S. EPA 2015).

The associated economic benefits of implementing this standard could be significant. Hagen, Vincent, and Welle (1999) survey more than 2,500 Minnesota households and find a willingness-to-pay of $212 million for a proposed 50% reduction in regional Midwestern emissions. In addition, the EPA declares in its 2011 regulatory impact analysis report for MATS that the monetized benefits from reducing mercury emissions are expected to be $4 million to $6 million (2007 dollar) in 2016 (U.S. EPA 2011). Nonetheless, 12 leading mercury researchers in the United States argue that the EPA greatly underestimated the social and environmental benefits of implementing MATS,

[1] Initially, the 1990 CAAA gave the EPA broad discretion in crafting regulations to reduce power plant mercury emissions. Under Section 112 of the CAAA, Congress identified 189 substances, including mercury, as hazardous air pollutants. In 2005, the EPA issued the Clean Air Mercury Rule (CAMR), which placed limits on 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 emissions in the U.S. in two phases. However, the Supreme Court vacated this rule three years after it was issued. In 2011, the EPA announced the Mercury and Air Toxics Standards (MATS) aimed at limiting mercury, acid deposition, and other toxic pollution from power plants. The Supreme Court overturned MATS in 2015, declaring that cost should be considered when the EPA finds it is “appropriate and necessary” to regulate electric utilities. In April 2016, the EPA provided final evidence to promote MATS, including the cost, and continued to maintain that it is appropriate and necessary to set standards for emissions of air toxins from coal- and oil-fired power plants. At almost the same time, the Supreme Court changed its perspective and refused to stay the MATS release. Therefore, MATS became the first standard in the United States for mercury emissions from power plants.

and emphasize the importance of benefits to human health, wildlife, and ecosystems (Sunderland et al. 2016).

Using property values as a metric, this paper investigates the implicit value of mercury pollution reduction in waterbodies, which are an essential part of the ecosystem and highly valued by the public—yet they are the direct recipients of mercury deposition (Keeler et al. 2012). Thus, measuring the economic values of water quality and related ecosystem services will enable us to quantify the benefits of mitigating mercury emissions. This paper builds on a rich literature of property-value-based hedonic studies on water quality and offers insights into homeowners' willingness-to-pay for mercury reduction in nearby lakes.

The effects of mercury pollution are not directly observable in most situations, which poses a challenge to measuring its impacts on property values—unless severe pollution events result in observable effects, such as the outbreak of Minamata disease in Japan in 1970 (Chang 1977). The most common available measure of mercury pollution is mercury concentration in fish tissue (i.e., fish mercury). Although this measure provides direct information about the mercury pollution in a lake and correlates with potential health consequences of exposure to mercury pollution, it is rarely released to, or understood by, the public. Thus, using a scientific measure of mercury pollution, such as fish mercury, in a hedonic model raises concerns, since the perfect information assumption is likely not satisfied (Leggett 2002; Parmeter and Pope 2009). Previous studies suggest that failure to prove that both buyers and sellers are fully informed about the property may result in the erroneous conclusion that housing prices reflect buyers' and sellers' real preferences

(Pope 2008b, 2008a). Indeed, housing attributes that are imperceivable to economic agents are unlikely to be capitalized into property values (Brashares 1985). [2]

We set out to mitigate this problem by incorporating the designation of fish consumption advisories (FCAs) as an observable measure of mercury pollution in our hedonic model. Issuing an FCA is an official attempt to mitigate the health impacts of eating contaminated fish. In our study area, New York State, FCAs are issued and managed by the State Department of Health (NYSDOH). At least 10 types of information on FCAs are available for download on the NYSDOH website, ranging from general advice to advice on specific regional fish species. Consumers can also request this free information directly from the NYSDOH. Materials on FCAs are also available in visitor centers around the state and when purchasing a fishing license. In addition, the NYSDOH partners with a wide range of entities (e.g., state parks, boat clubs, nonprofit groups, etc.) and conducts statewide outreach and extension activities to promote information about FCAs. Thus, FCAs are a direct source of information about mercury pollution that is widely available to the general public. Although FCAs are an official recommendation to consumers, rather than a regulation imposed on firms, the values we are able to measure related to this information could serve as an important indicator of the benefits of mercury mitigation programs such as MATS.

In this study, we perform a hedonic analysis of the FCA status of 131 individual lakes in New York State using approximately 83,000 property transactions that occurred between 2004 and 2013.[3] Our 10-year repeated cross-section transaction data provide us with sufficient between- and

[2] Using scientific monitoring data on average fish mercury levels for 131 lakes in New York State, we find no significant relationship between housing prices and actual fish mercury levels. Regression results are available upon request.

[3] Our main hedonic results focus on about 21,000 transactions within 1 mile of included lakes. We use transactions farther from lakes (up to 5 miles) to gauge how the effects of FCAs vary by proximity.

within-variation to estimate the change in average property values near lakes before and after FCA designation. We first use the pooled data to estimate the impacts of FCA designation on properties within one mile of the included lakes. The variable for FCA designation has a difference-in-differences (DiD) interpretation, by which the FCA designation effect is identified by variations in property values near a lake before and after the designation compared with property values near lakes without an FCA designation. In addition to controlling for as many observable variables as possible, we introduce spatial fixed-effect terms at various levels (i.e., census block group and lake level) to control for any unobservable, temporally invariant characteristics. We find that a lake's FCA designation depreciates nearby property values by 6% to 7%.

Of the 131 included lakes, 52 had been designated with an FCA by 2005 and an additional 76 by 2007—that is, almost all included lakes had been issued an FCA by 2007.[4] Our FCA dataset offers a unique setup in which the effect of FCA designation can be estimated twice. We separately estimate the treatment effect of an FCA on property values near two groups of lakes that were issued FCAs in two different periods, using the other group of lakes as a comparison. This practice has important implications on identifying the effect of FCA designation and helps to detect potential endogeneity problems. For example, FCA designation may only affect properties around small lakes or only around large lakes. By estimating the effect of an FCA designation twice in two individual regressions, which differently deploy two groups of lakes as treatment and control groups, we can determine whether the effect is consistent. We find very similar results from the two separate estimations, which lends credibility to our main finding.

[4] Only three lakes are free from designation by a specific FCA during our study timeframe. The NYSDOH removes an FCA only when monitoring data show that the lake's fish mercury level is consistently low in at least two consecutive years. In our sample period, none of the lakes with an FCA had that advisory removed.

We test the robustness of our analysis by evaluating the balance and overlap of covariates used in the hedonic model across treated and control lakes. The results of the covariate balance check indicate that most covariates entered in our hedonic model are relatively well balanced, with only a few varying differently in the two groups. We apply a matching technique to further balance covariates and improve the estimation of our hedonic model. Specifically, in the two separate regressions based on FCA designation in 2005 and 2007, we use the Mahalanobis metric to match transactions associated with treatment and control lakes based on lake and property characteristics. The matching process helps to discard observations that have no proper counterfactuals in either the treatment or control group. We run regressions based on matched samples and find an even larger treatment effect of FCA designation, ranging from 7% to 10%.

This paper contributes to the literature by providing empirical evidence on the effects of FCA designation on property values. To the best of our knowledge, our paper is the first to explore the effect of mercury pollution using property-based hedonic models in this manner. Like other water quality issues, mercury pollution directly reduces people's welfare through reduced recreational benefits. Furthermore, it poses negative health impacts to those who consume tainted fish. Analyzing the effect of FCA designation on property values provides a unique avenue to examine the benefits of mercury emission standard such as MATS or similar policies.

The remainder of the paper is organized as follows. Section 2 provides more background on mercury pollution and FCAs in New York State and describes the study area and data used in the empirical analysis. Section 3 outlines the main identification strategy. Section 4 illustrates and discusses the regression results, and Section 5 concludes.

2. Background

2.1 Mercury Pollution and FCAs

Eating fish is the primary route by which humans are exposed to mercury pollution. A recent study conducted by the EPA detected mercury in every fish sampled from 500 lakes and reservoirs across the United States (U.S. EPA 2009). Furthermore, mercury concentrations in fish fillet samples from 49% of the sampled population of 76,559 lakes nationwide exceeded the EPA's recommended tissue-based water quality criterion of 0.3 ppm. Since the developing brain's vulnerability to mercury is high, infants and children were found to be the most affected population (Sakamoto et al., 2004; Trasande et al., 2005).

According to the New York State Department of Environmental Conservation (NYSDEC), atmospheric deposition of mercury ranks among the 10 most prevalent causes of water quality impairment in New York State. An estimated 64% of all impaired lake acres in the state are heavily degraded by mercury deposition, which primarily originates in coal-fired power plants that operate locally or elsewhere upwind of the state (NYSDEC 2015). Fishing in these lakes is important recreationally; there are about 1.9 million regular anglers in New York State, and more than 1.9 billion dollars was spent on fishing by New York residents in 2011 (U.S. Fish and Wildlife Service and U.S. Census Bureau 2011).

