The Value of Water Quality: Separating Amenity and Recreational Benefits

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(Preliminary results – Please don't distribute)

Abstract

Hedonic property studies that value water quality improvements generally focus on waterfront homes, or those very near to affected water bodies. Estimated marginal willingness to pay (MWTP) for pollution reduction in these studies is typically small and drops sharply with distance. One challenge with the hedonic approach is that it is unclear what MWTP estimates capture. Unlike in the case of air pollution, health effects from ambient water quality improvements are unlikely to be a significant share of estimated MWTP. Existing estimates likely combine primarily amenity benefits of water pollution reductions and recreational benefits. While amenity benefits may be highly localized, as prior studies have shown, recreational benefits may not be, and prior hedonic work may have failed to capture the potentially significant influence of recreation on MWTP for water quality improvements. Using the case of nutrient pollution reductions in Tampa Bay, Florida, we estimate a two-stage model combining a random-utility recreational demand model with a hedonic housing model, allowing households to optimize over regional aquatic recreation opportunities (influenced by pollution in recreational waters), as well as local ambient water quality very close to homes. Preliminary results indicate that Tampa homeowners have significant MWTP for both improvements in local ambient water quality, and improvements in regional recreational waters.

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1 Introduction

U.S. water quality has improved significantly since the passage of the Clean Water Act in 1972 in both obvious and subtle ways. The elimination of once-frequent river fires in heavily polluted areas is often-cited evidence in the obvious category (Olmstead 2009); improvements in fish catches and other indicators of ecosystem health are more subtle. Recent estimates suggest a causal link with the CWA, especially with regard to the regulation of effluent from municipal sewage treatment plants and, perhaps more directly, the provision of subsidies for their construction and improvements in these plants' treatment processes (Keiser & Shapiro 2017). This work is a major contribution to economists' understanding of U.S. water quality regulation; while dozens of studies by economists have established causal impacts of the Clean Air Act on emissions and outcomes such as infant mortality (Chay & Greenstone 2005), industrial activity (Greenstone 2002), and adult income (Isen et al. 2017), Keiser & Shapiro (2017) provide the first aggregate causal estimate of the CWAs impact on ambient water pollution concentrations, an astonishing fact for a major environmental statute approaching 50 years old.

If U.S. water quality regulation has improved ambient water quality, this does not prove that it is efficient; efficient policies equate marginal benefits with marginal costs. Studies by economists dating to the 1980s suggest that the marginal benefits of the CWA may be well below its marginal costs (Freeman 1980, Lyon & Farrow 1995), a finding confirmed, albeit via much more detailed analysis, by Keiser & Shapiro (2017). However, as in most economic analyses of environmental policy, obtaining comprehensive benefit estimates is more challenging than obtaining comprehensive cost estimates. Thus, when interpreting the existing literature, there is a risk of erroneously concluding that water quality regulation should be less stringent, simply because benefits have not been sufficiently captured.

In this paper, we test an alternative way to estimate the marginal benefits of water quality improvements. Our basic intuition is that, while property owners likely have some marginal willingness to pay (MWTP) for pollution reductions in the small creeks, canals, streams, ponds, lakes and other water bodies that dot the landscape in many residential areas, their MWTP for water quality is likely also affected by the degree to which regional water quality affects recreational opportunities. For example, a resident of Brooklyn, New York, may value improvements in water quality in the Gowanus Canal, particularly if they live very nearby, due to amenity changes – it may smell and look better, for example. But they may also value improvements in water quality at Brighton or Rockaway beaches, or the fact that they can compete in the New York City triathlon with a swim portion in the Hudson River. Unfortunately, existing estimates of MWTP for water quality tend to focus either on the impacts of highly-localized water quality improvements on housing values (Leggett & Bockstael 2000, Poor et al. 2001, 2007, Walsh et al. 2017), or on the impacts to recreational fishing, swimming, boating and general visitation (Haab & McConnell 2002, Lew & Larson 2005, Timmins & Murdock 2007). A comprehensive economic valuation framework is needed in order to evaluate the benefits of major water quality improvements and compare them with costs.

We apply an integrated, two-part theoretical model of recreational and housing demand developed by Phaneuf et al. (2008) to the phenomenon of ambient water quality improvements Tampa Bay, Florida. First, we use a random-utility recreational demand model to estimate Tampa Bay households' indirect utility from recreational fishing trips to 85 sites in the region between 1998 and 2014. Second, we estimate a panel fixed-effect hedonic property model, exploiting variation from more than 140,000 repeat sales between 1998 and 2014. The independent variables in the hedonic model include both local ambient water quality very near each home, and our indirect recreational utility estimate at the zip-code level, so that the hedonic estimates of MWTP include both amenity and recreational improvements due to water pollution reductions.