The NYSDOH has released FCA information every year since 1977. Generally, the NYSDOH issues two types of FCAs: general advice and specific advice. The former covers all freshwater in the state and aims to reduce the risk of consuming unhealthy levels of chemicals, and the latter targets specific fish species in certain waterbodies due to specific contaminants (e.g., mercury, PCBs, etc.). In general, FCAs focus on protecting women under 50 years and children under 15 years from exposure to mercury pollution. [5]

[5] The NYSDOH uses perch as the indicator species in the design of FCAs, since it is one of the most prevalent sport fish in New York State. FCAs in the state are designed for two population groups: (*a*) men over 15 and women over 50; and, (*b*) women under 50 and children under 15. People in the first group can eat yellow perch from any lake

This study focuses on 131 lakes located across 34 counties of New York State.[6] The study area is shown in Figure 1. We chose these lakes and related areas for two reasons. First, the included lakes are among those that are most heavily impacted by mercury deposition and acid rain. Second, many included lakes—especially those in the Adirondack Park and the Finger Lakes Region—are important destinations for fishing and recreation, and are thus most likely to experience capitalized impacts on property values from water quality.

2.2 Data

FCA data

Our FCA data are collected from the National Listing of Fish Advisories (NLFA). The U.S. EPA compiles FCA information from all 50 states, the District of Columbia, the U.S. territories of American Samoa and Guam, and five Native American tribes every year. The EPA has made the NLFA available to the public since 1993. We are able to identify the location of each lake with an FCA within our study area and the start year of FCA designation based on the Fish Consumption Advisories and Fish Tissue Sampling Stations NHDPlus Indexed Datasets.[7] Of the 131 included lakes, 52 lakes had been designated with an FCA by 2005 and an additional 76 lakes had been issued an FCA by 2007.

Within our study area, mercury is the primary chemical of concern for FCA designation. Other chemicals of concern include PCBs, chlordane, and dioxin; unfortunately, our FCA dataset does

without a specific advisory up to four meals per month, while people in the second group are advised to not eat any yellow perch more than 10 inches long.

[6] The 34 counties are 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, and Yates.

[7] The detailed dataset and shapefile are available for downloading using the EPA "Clip N Ship Application": https://edg.epa.gov/clipship/. Specific information on fish advisories can be found on the EPA's NLFA Technical Advisories Search website: https://fishadvisoryonline.epa.gov/Advisories.aspx

not allow us to distinguish the specific type of FCA. In the hedonic model, we incorporate FCA information regardless of pollutants and fish species. Therefore, we assume that FCAs have a similar impact on property values regardless of unobservable details. The treatment effects estimated by our model should thus be considered to be the general impact of FCA designation.

The FCA data only allow us to identify the year an FCA is issued. For the FCA dummy variable, we use a conservative approach to mark all transactions that occurred in and after the FCA designation year as one and zero otherwise. In this way, we assume that all FCAs were issued on the first day of a year. This approach could potentially underestimate the FCA effect, since we may include transactions that are not affected by the FCA in the treatment group. We run robustness checks by dropping transactions that occurred in the same year of an FCA designation, and our results are largely unaffected (see appendix for detailed results).

Transaction data

Earlier hedonic studies on water quality agree that degraded water quality depreciates waterfront property values. However, early hedonic studies reached their conclusions by including waterfront transactions exclusively, assuming that only waterfront properties would be affected by water quality. Poor, Pessagno, and Paul (2007) were the first to challenge this assumption and argue that water quality also has effects on sales of non-waterfront property. Phaneuf et al. (2008) build on that result and develop a novel model that integrates information on both recreation and residential location decisions. They show that proximity to water resources, access to recreation sites, and the water quality at these sites are all positively correlated with property values.

Walsh, Milon, and Scrogin (2011) take this a step further and investigate the wide-reaching property-value effects of improved surface water quality. The authors explicitly show that, first, the positive price effects of waterbodies extend hundreds of meters into the surrounding community, and second, that lake size also affects property values, with water quality of larger lakes valued more than that of smaller ones. Including non-waterfront properties in a hedonic model is especially important in terms of further cost-benefit analysis, which may represent a considerable share of the total benefits of water quality improvement. In this study, we primarily focus on actual residential property transactions within 1 mile of included lakes from 2004 to 2013.[8] We link every parcel to its nearest included lake. We assume that this specific lake is the major recreation destination for the household, and therefore the water quality of this lake would influence consumer decisions related to both recreation and home purchases.

We collect housing transaction data from the New York State Office of Real Property Taxation Services (NYSORPTS), which also provides detailed parcel and property characteristics for all transactions. In the data-cleaning stage, transactions that have incomplete and/or abnormal records, fewer than one bedroom, or fewer than one story are dropped. Outlier observations, such as those with a sales price lower than $10,000 or living areas less than 100 square feet, are discarded as well. We also remove transaction data with unidentified/incomplete address information. In addition, our database of property transactions includes detailed parcel-level information, such as building characteristics and property type. Non-arms-length transactions and observations with incomplete data for structural characteristics are dropped from the final dataset. We also use ESRI ArcGIS to obtain the locational characteristics of each property. Euclidean distances between each parcel and the nearest facilities—such as public schools, hospitals, and population centers—and to the nearest lake are calculated in ArcGIS and compiled in the final dataset.

After cleaning, the transaction dataset contains approximately 83,000 real property sales in total (within 5 miles of an included lake) to be used for hedonic analysis. Our main hedonic analysis

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[8] We also explore how the impact of FCA designation changes by distance, and show results for property values within 5 miles of included lakes.

focuses on about 20,000 transactions within 1 mile of 111 included lakes. [9] All prices are 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).[10] Specific HPIs for major MSAs, if available, are used; otherwise, the HPI for nonmetropolitan New York State is used. The log form of the deflated sale price is used as the dependent variable in the hedonic model. Table 1 presents summary statistics for all transacted properties within 1 mile of 111 included lakes.

3. Identification Strategy

The most important question when identifying the impact of an FCA designation on nearby property values is whether the designation mechanism is exogenous in the hedonic model. Ideally, one would randomly issue FCAs to lakes and observe changes in adjacent property values before and after the designation. This random process would avoid unobservable factors that drive property values being correlated with FCA designation. However, FCA designations are determined by actual water quality, which may be correlated with other unobserved factors. If the health department were to assign FCAs to individual lakes perfectly in line with the actual fish mercury level of each lake without consideration of any other factors, the FCA designation would be considered exogenous in the hedonic model, because home prices would not in any way affect designation.

[9] We run regressions on transactions within different distance zones (up to 5 miles) of 131 lakes and show results in Figure 2. Our main regression analyses are only based on 111 lakes, since the other 20 lakes have no transactions within 1 mile.
[10] Those 7 MSA are: Albany-Schenectady-Troy, NY; Ithaca, NY; Syracuse, NY; Watertown-Fort Drum, NY; Glens Falls, NY; Rochester, NY; Utica-Rome, NY.

In practice, an FCA designation is a data-driven process and limited to lakes with available fish mercury data.[11] The NYSDOH assigns a species-specific FCA to a lake when available data provided by the NYSDEC show that certain fish species in that lake contain elevated levels of mercury. The NYSDEC sets priorities by monitoring lakes that are popular fishing destinations, face intense fishing pressure, and are historically stressed by mercury or other nonpoint source contamination, as well as those that are considered important aquatic habitats or are vulnerable to pollution in ecological health assessments. Occasionally, the NYSDEC monitors and provides fish mercury data from specific lakes upon public request. Therefore, FCA designation is potentially correlated with lake characteristics other than the mercury pollution level alone, and some of these may influence nearby property values. This would potentially cause an endogeneity problem in our hedonic model. Lakes with FCAs may be popular fishing destinations, and the property values near the lakes could be systematically different from those near lakes without an FCA due to data inadequacy. Failure to control for lake characteristics correlated with FCA designation that affect property values would result in omitted variable bias in our hedonic model.

We begin our estimation with a simple semi-log hedonic price function that relates property values to FCA designation of the nearest lake:

$$\mathbf{ln}(\boldsymbol{Price_{it}}) = \boldsymbol{\alpha} + \boldsymbol{\beta FCA_{it}} + \boldsymbol{\delta X_{it}} + \boldsymbol{\varepsilon_{it}} \quad (1)$$

where $Price_{it}$ is the sale price of property i at time t. FCA_{it} stands for the FCA designation status of the lake linked to property i at time t; this variable enters the hedonic model as a dummy variable equal to one if the linked lake has an FCA at time t when property i was transacted, and zero otherwise. X_{it} stands for a vector of variables that represent housing characteristics. β is the

[11] Detailed information about the FCA designation process was collected through personal communication with staff at the NYSDOH. The NYSDEC is responsible for mercury level monitoring and data management. The NYSDEC began monitoring the mercury concentration in fish tissue in the late 1960s. Many monitoring programs that track trends in fish mercury levels in New York State have since been launched.

FCA effect we seek to estimate and ε_{it} is the error term. Successful estimation of the FCA effect relies on two sources of variation: (*a*) variation in property values over time due to the change in FCA status during our study timeframe (within-variation) and (*b*) variation in property values at a given time, across space from the differences in FCA status between lakes (between-variation).