The water pollution problem we examine in the paper is nutrient over-enrichment – a common problem, especially in coastal areas that are the ultimate destination (prior to the oceans) of urban and agricultural runoff from very broad geographic areas. This phenomenon involves the addition of too many nutrients, primarily nitrogen and phosphorous, to water bodies via agricultural and urban nonpoint source pollution, which stimulates excessive algae growth. When the algae die, they decay and deplete dissolved oxygen (Morrison & Greening 2006). Among the serious consequences of nutrient pollution are dead zones, in which marine life that cannot escape the low-oxygen zone cannot be supported. Reported dead zones worldwide doubled from 1995 to 2008 to more than 400 zones, and increased to 515 sites in 2011 (Rabotyagov et al. 2014). U.S. coastal waters that experience this phenomenon include Tampa Bay, the Gulf of Mexico, Chesapeake Bay, Puget Sound, Long Island Sound, and the North Carolina coast.

Economists have estimated significant impacts of dead zones on commercial and recreational fisheries (Massey et al. 2006, Smith et al. 2017), though other economic damages from sustained dead zones are largely unknown (Barbier 2012). Anecdotal evidence suggests that recreational impacts other than fishing could be significant. In 2005, one of the years during our study period, Floridas swimming beaches had more than 3,482 beach closures and health advisories due to high levels of bacteria caused by algal blooms, including cyanobacteria (blue–green algal) blooms (Clean Water Network of Florida 2008). Prior hedonic work suggests that amenity values of nutrient pollution are capitalized into housing prices (Poor et al. 2007, Walsh et al. 2011, Guignet et al. 2017). Effects seem particularly strong for homes directly on the water; for example, Walsh et al. (2017) find that the impacts of nutrient pollution reductions on properties in the Chesapeake Bay diminish dramatically at a distance of 1,000 meters.

We find significant household MWTP for nutrient pollution reduction in Tampa Bay due to both the local amenity benefits and improved recreational opportunities; both factors are capitalized into housing prices and both are statistically and economically significant. Marginal willingness to pay for improvements in very local water quality - an indicator of amenity values - is about $230 per home, on average. Preliminary estimates suggest that Tampa homeowners have significant MWTP for the impact of water quality improvements on regional recreation opportunities, as well. This suggests that prior work may have underestimated the value of water quality improvements to homeowners.

We make three main contributions to the literature. First, we provide evidence of the importance of considering both the local and the regional recreational impacts of water quality improvements in estimating economic benefits. We find that recreational benefits left out of prior hedonic studies are very significant. Our empirical tests, which use housing transaction data and recreational fishing data available in consistent formats for the entire United States, could potentially be applied on a much larger scale to value changes in federal water quality standards. Second, while we do not break new theoretical ground - we adopt our two-step approach from Phaneuf et al. (2008) - to our knowledge, we are the first to use repeat-sales data in a panel hedonic model to estimate the combined amenity and recreational value of water quality improvements, increasing our confidence that our estimates are causal, relative to the only prior empirical application in Phaneuf et al. (2008). Third, we generate estimates of the aggregate benefits of nutrient pollution reductions in Tampa Bay, a major U.S. coastal city. The Florida Department of Environmental Protection implemented a set of new numeric nutrient standards in accordance with the CWA in 2013; our results can be used to estimate the benefits of these new standards, and compare them with the costs of policy options on the table .

The rest of the paper proceeds as follows. In Section 2, we review the prior literature on hedonic property and recreational demand models of the benefits of water quality improvements. Section 3 presents our theoretical model. The data and study area are described in Section 4, and econometric models are presented in Section 5. Section 6 summarizes results and robustness checks, and Section 7 concludes.

2 Literature Review

The hedonic analysis technique was established by Rosen (1974) and has been used to estimate marginal implicit prices of numerous environmental amenities and disamenities including air quality, water quality and hazardous waste sites (Smith & Huang 1993, Boyle & Kiel 2001, Greenstone & Gallagher 2008, Gamper-Rabindran & Timmins 2013, Muehlenbachs et al. 2015, Keiser & Shapiro 2017) [1].

With respect to nutrient over-enrichment, in particular, Leggett and Bockstael(2000), Poor et al.(2007), Guignet et al.(2017) and Walsh et al.(2017) investigate the impacts of water quality in Chesapeake Bay on nearby property prices. For example, Guignet and his coauthors use residential transaction data from 1996-2008 in 11 counties of Maryland to estimate the implicit value residents place on submerged aquatic vegetation (SAV) degradation resulting from nutrient over-enrichment (Guignet et al. 2017). Poor et al.(2001) use water quality data from 24 monitors throughout the St.Mary's watershed in Maryland to examine the impacts of non-point source water pollution via change in water clarity. Gibbs et al.(2002) also use data on water clarity in New Hampshire lakes as a measurement of the degree of eutrophication from nutrient over-enrichment. It is important to understand that nutrient over-enrichment is typically a regional phenomenon. Nitrogen and phosphorous enter water bodies from stormwater and other sources over a broad catchment area, so that the impacts are absorbed not only locally in small streams but also in large streams, rivers and in coastal areas, in bays and estuaries.

Prior work on water quality has focused on estimating the benefits of water quality improvements for waterfront properties (Leggett & Bockstael 2000, Gibbs et al. 2002, Poor et al. 2001, Horsch & Lewis 2009, Zhang & Boyle 2010). Leggett and Bockstael(2000) is an early study utilizing hedonic analysis to study the impact of water pollution. They use fecal coliform counts as the quality indicator in an analysis of waterfront homes on the Chesapeake Bay. Based on their analysis, water quality matters to waterfront homeowners, and the projected increase in the residential waterfront properties due to a reduction in fecal coliform counts to below 200 counts per 100 mL is \$12.145 million(Leggett & Bockstael 2000). However, until recently, it was often difficult to find a sufficient number of waterfront

[1] Theoretically, hedonic analysis has two stages. The first stage is the use of property prices and characteristics to obtain the implicit marginal willingness to pay. The second stage uses the marginal implicit prices to estimate the welfare changes resulting from changes in environmental amenities. Given limitations in data availability, most empirical analyses focus on the first stage. Only a limited number of studies have estimated welfare changes (Phaneuf & Requate 2016).

properties and enough variation in water quality to conduct large-scale hedonic analysis (Phaneuf et al. 2008, Freeman et al. 2014).

Poor et al.(2007) is the first study to include both waterfront and non-waterfront properties. The authors investigate the value of ambient changes in nutrient pollution in the St.Mary's watershed, Maryland. They find that the marginal implicit prices associated with a one-milligram-per-liter increase in total suspended solids and dissolved inorganic nitrogen, are -$1086 and -$17,642, respectively (Poor et al. 2007). More recent studies that focus on both waterfront and non-waterfront properties find the impacts of water quality diminish for properties located further away from the affected water bodies. Walsh et al.(2011) investigate the effects of enhanced water quality on both waterfront and non-waterfront property prices, using hedonic models in Orange County, Florida. Their findings indicate that the value of increased water quality depends upon the property's location and proximity to the waterfront (Walsh, Milon & Scrogin 2011). Walsh et al. (2017) find the impacts of water quality on properties in the Chesapeake Bay region diminishes when distance from a waterbody reaches 1000 meters.

While water pollution seems to have negative impacts on residential property prices located close to water, prior hedonic models have not attempted to tease out the different impacts of local nutrient pollution reduction and the water quality changes from major coastal water bodies, which may affect recreation. For example, most neighborhoods in the Tampa Bay area do not abut to the Bay itself, and may even be many miles from the nearest access point. But many households in these non-Bayfront areas may still have some willingness-to-pay for improvements in water quality that would reduce regional beach closures or fishing opportunities in addition to improvements in their own backyard.

In theory, hedonic property studies like those cited above could pick up both amenity and recreational benefits of water quality improvements. In many cases, when analysts have looked for effects outside of a very tight radius (of 2-3 kilometers), they have not found such effects (Walsh et al. 2011, Keiser & Shapiro 2017). This has been interpreted as evidence that homeowners only value water quality very near to their homes. However, Figure 1 demonstrates our concern about interpreting standard hedonic estimates in this way. Consider a household located in the black box in Figure 1. The blue and green dots represent hypothetical water quality monitors. The smaller of the two circles in Figure 1 represents the typical relatively small zone of influence of water quality on property values. The larger of the two circles in Figure 1 represents a much larger zone of influence, which in a typical U.S. city is likely to contain many water quality monitors, but only a small number of (if any) monitors on larger, charismatic water bodies used for recreation. For example, in Figure 1, there are 12 monitors on waterbodies in the larger circle that would be counted in an average at this larger radius in the standard hedonic approach, but only 6 (in the Tampa Bay waterbody) that might matter for household recreation. If this is the case, it would not be surprising if we regressed housing prices on an average measure of water quality within the large circle around each home and found no effect. The impact of water quality in small water bodies in other homes' backyards, which might approach zero, could easily obscure any impact of a small number of monitors in a distant, larger recreational waterbody. In addition, households may travel quite far to recreate; for example, in our sample, the average travel time for recreational fishing outings among Tampa residents is almost one hour. Thus, the traditional hedonic approach may be inadequate to capture potentially significant recreational values.

Much existing literature on recreational demand for water amenities use random utility model (RUMs) to depict a consumer's decision-making process (McFadden 1973, 1981, Freeman et al. 2014). Past studies using RUMs have studied the demand for recreational fishing (Greene et al. 1997, Jakus et al. 2000, Haab & McConnell 2002, Timmins & Murdock 2007), swimming (Bockstael et al. 1987), boating, land-based activities at water sites (Breen et al. 2017), and general visitation (Lew & Larson 2005, Keeler et al. 2015). Similar to the hedonic property studies, the recreation demand literature also focuses on one large regional water body, or on local lakes, rivers and waterways. One group focuses on the valuation of recreation in large coastal waters. Greene et al. (1997) uses the Marine Recreational Fishing Statistics Survey to find that average annual values of recreational fishing in Tampa Bay is \$18.14 for participants and \$0.048 for nonparticipants. Keeler et al. (2015) uses geotagged recreation trip photos in social media as a proxy for recreational visits to lakes in Minnesota and Iowa to estimates the valuation of water quality improvement (Keeler et al. 2015).