Our first approach to address the endogeneity problem of FCA designation is to control for potential confounders in our hedonic model directly. Several variables relating to lake amenities are included in the hedonic model. The first is surface area; many previous hedonic studies have shown that the size of a lake is positively correlated with property values (Walsh, Milon, and Scrogin 2011; Leggett and Bockstael 2000). We also include two dummy variables that indicate the presence of a boat launch and the accessibility of fishing based on data provided by the NYSDEC. We have no expectations on the signs of those two variables, since they are based entirely on property owners' preferences. Some property owners may purchase property close to a lake for water-related activities, while other buyers may only enjoy the natural water amenity separate from human activities. Another potential confounder is the overall water quality of study lakes. The NYSDEC delineates eight classes: N; AA-special (AA-S); A-special (A-S); AA; A; B; C; and D (Strategy 2000). Class N waters are the most pristine and support the greatest number of uses, with each subsequent class supporting fewer uses. Restrictions and discharge into waterbodies become less strict as the water class descends. All waterbodies ranked as class A or above (i.e., AA-S, A-S, AA) can be used as drinking water sources. We introduce a dummy variable of AA/A water into the hedonic model as a general metric of the overall superior water quality of a given lake.

In our study, transacted properties are linked to the included lakes using Euclidean distances. Small ponds could be located even closer to transacted properties, for which we cannot observe water quality based on current data. One concern is that households presumably care about the water quality of smaller and closer waterbodies in addition to the water quality of those we are able to measure. We partially control for this case by creating a dummy variable to indicate the existence of at least one small pond between the parcel and the nearest study lake. The Adirondack Park is a “hot spot” for mercury pollution; however, it is also an important destination for outdoor activities due to its pristine natural landscape. Average property values within this region are higher than those outside the park boundary (Tuttle and Heintzelman 2013, 2015). Arguably, the housing market in this region could be regarded as unique within our study area. To control for any bias due to differences in housing markets, we introduce a dummy variable to distinguish all property transactions that occurred within the Adirondack Park. Lastly, we also include a dummy variable to identify properties within 50 meters of a lake and the logarithmic form of distance from each transacted property to the nearest lake.

Our second approach to address the endogeneity problem and dampen omitted variable bias introduces fixed-effect terms in our hedonic model (Kuminoff, Parmeter, and Pope 2010). The application of spatial fixed-effect analysis is similar to employing a spatial lag model that accounts for any potential spatial interactions within a neighborhood based on a spatial weight matrix (Kim, Phipps, and Anselin 2003). Like the scale of a spatial weight matrix, the geographical resolution of the “neighborhood” considered in the fixed-effect analysis matters. Census block, census block group, and census tract are common scales of spatial fixed effects. In general, the smaller the fixed-effect resolution, the better it controls for omitted variables. However, a fine fixed-effect scale may suppress the variance in independent variables when the sample size is small, therefore reducing statistical power. In our case, we employ two levels of spatial fixed effects: lake and census-block-group. The lake fixed effect defines each included lake as a natural neighborhood and controls for any time-invariant lake amenities that affect property values linked to that lake (Horsch and Lewis 2009). However, considering the actual area within a 1-mile radius of a lake, the lake fixed effect is still too coarse to control for local omitted variables. The census-block-group level is a finer scale fixed effect and allows better control of unobservable variables. A caveat of using census-block-group fixed effects in our setting is that it may incorrectly control for within-variations when multiple lakes are located within a single block group. Our preferred specification addresses both problems at the same time by introducing the census-block-group-level fixed effect and incorporating dummies for each lake in the hedonic model. In this way, when *N* lakes are clustered within a single block group, the census-block-group fixed effect, along with the (*N*-1) lake dummies, can uniquely identify each individual lake. We also include temporal fixed-effect terms (i.e., sale year and month dummies) to control for temporal housing market trends in the dataset. We allow clustering of error terms within a fixed-effect group and assume independence across different groups, which corrects biased standard errors of model estimation due to heteroskedasticity (Bertrand, Duflo, and Mullainathan 2004).

One concern about the hedonic price model is that properties associated with our 131 lakes may belong to different housing markets and experience different local temporal trends during our study timeframe. A downward or upward temporal trend of property values around a lake may mask any effects of FCA designation. We introduce lake-specific time trends (year and month) to allow for such diverse temporal trends. The updated hedonic model is specified as follows:

$$\mathbf{ln}\left(\boldsymbol{Price_{ijt}}\right) = \boldsymbol{\alpha} + \boldsymbol{\varphi_j} + \boldsymbol{\theta_t} + \boldsymbol{\phi_k} + \boldsymbol{\beta FCA_{ijt}} + \boldsymbol{\delta X_{ijt}} + \boldsymbol{\eta M_{ijt}} + (\boldsymbol{\phi_k} \times \boldsymbol{t}) + \boldsymbol{\varepsilon_{ijt}} \quad (2)$$

where φ_j stands for the spatial fixed effect; θ_t denotes the temporal fixed effect; ϕ_k stands for a series of dummies that identify each individual lake; M_{ijt} is a vector of variables for lake-related characteristics discussed earlier; and, $(\phi_k \times t)$ is the term for linear lake-specific temporal trends. Other annotations are defined as in equation (1).

4. Results & Discussion

4.1 Main results

Table 2 shows the main results of our basic hedonic model. The transaction sample size is restricted to properties within 1 mile of 111 included lakes. Columns 1 through 6 contain regression results of our hedonic model with different specifications. Model specifications include increasingly fine controls for spatial and temporal unobservables from the left to right columns. Model (1) (Table 2, Column 1) is the basic OLS model without any controls for lake characteristics. The model indicates that FCA designation significantly depreciates property values nearby by as much as 30%. However, the model is vulnerable to omitted variables bias due to its failure to control for possible confounders and the exclusion of fixed-effects terms. As a comparison, the model in Column 2 contains all lake-related characteristics discussed previously, and the model in Column 3 also includes census-block-group fixed effects. Fixed effects effectively control for unobservables and reduce the effect of an FCA designation to 7%. We add the lake-specific temporal trend term in the model shown in Column 4 of Table 2. The estimate of the FCA effect is consistent at 7%, which suggests the robustness of our model specification. In model (5), we change the scale of the fixed effects to lake level. The number of spatial fixed-effects groups decreases from 410 to 111 (i.e., 111 included lakes), and the estimate of the FCA effect decreases to 6%. Estimates of the FCA effect by models (4) and (5) are not significantly different. Lastly, Column 6 shows our preferred specification, which incorporates census-block-group fixed effects and dummies for individual lakes. Of the 111 included lakes, 49 lakes reside with one or more other lakes within a single block group. The inclusion of lake dummies can be considered as applying lake fixed effects when the census-block-group is unable to identify within-variation in property values near included lakes correctly. Estimation of the FCA effect in this model remains consistent with prior models.

Table 2 also shows estimation results for other important variables in our hedonic model. For example, property values decrease as the distance between a property and the nearest included lake increases, and waterfront properties are valued about 30% higher than non-waterfront properties. Our results also indicate that having a smaller pond right next to a property has a positive effect on property values (estimation of variable *Lake_tag*).

Figure 2 shows the effect of FCA designation on property values based on 82,175 transactions within 5 miles of the original 131 included lakes. Based on our preferred model specification (Model 6 in Table 2), we run separate regressions using properties residing in fixed distance zones from the nearest lake: 0–1 mile; 1–2 miles; 2–3 miles; 3–4 miles; and 4–5 miles. We find that the negative impact of FCA designation persists on property values up to 3 miles from the lakes. However, this negative effect is statistically insignificant on properties at a distance of more than 1 mile.

There is a substantial literature on the appropriateness of integrating objective and subjective measures of water quality into hedonic models (Poor et al. 2001). As noted previously, property values do not respond to actual fish mercury levels, since households normally cannot directly observe this information. However, we are interested in knowing whether issuing an FCA can raise households' awareness of mercury pollution and motivate them to search for and collect information about the actual concentration and load of mercury in a lake that could pose risks to them. To accomplish this, we include a variable that incorporates fish mercury data in our hedonic model and interact this variable with the FCA designation variable.[12] Regression results are presented in Table 3. The estimate of the interaction term (FCA* Fish Mercury) is negative, but not statistically significant. This result provides evidence to suggest that FCAs are the primary path by which people obtain information about mercury pollution. This underscores the importance of FCAs as an official signal on environmental pollution in informing real estate markets.

4.2 Treatment effect of FCAs in the years 2005 and 2007

We next separately estimate the effect of FCA designation using two groups of data: lakes that were issued an FCA in 2005 and in 2007. In the first model, we include 102 lakes and the associated 8,211 transactions within 1 mile between 2004 and 2006. Of the 102 included lakes, 50 were issued an FCA in 2005 (treated lakes), while the other 52 (control lakes) were not issued an FCA until 2007. In the second model, 110 lakes and the associated 17,288 transactions within 1 mile between 2005 and 2013 are included, and of these, 56 (treated lakes) were issued an FCA in 2007, while nearly all of the others had previously been designated with an FCA. In this way, in the two models, treated lakes and control lakes are switched. Regression results are presented in Table 4. The model specification for models (1)–(3) is identical to that for models (4)–(6) in Table 2. Panel A includes FCAs from 2005, and panel B includes FCAs from 2007. Estimates of the FCA effect on property values in both panels are consistent with our main results, ranging from 6% to 7%.