While hedonic price models and recreation demand models are widely used in estimating the marginal implicit prices of environmental quality characteristics, they are not without limitations.

First, hedonic models do not estimate total economic value or total willingness-to-pay to the environment, but only capture the perceived differences in environmental attributes, and only measure the willingness-to-pay of single-family homeowners, a subset of local populations. In places like Tampa Bay, tourists may value water quality improvements even more than residents, but the willingness-to-pay of visitors are not captured in the hedonic price models. Third, some assumptions of the hedonic property model can be problematic. Hedonic analysis assumes buyers and sellers have complete information on housing characteristics, and that consumers are free to choose from a set of houses with any combination of characteristics. In real housing markets, consumers usually have a limited list of properties they can choose from and may satisfice instead of maximizing their utility. Given these caveats, however, hedonic analysis is one of the best available economic methods for valuing changes in environmental quality.

One important limitation of recreation demand models is that they are largely static in nature. Most models assume a fixed and exogenous choice set and few interactions among trips taken by an individual over time. However, the choice set is dynamic as consumers will learn about new possible sites and site characteristics over time (Freeman et al. 2014). Most recreation demand models also treat site attributes as exogenous factors and ignore potential endogenously-determined and unobservable site characteristics (Moeltner & von Haefen 2011). One such characteristic is site congestion (Timmins & Murdock 2007). Unobservable site attributes that determine the decision of one angler's recreation choice could also affect the decisions of other anglers. Congestion of a recreation site occurs when many anglers visit the same site that it diminishes the utility and the willingness to pay of these anglers and could be correlated with water quality. We will discuss this issue further in Section 7.

3 Theoretical Motivation

We build on the integrated property value and recreation model of Phaneuf et al. (2008), incorporating multiple aspects of water quality from major coastal water bodies in local property purchase decisions.

We assume that consumers make long-run and short-run decisions that may be related in housing prices. In the long run, consumers evaluate neighborhood and property amenities to make residential location decisions. Pollution in nearby water is an attribute purchased along with the homes, and thus enters the long-run decision-making process. Once the location is chosen, a household can allocate its remaining resources (including time) on market goods and recreation. In the short run, households evaluate the benefits of outings to recreational sites conditional on their residential locations. Since short-run recreational decisions are affected by long-run residential location choices, we can assume that when making property purchase decisions, consumers will consider each location's accessibility to recreational opportunities.

Let a household's utility from recreational trips be $x(Q)$ where Q measures the water quality of recreational water bodies, z be a numeraire good with price 1, and $h(a, q)$ be housing services as a function of property attributes and nearby water quality q. In the short run, a household faces the following maximization problem:

$$\max_{x,z} \quad U(x(Q), z|h(a, q)) \quad \text{s.t.} \quad m = p_x x(Q) + z \tag{1}$$

A household is maximizing its utility for recreational trips and market goods conditional on its income after housing expenditures, where m is their income net of the housing price. Note that the model assumes that consumers can perceive the change of water quality Q. For instance, if nutrient pollution causes excessive amount of algae in the water, households are assumed to notice the color change in water and may change behaviors, like spending less time recreating in or near polluted water. Maximizing utility subject to the budget constraint yields the conditional indirect utility function for the short-run problem:

$$V = V(p_x, m, Q, q, \epsilon) \tag{2}$$

where ϵ measures the unobserved heterogeneity of each property.

We can estimate the indirect utility from recreation using a recreational demand model. Let $CS(Q, \epsilon)$ measure the gains to a household from visiting recreation sites in Tampa Bay with water quality Q. When households make decisions about taking recreational trips, they consider potential benefits from visiting each possible site. If water quality and recreation costs vary spatially, different neighborhoods will offer different potential net benefits of recreation. As a result, we can model expected recreation benefits as an attribute of location. The expected benefits of recreation for a residential location can be given as:

$$ECS(Q) = E[CS(Q, \epsilon)] \tag{3}$$

In long run equilibrium, the average recreational opportunity of a location can be capitalized into housing prices. Note that the recreational benefit index is not at the individual household level, but at the neighborhood level. It measures the average recreation opportunity that one could expect living in a neighborhood. Since recreation decisions are made conditional on residential location decisions, we replace the $x(Q)$ in equation 1 with $ECS(Q)$ generated from the previous section. The long-run utility maximization problem becomes:

$$\begin{aligned} max \quad & U = U(ECS(Q), h(a,q), z, \epsilon) \\ & \text{s.t.} \quad m^* = p_h(a,q) + p_x\tilde{x} + z \end{aligned} \tag{4}$$

Households choose their residential locations at which their marginal benefit from the expected recreation utility and from the environmental services that are immediately available at the home's location is equal to the marginal property purchase price [2].

4 Study Area and Data

Tampa Bay and its watershed (Figure 2) stretches more than 400 square miles. It is Florida's largest open-water estuary and the second-largest metropolitan area in the state. The Bay provides important value for its economic opportunities, habitats, ecosystem services, recreational use such as boating and fishing, power plant heat exchange, ports and much more. More than 2.3 million people live in the study area and almost 90 percent of the total employment within the three counties – Hillsborough, Pinellas, and Manatee – is located in the watershed (Tampa Bay Estuary Program & Tampa Bay Regional Planning Council 2014).

Florida has a long history of regulatory attention to restore, protect and manage its abundant surface water resources. In Tampa Bay, seagrass coverage, an important indicator of the healthiness of an aquatic ecosystem, declined from about 16,000 ha in 1950 to near 8800 ha in 1982 as a result of the excessive nutrient discharge to the Bay (Avery & Johansson 2010). Recognizing the need to place extra emphasis on surface water protection, especially on point and non-point source pollution, the Florida Legislature passed the Surface Water Improvement and Management(SWIM) Act in 1987 to direct state's water management districts to design and implement plans for the improvement of surface water quality (Southwest Florida Water Management District 1999). Tampa Bay is the top priority of surface water management programs in the Southwest Florida Water Management

[2] Local water quality q and recreation water quality Q may be correlated. Future work is needed on this issue.

District(SFWMD). While water quality in the Tampa Bay watershed has improved over time, nutrient pollution still contributes to severe degradation of aquatic resources (Office of Water 2012). In 2010, the Florida Department of Environmental Protection (FDEP) developed a numeric Total Maximum Daily Load(TMDL) – effectively a water pollution "budget" under the Clean Water Act – to ensure that the designated uses of Florida's waters are maintained (Florida Department of Environmental Protection 2016). Figure 3 shows that the annual mean dissolved oxygen increased substantially between 2010 and 2014.

4.1 Recreational Demand Data

For the recreation demand model, we use angler data from the Marine Recreational Fisheries Statistics Survey (MRFSS) and Marine Recreational Information Program (MRIP) conducted by the National Ocean and Atmospheric Administration (NOAA) (NOAA Fisheries 2008). The MRIP collects information from recreational anglers around the United States about where and how often they fish and their catch rate using surveys. While the main purpose of the MRIP is to provide estimates of the recreational catch and effort that fishery managers, stock assessors and marine scientists need to ensure the sustainability of ocean resources (NOAA Fisheries 2013), it also has limited information on anglers' characteristics. From the MRIP, we know the year, month and time that each interview takes place, zipcode of anglers' residential address, the fishing site latitudes and longitudes, number of people in each fishing group, and catch counts.

Since the MRIP data doesn't have anglers' full address or self-reported travel cost, we use the fishing site latitudes and longitudes and anglers' residential zipcode to estimate travel cost for each angler. We assume that all anglers live in the population-weighted center of their zipcodes. The Census Bureau generates Zipcode tabulation areas (ZCTAs) to represent USPS zip code service areas [3]. We use the 2010 Census Bureau ZCTA maps and population data to create a population-weighted center for each zipcode in the three counties using ArcGIS. The locations of fishing sites and population-weighted zipcode centers can be found in Figure 4. We then use the Open Source Routing Machine API to calculate round-trip travel time from the zipcode-weighted population centers to fishing sites (Luxen & Vetter 2011). The mean round trip travel time is 57.22 minutes, or about one hour (Table 2).

[3] In this paper, we refer to the US Census ZCTAs as zipcodes given the fact that in most instances they are the same.

4.2 Property Transaction Data

We collected property sales data from the property appraiser's offices in each of the three counties. In order to better identify the effect of water quality on residential property prices and be consistent with prior hedonic analyses, we restricted the sample to single-family homes. The data include sales dates, dates of construction, the size of the parcel and historical sale prices. The data from the Hillsborough County Property Appraiser's Office contains more detailed information, including dates of major improvements, size of living spaces, number of stories, number of bedrooms and bathrooms. Because we use the repeat-sales method, we restrict our data to houses that have 2 or more sales between 1998 and 2014. Hillsborough county has 186,289 qualified property sales that occurred over the 1998-2014 sample period. Pinellas county has 107,701 repeated sales, accounting for 1998-2014. Due to data limitations, we only have sales data for Manatee county from 2005-2014. Over the 10 years, 20,699 properties have repeated sales in Manatee[4].