The consistency of the estimated FCA effect has important implications for identifying the impact of FCA designations on property values. By estimating the FCA effects on property values near

[12] The fish mercury concentration data used in this analysis were part of the integrated fish mercury database maintained by the Division of Fish, Wildlife and Marine Resources of the NYSDEC. The database contains almost all analyses done by or for the Division of Fish, Wildlife and Marine Resources' contaminant monitoring program between about 1970 and 2015. In addition, we include fish mercury monitoring data from 2008 to 2012 collected by the Adirondack Lakes Survey Cooperation (ALSC). The ALSC monitoring project collected approximately 600 fish samples, covering 36 lakes within the Adirondack region. The fish mercury concentration data on individual fish sample from each lake is standardized using a mixed effects model. See Heintzelman, Holsen, and Tang (2016) for more details on preparation of fish mercury concentration data.

two groups of lakes at different times, we actually estimate the FCA effect two times and also mitigate the potential endogeneity problem. Suppose that we are able to estimate the FCA effect only once using the specification in panel A. Then, although the DiD approach can help to mitigate temporally variant unobservables and temporal trends faced by both treated and untreated lakes, it cannot detect whether FCA designation is correlated with unobservables associated with the 50 treated lakes. In that case, the claim that FCA designation has a negative impact on property values would not be valid. Therefore, the consistent result found in panels A and B further confirms the robustness of our estimation of an FCA effect on property values.

4.3 Robustness check: Matching and post-regression

Using regression methods to estimate average treatment effects and predict causal relationships can be sensitive to functional form and minor changes in model specification if the distribution of covariates in the treatment and control groups is substantially different (Imbens 2004, 2015). Even if the treatment effect is exogenous (a random process) in the model, the causal inference would be less credible when covariates are not balanced (Imbens and Rubin 2015). Balance in covariates that enter the hedonic model is thus a prerequisite for causal inference that is robust and convincing. In our case, as discussed in previous sections, it is possible that lakes receiving "treatment" are systematically different from those without FCAs. If this is the case, the covariate space of those two groups of lakes (and associated property transactions) may not be well balanced, and inference will need to rely on extrapolation and become less credible. From the perspective of causal inference, therefore, it is necessary to find lakes without an FCA that are sufficiently similar to those with an FCA to serve as counterfactuals (Rubin 2005). By requiring that lakes with or without an FCA be sufficiently similar, we also imply that properties close to those lakes with different treatment status are also similar.

We deploy several statistical methods to evaluate the balance and overlap assumptions of our data.[13] In particular, we first use normalized differences to assess the difference between the locations of the covariate distribution. The objective of this measure is to evaluate the differences between two distributions and assess whether simple adjustment methods, such as regression adjustment, can remove most biases (Austin 2009). We also use the logarithmic form of the ratio of standard deviations to assess the dispersion in the two distributions. As to the overlapping assumption of two distributions, we check the probability mass of the covariate distribution for the treated (control) samples that are in the tails of the distribution of the covariate values for the control (treated) samples, noted as $\pi^{0.05}$. As to a fixed limit (e.g., 0.05), the probability mass of covariate distribution for treated lakes that falls in the region outside the 0.975 quantiles of covariate distribution for the control lakes is considered to lack sufficient overlapping counterfactuals (Imbens and Rubin 2015). The higher the measure, then, the higher the number of treated (control) samples that would not find a proper counterfactual. Tables 5 and 7 show the summary of covariate balance checks for 2005 FCA samples and 2007 FCA samples, respectively. The covariate balance check includes all important housing and lake characteristics in our hedonic models. Comparison of covariate distributions is limited to properties within 1 mile of a lake. In general, results of the covariate balance check indicate that treatment groups and control groups in both FCA events are relatively balanced. As to housing characteristics, all properties near the treatment and control lakes are actually very similar. For the 2005 FCA event, lakes in the treatment group are larger than those in the control group on average, and the water quality of lakes in the treatment group is lower than that of lakes in the control group on average, as we would hope. On the other hand, for the 2007 FCA event, lakes in the treatment group are smaller

[13] See appendix for mathematical expressions of those methods.

and have poorer water quality than those in the control group, since most of the control lakes were previously treated (in 2005) (Table 7). Since the normalized differences of those two covariates are not substantial, linear regression is sufficient.

Nonetheless, as a robustness check, we use the Mahalanobis metric matching method (Rubin 1978a; Gu and Rosenbaum 1993) to further balance the covariates and alleviate bias in covariates between the treatment group and the control group. We then rerun our hedonic model using matched samples. Regression based on matched samples is a highly effective method for controlling bias in covariate distributions and enhancing the credibility of causal inference (Rubin 1978b). The matching process can be considered a preprocessing procedure that corrects biases that are present in covariate distributions of treatment and control groups. We perform the matching process separately for the two FCA treatment events. Matching proceeds based on the five nearest matched units (i = 5), which means that for each treated transacted property, we find the five "nearest neighbor" properties that are most similar in the covariate space of the control group. Matched transactions near control lakes serve as counterfactuals for transactions near treated lakes, as if they would not have been treated. [14]

We re-assess the covariate balance between treated lakes and control lakes using matched samples and find that the matching process substantially improves the balance in covariate distributions (see Tables 6 and 8 for covariate balance results).[15] Taking the 2007 FCA treatment event as an example, the normalized differences of the lake area is reduced from 0.47 to 0.22 after matching. The proportion of treated lakes that have AA water quality comes closer to that of control lakes

[14] Note that we match transactions based on lakes with different treatment status regardless of whether the difference in transacted properties occurred before or after the FCA treatment. Although our dataset is not a true panel, we find that covariate distributions of transacted properties near the same lake before and after the FCA treatment are well balanced. See the appendix for results of the covariate balance check of only properties around 2007 FCA treated lakes that occurred before and after the treatment.

[15] Since we have fewer control samples than treatment samples for the 2005 FCA treatment event, the matching process only makes a slight improvement on covariate balance for this event.

(normalized differences = 0.03) based on matched samples. Post-matching regression is then performed for the two FCA events separately using the matched samples. Results are presented in Table 9. The matching process trims our original sample by automatically discarding observations that have no counterfactuals. We find an even larger FCA treatment effect on property values using the matched sample, ranging from 7% to 10% based on our preferred specification.[16]

5. Conclusion

This paper investigates the effect on property values of issuing a fish consumption advisory (FCA) for lakes in the State of New York. We find that property values within 1 mile of 111 included lakes decrease 6% to 7% on average due to an FCA designation. This negative impact decreases as the distance between properties and lakes increases. After 1 mile, the impact is statistically insignificant, but remains negative up to 3 miles. We take advantage of our dataset to estimate the effect of FCA designation on property values two times, based on two different designation events, and find the result to be consistent across these events. We also use matching techniques in a robustness check to alleviate bias in covariate distributions of treatment and control groups and advance the credibility of our causal inference. In this specification, we find an even larger FCA effect, ranging from 7% to 10%. Our results can serve as a partial indication of the benefits of the Mercury and Air Toxics Standards (MATS), which includes the first mercury emission standard in the United States.

This paper also provides a case study in the hedonic literature on valuing water quality when consumers rarely have perfect information. Households are unlikely to respond to scientific

[16] Results presented in Table 9 are estimated using matched samples without weighting based on the frequency of matching. Abadie and Spiess (2016) point out that standard errors may be incorrect using matching with replacement. The degree of bias in the standard errors of results using weighting is unclear in our case. However, we present these results based on matched samples without frequency weighting in the appendix, and the results are consistent.

measures of water quality due to unawareness, but are sensitive to official signals and information. As for mercury pollution, an FCA designation acts as an important tool by which consumers retrieve mercury pollution information, and can then have a significant influence on consumers' decision-making. Due to the large impact of an FCA designation on nearby property values, regulatory agencies should carefully evaluate the costs and benefits associated with FCA designation.

The estimated negative impact on prices we identify in our analysis is consistent with anecdotal evidence. Local regulatory departments have sometimes experienced resistance to warning signs near lakes plagued by mercury pollution; local homeowners, it has been suggested, remove such warnings to prevent uninformed agents from learning about local conditions. Leggett and Bockstael (2000) point out that changes in the predicted value of a property amount to a windfall gain that the property owner could recover if she sells the property to an individual with a higher expectation for the amenity.

Considering the broad region and total number of lakes involved in our analysis, as well as the widespread nature of mercury impairment, an improvement in mercury deposition—and thus a change in fish advisory status—would likely affect a large number of properties in these markets; the hedonic price function is likely to shift (Kuminoff and Pope 2014), causing errors in welfare estimation. Therefore, our model provides only an upper bound to the benefits of a widespread, nonmarginal improvement in water quality (Bartik, 1988; Leggett and Bockstael, 2000).