We geocoded the sales records and related them in ArcGIS with shapefiles of house locations and characteristics from the county property appraisers' offices. We related the property data with water quality data in ArcGIS, and only use properties that have water quality monitors within a 3 km radius. 153,301 properties are dropped from our dataset because they do not have water quality monitors within a 3 km radius. Hillsborough county has 76,846 properties with water quality monitors nearby. Pinellas county has 68,848 properties with water quality data. Manatee county has 15,696 properties[5]. Table 2 reports summary statistics. The mean property price in the three counties is $230,561[6]. Properties in our dataset were sold on average 3 times from 1998-2014, and were about 32 years old when a transaction occurred. We also include a list of property attributes from Hillsborough county because Hillsborough county has the most qualified sales in our dataset, accounting for 47.62%.

4.3 Water Quality Data

We use local water quality measures from the STOrage and RETrival (STORET) data warehouse from the United States Environmental Protection Agency (US EPA), which in-

[4] Repeat sales represent 63.2% of total sales in Hillsborough county (1998-2014), 59.7% of all sales in Pinellas county (1998-2014) and 44.9% in Manatee (2005-2014).

[5] 41.3% of repeated sales in Hillsborough (1998-2014), 63.9% of repeated sales in Pinellas (1998-2014) and 75.8% of repeated sales in Manatee (2005-2014) have water quality monitors nearby.

[6] All prices are given in 2014 dollars.

cludes water quality monitoring data collected by water resource management groups across the country. Organizations, including states, tribes, watershed groups, federal agencies, volunteer groups and universities, submit data to the STORET Warehouse so that their data are publicly available. We first keep all non-missing observations with monitoring date, station latitude and station longitude. The analysis sample includes 209,336 observations coming from 5,913 monitoring stations. The mean number of readings from each station per year is 53, and the monitors report on average for 8 years. The basic descriptive statistics of dissolved oxygen (DO) from STORET can be found in Table 1. Because some stations change name slightly, and some stations across counties have the same identification number, following Kaiser and Shapiro (2017), we define a station as a unique latitude and longitude pair in the process of linking sold properties with nearby water quality measurement stations.

Figure 5 depicts the location of the Tampa Bay watershed (University of South Florida Water Institute 2017), locations of water quality monitors from STORET and the properties with repeated sales in the study. As mentioned before, the properties sold in a given calendar year were matched with monitors within a 3 kilometer radius. We then calculate the annual mean DO concentration of all the monitoring sites within 3 km radius to generate the local water quality measure for each property. The 3 kilometers radius is chosen on the base of Keiser and Shapiro's finding that nationwide water pollution impacts were significant for homes within 3 kilometers of monitors (Keiser & Shapiro 2017). We also test the robustness of our results to other choices – 300 m, 500 m and 1000 m radius, as well as another traditional method that matches houses with the closest water quality monitor. We use the average dissolved oxygen readings of each year the home was sold to capture the temporal variation in water quality. In Section 7, we test the robustness of results to utilizing the average of spring and summer water quality(Netusil et al. 2014, Walsh et al. 2017).

There is no single accepted best indicator for water quality in hedonic analysis. While STORET has information on many water quality measurements, we focus on DO as our primary local water quality indicator. DO is the most common measure of water quality in research on water pollution's economic impacts (Keiser & Shapiro 2017), and it is a key indicator of nutrient pollution. It measures the amount of oxygen in water and is essential to a healthy ecosystem. Water quality measures used in past hedonic studies include dissolved oxygen, fecal coliform, total suspended solids, dissolved inorganic nitrogen, pH, Secchi depth and harmful algal concentrations (Leggett & Bockstael 2000, Poor et al. 2001, 2007, Netusil et al. 2014, Walsh et al. 2011, 2017, Wolf & Klaiber 2017)[7]. The existing literature argues

[7]Exploring the sensitivity of our results to the choice of water quality indicators is an important issue

that water quality measurements most visible to people, such as clarity and turbidity, are most likely to explain variation in property prices. Areas with low DO would have noticeable impacts, such as decreased number of aquatic animals, or even fish kills. DO measures an important consequence of nutrient pollution. It is critical for the survival of fishes, and water quality that meets the criteria for fish also meets the criteria for most other beneficial uses and is often of good ecological status (The Environmental Protection Agency 2001). A DO concentration of 5 mg/L is a critical value for fish survival; at lower concentrations, salmonid fishes will be affected (Environmental Protection Agency 1994). Thus, we also create a dummy variable indicating whether the DO level is above 5 mg/L or not. Table 2 shows that the mean dissolved oxygen value in our sample is 5.82 mg/L, with about 35 percent of properties near waters that have less than 5 mg/L dissolved oxygen, on average.

For the recreational demand model, we use DO values from STORET monitors near fishing locations located in Tampa Bay and also seagrass acreage from the Tampa Bay Estuary Program (TBEP) (Johansson 2016). Tampa Bay seagrass meadows have become an important issue in the past three decades as scientists and environmental managers have worked to reverse the effects of nutrient pollution upon this important habitat. In 1997, the TBEP coordinated the creation of a bay-wide fixed transect seagrass monitoring program. The primary goal of the program is to document temporal and spatial changes in seagrass species composition, abundance, and distribution along a depth gradient. Data collection from 60 transects began in 1998. Currently, 62 transects are monitored due to revisions in transect selection and location(Florida Fish and Wildlife Conservation Comission 2003). Tracking the attainment of Bay-segment-specific targets for seagrass coverage provides the framework from which Bay management actions are developed and initiated (Sherwood & Kaufman n.d.). Note that, while seagrass coverage is an important positive indicator of ecosystem health and fish abundance, it could also have disamenity value to anglers because plants can catch on their fishing lines or propellers (Guignet et al. 2017).

Following the methods we used to define water quality of local water bodies, we spatially join all monitors within 3 km radius of a fishing site and calculate the annual mean DO of each year as the water quality of the site. We also match fishing sites with the closest seagrass transects within 11,000 m as another measure of water quality. Seagrass transects spread out around coastal lines in Tampa Bay. We exclude seagrass transects over 11,000 m from fishing sites since we don't want to spatially join the fishing sites that locate along the west coast of Pinellas county with seagrass transects in Tampa Bay (Figure 4). The

for future work.

locations of Tampa Bay water quality monitors can also be found in Figure 4. The mean DO level in Tampa Bay is 6.38 mg/L and the variance is smaller than DO in local waters (Table 2). One reason could be that DO monitors in Tampa Bay also include water quality monitors in the Gulf of Mexico, part of which belongs to the Tampa Bay watershed (Figure 2); the Gulf has better water quality than the Bay. Moreover, monitors are concentrated near Pinellas county where the variance can be small. The average acreage of seagrass is about 29,920 ha from 1998-2014 (Table 2).

For proximity, we calculate each property's distance to the closest local water bodies and the distance to Tampa Bay in ArcGIS. We define ponds, lakes, wetlands, rivers, swamps, reservoirs and canals as local water bodies. Water shapefiles are obtained from the Tampa Bay Water Atlas website (University of South Florida Water Institute 2017). The Atlas contains 749 water resources which includes 12 bays and 506 lakes and 230 rivers and the Gulf of Mexico. It derived data from the 1:24,000 USGS National Hydrography Dataset.

Table 3 divides observations by our principal independent variable, the DO level in local water bodies. As Table 3 reports, properties near polluted water bodies are older, smaller and have fewer bedrooms, bathrooms and stories on average. They also are located further from nearby water bodies and from Tampa Bay. Properties near polluted local water bodies are also located near the part of Tampa Bay with worse water quality. The mean percentages of properties that are adjacent to local water bodies and are adjacent to Tampa Bay are the same across the two groups. The differences across groups in Table 3 highlight the importance of controlling comprehensively for unobservables in the hedonic model.

5 Methodology

5.1 Random Utility Specification

In the random utility model of site choice, we divide neighborhoods in Tampa Bay into J zipcodes. There are K recreation sites in Tampa region where households can choose to fish. Each site has an environmental quality, for instance water quality, q_k. For each individual i who recreates in site k in year t, her utility of recreation can be expressed as a function of individual characteristics (X_{it}), site characteristics (S_{kt}) and unobservables (ν) :

$$U_{ikt} = U(X_{it}, S_{kt}, \nu) \tag{5}$$

Past literature recognizes the need to control for unobserved site characteristics in random utility models(Murdock 2006, Timmins & Murdock 2007, von Haefen & Phaneuf 2008, Melstrom & Jayasekera 2017). Failure to control for unobservables in RUM models can lead to biased parameter and welfare estimates (Moeltner & von Haefen 2011). One strategy to account for the unobserved site characteristics in the literature is a two-stage model. In the first stage,one can incorporate a list of Alternative Specific Constants (ASCs)–equivalent to site fixed effects– in the basic RUM model. The second stage would regress the observable site characteristics on the coefficients of the ASCs to generate an accurate estimate of site characteristics (Timmins & Murdock 2007, Melstrom & Jayasekera 2017). However, because the site characteristic we are interested in is water quality at fishing sites, which varies across sites and also over time, we use a site fixed effect that captures the site unobservable characteristics in our random utility model. Following Phaneuf et al. (2008), we assume the indirect utility for a visit to site k by person i is a linear function.

The preferred RUM specification is:

$$\mathrm{V}_{ikt} = \alpha_0 + \alpha_1 \mathrm{Travel}_{ikt} + \alpha_2 \mathrm{WQ}_{kt} + \gamma_t + \eta_k + \nu_{ikt} \tag{6}$$

where V_{ikt} represents indirect utility of the fishing trips, Travel_{ikt} denotes the round-trip travel time each individual i takes to recreate in site k in year t. WQ_{kt} is the water quality of the recreation site k in year t. Since all the public access fishing sites are along Tampa Bay, we use seagrass abundance data from TBEP and dissolved oxygen readings from STORET monitors located in the Bay to represent water quality. γ_t is a year fixed effect to capture variation in recreation utility over time. η_k is a site fixed effect that captures any site characteristics that vary across sites but not over time. The characteristics could include the number of boat ramps, or slips, whether the fishing site has lodges, and other things we assume remain constant over time. ν_{ikt} is an error term distributed type I extreme value. We use a conditional logit model that allows us to include alternative-specific characteristics in the model (Maddala 1983, Cameron & Trivedi 2010).