We acknowledge some limitations to this study. First, we are unable to distinguish actual designation dates of FCAs based on available data. We were thus required to partition transacted properties into treatment or control groups on a yearly basis, which may underestimate the impact of FCA designation. Another limitation is that we do not include detailed information on the specifics of each FCA designation and are unable to distinguish the type or cause of each FCA. We only provide evidence that consumers react to official information related to water pollution, and our results should only be interpreted as the general impact of an FCA designation. That said, we also find some evidence that FCA designation is, in fact, correlated with water quality, as one would hope. Whether consumers react differently to various types of FCAs warrants further evaluation in future research. In addition, since our FCA dataset does not include any lakes with an FCA designation that was removed during our study timeframe, we are unable to identify whether property values can recover after an FCA removal. It would be interesting to study whether consumers' perceptions of environmental amenities are conservative. That is, in the case of FCA designations, it may be that once an FCA is issued, households tend to believe that the lake's water quality is low and make lower bids for properties nearby, even if the FCA is later removed.

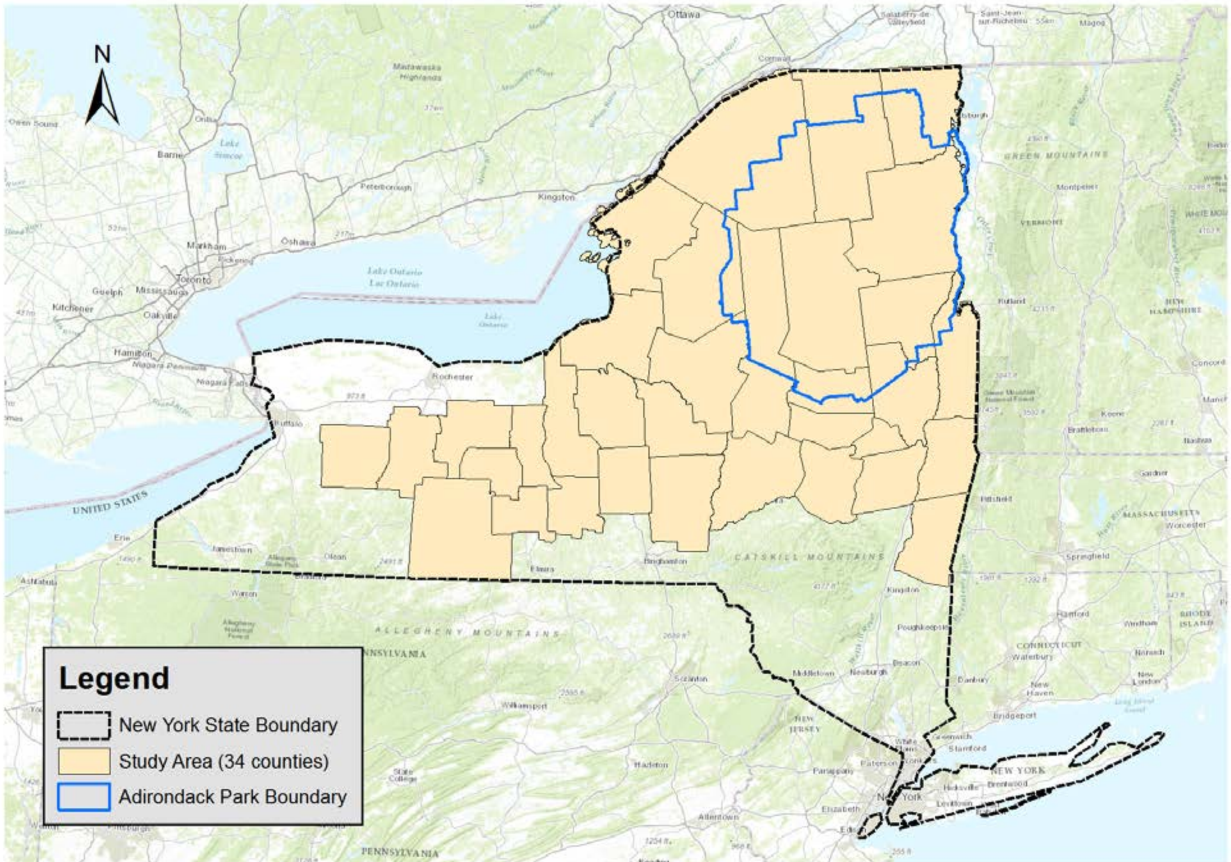

Figure 1. Study Area: 34 counties in northern New York State (Albany, Cayuga, Chenango, Clinton, Columbia, Cortland, Essex, Franklin, Fulton, Hamilton, Herkimer, Jefferson, Lewis, Livingston, Madison, Montgomery, Oneida, Onondaga, Ontario, Oswego, Otsego, Rensselaer, Saratoga, Schenectady, Schoharie, Schuyler, Seneca, St. Lawrence, Steuben, Tompkins, Warren, Washington, Wyoming, and Yates).

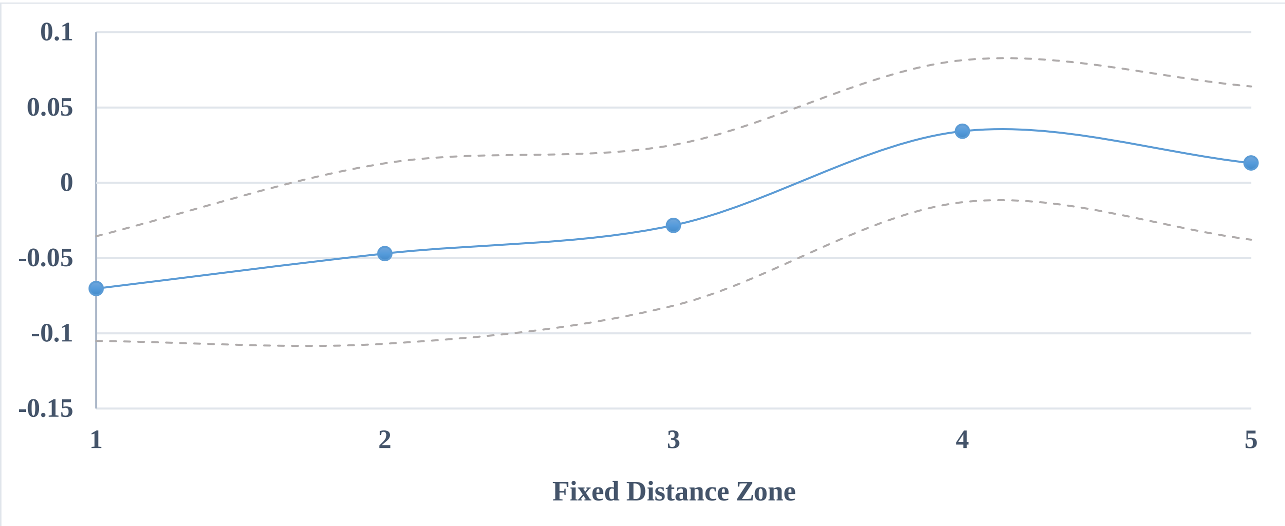

Figure 2. FCA effects based on the distance between property and lake (number in the axis stands for the upper bound of different distance zones; for instance, 1 stands for 0-1 miles distance zone; 2 stands for 1-2 miles distance zone).

Table 1. Summary Statistics (all properties within one mile of 111 lakes; *N* = 20,194)

Variable	**Description**	**Mean**	**S.D.**	**Min**	**Max**
sale_price	Real sale price	220,465	243,216	10,000	5,485,000
std_sale_price	log of standardized sale price (2004)	183,824	196,720	7,339	4,058,900
nbr_kitchens	Number of kitchens	1.08	0.307	1.00	4.00
nbr_full_bath	Number of full baths	1.52	0.665	1.00	5.00
nbr_half_bath	Number of half baths	0.32	0.489	0.00	5.00
nbr_bed	Number of bedrooms	3.00	0.994	1.00	7.00
nbr_fireplaces	Number of fire places	0.44	0.611	0.00	8.00
ln_sqft_living	Log of living area sq. ft.	7.30	0.420	6.22	8.94
central_air	Dummy for house has central AC	0.14	0.344	0	1
blt_his	Age of house in years	59.78	41.206	0.00	212.00
bsmnt_garage	Basement garage capacity	0.08	0.364	0.00	6.00
finished_bsmnt	Area of finished basement sq. ft.	65.79	240.523	0.00	3047.00
grade_sum_1	Property grade excellent	0.01	0.101	0	1
grade_sum_2	Property grade good	0.13	0.341	0	1
grade_sum_3	Property grade normal	0.71	0.453	0	1
grade_sum_4	Property grade fair	0.14	0.347	0	1
grade_sum_5	Property grade bad	0.00	0.057	0	1
prop_class_sum_1	Estate	0.00	0.019	0	1
prop_class_sum_2	Mobile Home	0.00	0.031	0	1
prop_class_sum_3	Residential	0.00	0.034	0	1
prop_class_sum_4	Residential Multi-Purpose	0.02	0.146	0	1
prop_class_sum_5	Rural Residence with Acres	0.01	0.115	0	1
prop_class_sum_6	Seasonal Residence	0.09	0.286	0	1
prop_class_sum_7	Single-family Residence	0.81	0.392	0	1
prop_class_sum_8	Three-family Residence	0.01	0.095	0	1
prop_class_sum_9	Two-family Residence	0.05	0.224	0	1
ln_Dis_Hosp	Log of distance to Hospital	9.03	1.177	4.14	11.12
ln_Dis_POP	Log of distance to Population Center	7.95	1.315	2.41	10.74
ln_Dis_Sch	Log of distance to Public School	7.63	1.153	3.68	10.03
ln_Dis_Univ	Log of distance to University	9.06	1.155	1.92	11.02
ln_Dis_Lake	Log of distance to study lake	5.70	1.465	0.00	7.38
AreaSqKm	Area of nearest study lake sq. Km.	66.92	75.896	0.003	207.70
waterfront	Waterfront property dummy	0.17	0.377	0	1
boatlaunch	Public boat launch site dummy	0.64	0.479	0	1
fishing_access	Fishing access site dummy	0.89	0.310	0	1
AA_water	AA or AAs classified watersheds	0.57	0.496	0	1
ADK	Lakes in the Adirondack Park	0.20	0.396	0	1
lakeTAG	Small pond nearby dummy	0.41	0.492	0	1
FCA	Fish advisory dummy	0.79	0.410	0	1

Table 2. Main Hedonic Analysis Results

	(1)	(2)	(3)	(4)	(5)	(6)
FCA	-0.324***	-0.201***	-0.074***	-0.066***	-0.058**	-0.070***
	(0.016)	(0.016)	(0.019)	(0.018)	(0.026)	(0.018)
Ln(Dis_lake)	-0.134***	-0.135***	-0.154***	-0.155***	-0.121***	-0.156***
	(0.005)	(0.005)	(0.012)	(0.012)	(0.016)	(0.012)
Waterfront	0.302***	0.303***	0.291***	0.290***	0.358***	0.289***
	(0.016)	(0.016)	(0.036)	(0.036)	(0.025)	(0.036)
Lake_tag	0.088***	0.103***	0.042**	0.042**	0.065**	0.043**
	(0.010)	(0.010)	(0.021)	(0.021)	(0.029)	(0.021)
Constant	8.421***	8.379***	7.494***	7.062***	7.631***	8.153***
	(0.229)	(0.225)	(0.524)	(0.898)	(1.119)	(0.907)
R-squared	0.594	0.608	0.734	0.737	0.687	0.736
FE-level						
Block Group			Y	Y		Y
Lake					Y	Y
# of Spatial FE			410	410	111	410
Year-Month FE	Y	Y	Y	Y	Y	Y
Controls						
House	Y	Y	Y	Y	Y	Y
Neighborhood	Y	Y	Y	Y	Y	Y
Lake		Y	Y	Y		
SE Clustering			Y	Y	Y	Y
Lake-specific Trend				Y	Y	Y
Observation	20,194	20,194	20,194	20,194	20,194	20,194

Note: This table contains results of hedonic price models with different specifications. All six models are based on transactions occurred between 2004 and 2013 and located within 1 mile of 111 included lakes. Robust standard errors in parentheses.
* p<0.10, ** p<0.05, *** p<0.01.

Table 3. Hedonic Analysis Results Using Fish Mercury Data

	(1)	(2)	(3)
FCA	-0.054**	-0.039	-0.058**
	(0.023)	(0.032)	(0.023)
Fish Mercury	-0.056	-0.040	-0.045
	(0.123)	(0.175)	(0.120)
FCA * Fish Mercury	-0.045	-0.074	-0.043
	(0.065)	(0.088)	(0.066)
Constant	7.055***	7.636***	8.207***
	(0.898)	(1.115)	(0.923)
R-squared	0.737	0.687	0.738
FE-level			
Block Group	Y		Y
Lake		Y	Y
# of Spatial FE	410	110	410
Year-Month FE	Y	Y	Y
Controls			
House	Y	Y	Y
Neighborhood	Y	Y	Y
Lake	Y		
SE Clustering	Y	Y	Y
Lake-specific Trend	Y	Y	Y
Observation	20,194	20,194	20,194

Note: This table shows results of three different hedonic price models with an interaction of FCA and actual fish mercury monitoring concentrations. Those models are aimed at investigating whether issuing an FCA can raise households' awareness of mercury pollution and motivate them to search for and collect additional information about the actual load of mercury in specific lakes near them. All three models are based on transactions that occurred between 2004 and 2013 and located with 1 mile of 111 included lakes. Robust standard errors in parentheses.
* p<0.10, ** p<0.05, *** p<0.01.

Table 4. Regression Results for 2005 and 2007 FCA Events

	A: 2005 FCA			B: 2007 FCA		
	(1)	(2)	(3)	(1)	(2)	(3)
FCA	-0.068**	-0.053*	-0.070**	-0.075***	-0.066**	-0.076***
	(0.0277)	(0.0296)	(0.0271)	(0.0204)	(0.0280)	(0.0202)
Constant	15.472***	17.190***	15.605***	6.393***	7.027***	7.678***
	(3.9634)	(5.3120)	(3.4413)	(1.0753)	(1.2068)	(1.0823)
R-squared	0.740	0.678	0.742	0.741	0.691	0.742
FE level						
Block Group	Y		Y	Y		Y
Lake		Y	Y		Y	Y
# of FE	386	102	386	403	110	403
Control						
House	Y	Y	Y	Y	Y	Y
Neighborhood	Y	Y	Y	Y	Y	Y
Lake	Y			Y		
SE Clustering	Y	Y	Y	Y	Y	Y
Lake-specific trend	Y	Y	Y	Y	Y	Y
Observations	8,211	8,211	8,211	17,288	17,288	17,288

Note: This table shows results of hedonic price models in terms of 2005 and 2007 FCA designation events. Panel A shows results for three hedonic models based on transactions that occurred between 2004 and 2006 within 1 mile of 102 lakes; Panel B shows results for three hedonic models based on transactions that occurred between 2005 and 2013 within 1 mile of 110 lakes. Robust standard errors in parentheses.
* p<0.10, ** p<0.05, *** p<0.01.

Table 5. Summary of Covariate Balance Checks (2005 FCA Lakes before Matching)

	Treated (N = 6,401)		*Control (N=1,810)*		*Normalized Differences*	*Log Ratio of SD*	$\pi^{0.05}$	
	Mean	*S.D.*	*Mean*	*S.D.*			*Treated*	*Control*
Lake Characteristics								
AreaSqKm	71.11	80.35	41.55	48.33	0.45	0.51	0.27	0.00
boatlaunch	0.60	0.49	0.74	0.44	-0.32	0.12	0.10	0.04
fishing_access	0.88	0.32	0.85	0.36	0.10	-0.11	0.03	0.08
AA_water	0.49	0.50	0.78	0.41	-0.64	0.19	0.16	0.05
waterfront	0.16	0.37	0.15	0.36	0.04	0.03	0.06	0.04
House Characteristics								
nbr_kitchens	1.11	0.35	1.06	0.29	0.15	0.18	0.10	0.02
nbr_full_bath	1.49	0.64	1.46	0.68	0.06	-0.05	0.04	0.06
nbr_bed	3.04	1.04	2.89	1.01	0.15	0.03	0.06	0.05
nbr_fireplaces	0.41	0.60	0.47	0.63	-0.10	-0.05	0.04	0.06
bsmnt_garage	0.08	0.35	0.11	0.43	-0.08	-0.20	0.02	0.11
nbr_half_bath	0.32	0.48	0.27	0.46	0.11	0.05	0.06	0.04
finished_basmnt	55.83	216.42	57.42	221.82	-0.01	-0.02	0.04	0.06
blt_his	60.87	41.72	51.72	33.33	0.24	0.22	0.13	0.02
ln_sqft_living	7.31	0.42	7.22	0.44	0.20	-0.04	0.05	0.06
central_air	0.13	0.33	0.06	0.24	0.22	0.33	0.17	0.01
grade	2.99	0.57	3.10	0.64	-0.19	-0.12	0.03	0.09
prop_class	6.97	0.88	6.89	0.61	0.11	0.37	0.18	0.01
Neighborhood Characteristics								
ln_Dis_Hosp	8.84	1.18	9.53	1.14	-0.59	0.04	0.10	0.08
ln_Dis_POP	7.71	1.18	8.71	1.48	-0.75	-0.23	0.05	0.20
ln_Dis_Sch	7.54	1.15	7.66	1.25	-0.10	-0.08	0.03	0.07
ln_Dis_Univ	8.81	1.08	9.78	1.19	-0.85	-0.09	0.10	0.17
ln_Dis_Lake	5.76	1.47	5.67	1.36	0.07	0.08	0.07	0.03
lakeTAG	1.42	0.49	1.39	0.49	0.06	0.01	0.05	0.05

Note: This table shows results of covariate balance checks of transactions associated with treated (with a 2005 FCA) and control (without a 2005 FCA) lakes before the matching technique is performed. The analysis includes 8,211 transactions that occurred between 2004 and 2006 within 1 mile of 102 lakes.

Table 6. Summary of Covariate Balance Checks (2005 FCA Lakes after Matching)

	Treated (N = 6,401)		***Control (N= 1,482)***		***Normalized Differences***	***Log Ratio of SD***	***$\pi^{0.05}$***	
	Mean	***S.D.***	***Mean***	***S.D.***			***Treated***	***Control***
Lake Characteristics								
AreaSqKm	71.11	80.35	41.07	48.12	0.45	0.51	0.27	0.00
boatlaunch	0.60	0.49	0.74	0.44	-0.32	0.12	0.10	0.04
fishing_access	0.88	0.32	0.86	0.35	0.06	-0.06	0.04	0.07
AA_water	0.49	0.50	0.78	0.42	-0.63	0.18	0.16	0.05
waterfront	0.16	0.37	0.15	0.36	0.03	0.03	0.06	0.04
House Characteristics								
nbr_kitchens	1.11	0.35	1.07	0.30	0.14	0.13	0.09	0.03
nbr_full_bath	1.49	0.64	1.48	0.68	0.02	-0.06	0.04	0.06
nbr_bed	3.04	1.04	2.90	1.00	0.14	0.04	0.06	0.04
nbr_fireplaces	0.41	0.60	0.50	0.63	-0.14	-0.06	0.04	0.07
bsmnt_garage	0.08	0.35	0.11	0.40	-0.07	-0.14	0.02	0.09
nbr_half_bath	0.32	0.48	0.27	0.46	0.10	0.04	0.06	0.04
finished_basmnt	55.83	216.42	65.63	237.78	-0.04	-0.09	0.03	0.07
blt_his	60.87	41.72	50.73	32.93	0.27	0.24	0.13	0.02
ln_sqft_living	7.31	0.42	7.24	0.44	0.16	-0.04	0.04	0.06
central_air	0.13	0.33	0.07	0.25	0.19	0.27	0.14	0.01
grade	2.99	0.57	3.07	0.64	-0.13	-0.11	0.03	0.08
prop_class	6.97	0.88	6.88	0.62	0.12	0.34	0.17	0.01
Neighborhood Characteristics								
ln_Dis_Hosp	8.84	1.18	9.55	1.01	-0.65	0.15	0.15	0.06
ln_Dis_POP	7.71	1.18	8.52	1.47	-0.62	-0.22	0.04	0.17
ln_Dis_Sch	7.54	1.15	7.81	1.21	-0.23	-0.05	0.04	0.07
ln_Dis_Univ	8.81	1.08	9.62	1.20	-0.71	-0.10	0.08	0.14
ln_Dis_Lake	5.76	1.47	5.66	1.37	0.07	0.07	0.07	0.04
lakeTAG	1.42	0.49	1.39	0.49	0.07	0.01	0.05	0.05

Note: This table shows results of covariate balance checks of matched transactions associated with treated (with a 2005 FCA) and control (without a 2005 FCA) lakes before the matching technique is performed. The analysis includes 7,883 matched transactions that occurred between 2004 and 2006 within 1 mile of 99 lakes.

Table 7. Summary of Covariate Balance Checks (2007 FCA Lakes before Matching)

	Treated (N = 3,342)		***Control (N=13,946)***		***Normalized Differences***	***Log Ratio of SD***	***$\pi^{0.05}$***	
	Mean	***S.D.***	***Mean***	***S.D.***			***Treated***	***Control***
Lake Characteristics								
AreaSqKm	42.22	49.80	73.35	79.70	-0.47	-0.47	0.01	0.26
boatlaunch	0.75	0.43	0.62	0.48	0.27	-0.11	0.04	0.09
fishing_access	0.86	0.35	0.91	0.29	-0.16	0.19	0.11	0.02
AA_water	0.77	0.42	0.53	0.50	0.53	-0.17	0.04	0.14
waterfront	0.17	0.37	0.18	0.38	-0.03	-0.02	0.04	0.06
House Characteristics								
nbr_kitchens	1.05	0.25	1.09	0.32	-0.13	-0.23	0.01	0.12
nbr_full_bath	1.51	0.70	1.54	0.66	-0.04	0.05	0.06	0.04
nbr_bed	2.89	0.99	3.03	0.99	-0.14	0.01	0.05	0.05
nbr_fireplaces	0.48	0.63	0.44	0.61	0.07	0.03	0.06	0.04
bsmnt_garage	0.11	0.42	0.08	0.35	0.08	0.18	0.10	0.02
nbr_half_bath	0.25	0.45	0.34	0.50	-0.17	-0.10	0.03	0.08
finished_basmnt	74.62	260.64	66.88	242.47	0.03	0.07	0.07	0.04
blt_his	52.26	33.14	62.15	42.96	-0.26	-0.26	0.01	0.14
ln_sqft_living	7.22	0.42	7.33	0.42	-0.26	0.02	0.06	0.05
central_air	0.07	0.26	0.16	0.37	-0.28	-0.35	0.01	0.18
grade	3.08	0.64	2.96	0.55	0.20	0.15	0.10	0.03
prop_class	6.85	0.64	6.94	0.81	-0.12	-0.24	0.01	0.12
Neighborhood Characteristics								
ln_Dis_Hosp	9.58	1.16	8.91	1.13	0.59	0.03	0.10	0.08
ln_Dis_POP	8.83	1.47	7.75	1.19	0.81	0.22	0.21	0.06
ln_Dis_Sch	7.75	1.22	7.61	1.13	0.12	0.07	0.07	0.04
ln_Dis_Univ	9.80	1.22	8.89	1.06	0.79	0.15	0.18	0.08
ln_Dis_Lake	5.56	1.36	5.73	1.49	-0.11	-0.09	0.03	0.08
lakeTAG	1.38	0.49	1.41	0.49	-0.06	-0.01	0.05	0.05

Note: This table shows results of covariate balance checks of transactions associated with treated (with a 2007 FCA) and control (without a 2007 FCA) lakes before the matching technique is performed. The analysis includes 17,288 transactions that occurred between 2005 and 2013 within 1 mile of 110 lakes.

Table 8. Summary of Covariate Balance Tests (2007 FCA Lakes after Matching)

	Treated (N = 3,342)		***Control (N=4,688)***		***Normalized Differences***	***Log Ratio of SD***	***$\pi^{0.05}$***	
	Mean	***S.D.***	***Mean***	***S.D.***			***Treated***	***Control***
Lake Characteristics								
AreaSqKm	42.22	49.80	54.55	62.74	-0.22	-0.23	0.02	0.13
boatlaunch	0.75	0.43	0.73	0.45	0.05	-0.03	0.04	0.06
fishing_access	0.86	0.35	0.91	0.28	-0.17	0.20	0.11	0.02
AA_water	0.77	0.42	0.75	0.43	0.03	-0.02	0.05	0.06
waterfront	0.17	0.37	0.21	0.41	-0.12	-0.09	0.03	0.08
House Characteristics								
nbr_kitchens	1.05	0.25	1.07	0.30	-0.09	-0.18	0.02	0.10
nbr_full_bath	1.51	0.70	1.53	0.67	-0.03	0.04	0.06	0.04
nbr_bed	2.89	0.99	2.95	0.95	-0.06	0.04	0.06	0.04
nbr_fireplaces	0.48	0.63	0.46	0.61	0.04	0.03	0.06	0.04
bsmnt_garage	0.11	0.42	0.11	0.41	0.01	0.02	0.05	0.05
nbr_half_bath	0.25	0.45	0.30	0.48	-0.09	-0.07	0.04	0.07
finished_basmnt	74.62	260.64	87.88	284.07	-0.05	-0.09	0.03	0.07
blt_his	52.26	33.14	58.19	37.79	-0.17	-0.13	0.03	0.09
ln_sqft_living	7.22	0.42	7.28	0.42	-0.15	0.02	0.06	0.05
central_air	0.07	0.26	0.09	0.29	-0.08	-0.12	0.03	0.08
grade	3.08	0.64	2.98	0.53	0.17	0.18	0.11	0.02
prop_class	6.85	0.64	6.93	0.69	-0.12	-0.08	0.04	0.07
Neighborhood Characteristics								
ln_Dis_Hosp	9.58	1.16	9.11	1.00	0.44	0.15	0.12	0.04
ln_Dis_POP	8.83	1.47	8.17	1.13	0.50	0.27	0.17	0.03
ln_Dis_Sch	7.75	1.22	7.89	1.13	-0.12	0.08	0.07	0.04
ln_Dis_Univ	9.80	1.22	9.15	0.93	0.60	0.28	0.19	0.03
ln_Dis_Lake	5.56	1.36	5.48	1.52	0.06	-0.11	0.03	0.08
lakeTAG	1.38	0.49	1.34	0.47	0.10	0.03	0.06	0.04

Note: This table shows results of covariate balance checks of matched transactions associated with treated (with a 2007 FCA) and control (without a 2007 FCA) lakes before the matching technique is performed. The analysis includes 8,030 matched transactions occurred between 2005 and 2013 within 1 mile of 109 lakes.

Table 9. Regression Results Using Matched Samples (w/o Weighting)

	A: 2005 FCA			B: 2007 FCA		
	(1)	(2)	(3)	(1)	(2)	(3)
FCA	-0.072**	-0.044	-0.074**	-0.107***	-0.103***	-0.107***
	(0.0331)	(0.0335)	(0.0325)	(0.0242)	(0.0292)	(0.0241)
Constant	13.985***	16.042***	14.750***	7.379***	8.875***	8.047***
	(3.9624)	(5.5032)	(3.6420)	(1.5548)	(1.2598)	(1.5739)
R-squared	0.741	0.692	0.743	0.735	0.695	0.732
FE level						
Block Group	Y		Y	Y		Y
Lake		Y	Y		Y	Y
# of FE	385	99	385	340	109	340
Control						
House	Y	Y	Y	Y	Y	Y
Neighborhood	Y	Y	Y	Y	Y	Y
Lake	Y			Y		
SE Clustering	Y	Y	Y	Y	Y	Y
Lake-specific trend	Y	Y	Y	Y	Y	Y
Observations	7,883	7,883	7,883	8,030	8,030	8,030

Note: This table shows results of hedonic price models in terms of 2005 and 2007 FCA designation events. Regressions are estimated using matched samples without weighting based on the frequency of matching. Transactions are matched based on lakes with different treatment status; the difference in transacted properties that occurred before or after the FCA treatment are ignored. The matching process trims the original transaction sample by automatically discarding observations that have no counterfactuals. Panel A shows results of three hedonic models based on matched transactions that occurred between 2004 and 2006 within 1 mile of 99 lakes; Panel B shows results of three hedonic models based on matched transactions that occurred between 2005 and 2013 within 1 mile of 109 lakes. Robust standard errors in parentheses.

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

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Supplementary Materials for

Mercury Pollution, Information, and Property Values

Table A-1. Regression Results for 2005 and 2007 FCA Events (Observations in Years 2005 and 2007 are Dropped)

	A: 2005 FCA			B: 2007 FCA		
	(1)	(2)	(3)	(1)	(2)	(3)
FCA	-0.077**	-0.064*	-0.074**	-0.085***	-0.078***	-0.087***
	(0.0356)	(0.0375)	(0.0349)	(0.0225)	(0.0292)	(0.0222)
Constant	16.082***	17.499***	16.914***	6.002***	6.712***	7.477***
	(4.1319)	(5.4789)	(4.0577)	(1.1055)	(1.2516)	(1.0663)
R-squared	0.754	0.688	0.757	0.741	0.692	0.743
FE level						
Block Group	Y		Y	Y		Y
Lake		Y	Y		Y	Y
# of FE	376	95	376	340	110	403
Control						
House	Y	Y	Y	Y	Y	Y
Neighborhood	Y	Y	Y	Y	Y	Y
Lake	Y			Y		
SE Clustering	Y	Y	Y	Y	Y	Y
County specific trend	Y	Y	Y	Y	Y	Y
Observations	5,332	5,332	5,332	15,144	15,144	15,144

Note: This table contains results of hedonic price models in terms of 2005 and 2007 FCA designation events. Panel A shows results of three hedonic models based on transactions that occurred in 2004 and 2006 (drops year 2005) within 1 mile of 102 lakes; Panel B shows results of three hedonic models based on transactions that occurred between 2005 and 2013 (drops year 2007) within 1 mile of 110 lakes. This table corresponds to Table 4 and drops observations in year 2005 and 2007, respectively, in panel a and panel b. Standard errors in parentheses.
* p<0.10, ** p<0.05, *** p<0.01.

Table A-2. Summary of Covariate Balance Tests (Before and After 2007 FCA)

	After (N = 2,303)		*Before (N=1,039)*		*Normalized*	*Log Ratio of*	$\pi^{0.05}$	
	Mean	***S.D.***	***Mean***	***S.D.***	***Differences***	***SD***	***Treated***	***Control***
Lake Characteristics								
AreaSqKm	41.62	49.64	42.99	50.01	-0.03	-0.01	0.05	0.05
boatlaunch	0.74	0.44	0.75	0.43	-0.02	0.01	0.05	0.05
fishing_access	0.85	0.36	0.87	0.34	-0.05	0.05	0.06	0.04
AA_water	0.76	0.43	0.78	0.41	-0.06	0.04	0.06	0.04
waterfront	0.17	0.38	0.16	0.37	0.03	0.03	0.06	0.04
House Characteristics								
nbr_kitchens	1.04	0.22	1.06	0.28	-0.09	-0.26	0.01	0.13
nbr_full_bath	1.53	0.71	1.47	0.68	0.09	0.04	0.06	0.04
nbr_bed	2.88	0.97	2.89	1.02	-0.01	-0.05	0.04	0.06
nbr_fireplaces	0.49	0.63	0.47	0.63	0.03	-0.01	0.05	0.05
bsmnt_garage	0.11	0.42	0.11	0.42	0.01	0.01	0.05	0.05
nbr_half_bath	0.26	0.46	0.24	0.43	0.04	0.07	0.07	0.04
finished_basmnt	89.92	286.09	55.19	222.75	0.14	0.25	0.13	0.01
blt_his	52.69	33.37	51.71	32.84	0.03	0.02	0.05	0.05
ln_sqft_living	7.22	0.42	7.21	0.43	0.04	-0.02	0.05	0.05
central_air	0.08	0.27	0.06	0.23	0.09	0.16	0.09	0.02
grade	3.06	0.63	3.11	0.64	-0.07	-0.02	0.05	0.06
prop_class	6.83	0.64	6.87	0.63	-0.07	0.03	0.06	0.04
Neighborhood Characteristics								
ln_Dis_Hosp	9.60	1.15	9.56	1.18	0.03	-0.03	0.04	0.06
ln_Dis_POP	8.85	1.45	8.80	1.50	0.03	-0.03	0.04	0.06
ln_Dis_Sch	7.80	1.21	7.69	1.23	0.09	-0.02	0.05	0.06
ln_Dis_Univ	9.79	1.23	9.82	1.22	-0.02	0.00	0.05	0.05
ln_Dis_Lake	5.53	1.36	5.61	1.35	-0.06	0.01	0.05	0.05
lakeTAG	1.38	0.49	1.39	0.49	-0.02	0.00	0.05	0.05

Note: This table shows results of covariate balance check of properties near 2007 FCA-treated lakes that occurred before and after the treatment. The analysis includes 3,342 transactions that occurred before and after 2007 FCA designation.

Table A-3. Regression Results Using Matched Samples (w/ Weighting)

	A: 2005 FCA			B: 2007 FCA		
	(1)	(2)	(3)	(1)	(2)	(3)
FCA	-0.080**	-0.065*	-0.079*	-0.118***	-0.116***	-0.119***
	(0.0401)	(0.0376)	(0.0404)	(0.0290)	(0.0349)	(0.0289)
Constant	17.810**	23.512	16.507**	7.946***	9.007***	7.606***
	(8.4853)	(14.7950)	(7.5394)	(1.9207)	(1.4178)	(1.8504)
R-squared	0.751	0.693	0.756	0.733	0.691	0.735
FE level						
Block Group	Y		Y	Y		Y
Lake		Y	Y		Y	Y
# of FE	386	100	386	340	109	340
Control						
House	Y	Y	Y	Y	Y	Y
Neighborhood	Y	Y	Y	Y	Y	Y
Lake	Y			Y		
SE Clustering	Y	Y	Y	Y	Y	Y
County specific trend	Y	Y	Y	Y	Y	Y
Observations	13,572	13,572	13,572	9,394	9,394	9,394

Note: This table shows results of hedonic price models in terms of 2005 and 2007 FCA designation events. Regression are estimated using matched samples with weighting based on the frequency of matching. Transactions are matched based on lakes with different treatment status; the difference in transacted properties that occurred before or after the FCA treatment are ignored. The matching process trims the original transaction sample by automatically discarding observations that have no counterfactuals. Panel A shows results of three hedonic models based on matched transactions that occurred between 2004 and 2006 within 1 mile of 100 lakes; Panel B shows results of three hedonic models based on matched transactions that occurred between 2005 and 2013 within 1 mile of 109 lakes. Standard errors in parentheses.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Statistical Methods for Covariate Balance Checking

(1) Normalized difference (Δ)

Define the conditional within-group sample variances of the covariate as below:

$$s_c^2 = \frac{1}{N_c - 1} \sum_{i:W_i=0} (X_i - \bar{X}_c)$$

where $\bar{X}_c$ and $\bar{X}_t$ denote the sample averages of the covariate values for the control and treatment group, respectively; W_i stands for the category to which an observation belongs: One denotes the treatment group, zero otherwise.

Then the normalized difference can be written as:

$$\Delta = \frac{\bar{X}_t - \bar{X}_c}{\sqrt{\frac{s_c^2 + s_t^2}{2}}}$$

where S_c and S_t stand for the conditional within-group sample variances of the covariate of treatment group and control group.

(2) Difference in dispersion (Γ)

$$\Gamma = \ln\left(\frac{s_t}{s_c}\right) = \ln(s_t) - \ln(s_c)$$

where S_c and S_t stand for the conditional within-group sample variances of the covariate.

(3) Probability mass overlapping (π)

$$\hat{\pi}_{c/t}^{\alpha} = (1 - (\hat{F}_{c/t}\left(\hat{F}_{t/c}^{-1}\left(1 - \frac{\alpha}{2}\right)\right) + \hat{F}_{c/t}\left(\hat{F}_{t/c}^{-1}\left(\frac{\alpha}{2}\right)\right)$$

where $\hat{F}_{c/t}(\cdot)$ stands for the empirical probability distribution function of X_i in the control or treatment group; $\hat{F}_{c/t}^{-1}(q)$ denote their inverse of probability distribution; α is the limit of probability.