The expected utility per trip for person i in year t is then:

$$EV_{it} = ln[\sum_{k=1}^{K} exp(\hat{V}_{ikt})] + C \tag{7}$$

where $\hat{V}_{ikt}$ is the observed element of utility, and C is an unknown constant showing that the absolute level of utility cannot be measured. The average consumer surplus is given by:

$$E(CS)_{it} = \frac{EV_{it}}{\hat{\alpha}_1} \tag{8}$$

Since home buyers can learn the recreational potential of a neighborhood when gathering information for home purchases, and sellers can advertise this information, our estimate of recreational utility doesn't reflect individual heterogeneity. Instead, it can be expressed as a regional index that varies across market areas and over time. We estimate E(CS) at the zipcode level, the average recreational consumer surplus from living in zipcode j can be expressed as the average utility of all person-trips (N_{jt}) originating from the zipcode:

$$\mathrm{ECS}_{jt} = N_{jt}^{-1} \sum_{i=1}^{N_{jt}} E(CS)_{it} \tag{9}$$

We incorporate this estimated ECS_{jt} into our hedonic housing price model to reflect how recreational impacts of water quality can be reflected in housing prices.

5.2 Basic Hedonic Specification

In the hedonic property model, each home price is the sum of implicit prices for individual characteristics of the house. The general form of the hedonic price equation is:

$$hp = f(S, L, E) \tag{10}$$

where hp represents the property prices, S denotes the structural characteristics of a property, L denotes location features, such as neighborhood economic status and school districts, and E denotes environmental conditions. An environmental condition, like water quality nearby, is an attribute purchased along with homes, thus variation in this attribute should be reflected by variation in home prices. In equilibrium the implicit price of environmental quality can be obtained by taking the partial derivative of hp with respect to E:

$$p_E = \frac{\partial hp}{\partial E} \tag{11}$$

We start our analysis with standard econometric identification of hedonic analysis using pooled data from the three counties:

$$lnP_{ijbt} = \beta_0 + \beta_1 X_i + \beta_2 lnWQ_{it} + \beta_3 ECS_{jt} + \gamma_b T_t + \epsilon_{ijt} \tag{12}$$

where we have specified the first stage regression as a log-log form specification with the inflation-adjusted price of house i sold in zipcode j census block b during year t given by P_{ijbt} [8]. $ln\mathrm{WQ}_{it}$ is the log transformation of water qualities nearby property i at time t. ECS_{jt} is the estimated recreational value in the household's zipcode j in year t. X_i is a vector of house-specific structural characteristics, including number of bedrooms, number of bathrooms, lot acreage and number of stories. All the specifications include census-block-by-year fixed effects ($\gamma_b T_t$) to control for unobserved differences across space and over time, such as school district quality, median income or the unemployment rate. ϵ_{ijt} is an idiosyncratic error term.

Given data limitations, our X_i vector includes the lot size (in acres), house heated area (in square feet), age of the house, number of bedrooms, number of bathrooms, and number of stories. Though there is no hard-and-fast answer of the correct list of structural variables from the theory, existing studies also include factors such as the presence of pools, basements, garages, and piers(Walsh et al. 2011, Walls et al. 2015, Walsh et al. 2017, Wolf & Klaiber 2017). We also estimate a series of regressions to examine the sensitivity of our coefficients with the dissolved oxygen dummy variable.

5.3 Property Fixed Effect Model

A preferable approach is the repeat sales model (Palmquist 1982). The repeat sales model differences out unobserved house attributes by focusing on the changes in housing prices for the same property over time. It has been used to estimate the value of wind power facilities, air pollution, views, and land use change, and other amenities and disamenities (Heintzelman et al. 2012, Bajari et al. 2012, Walls et al. 2015, Cohen et al. 2016), but not

[8]Hedonic theory does not provide guidance on the functional form of the estimated equation. Functional form is mostly determined by empirical analysis (Freeman et al. 2014). The most important literature on this issue is Cropper et al. (1988). The authors find that flexible econometric specification for the equilibrium price function performed best when all variables were included in the model, but simpler functional form, such as log-log, performed best in the presence of omitted variables(Cropper et al. 1988). Though an important later study used Monte Carlo analysis to evaluate over 540 different hedonic models and concluded that the more flexible functional forms, such a quadratic Box-Cox model, outperform the linear, log-linear, and log-log specifications (Kuminoff et al. 2010), we use a log-log specification so that our results can be comparable to existing literature. Estimating additional models with different functional forms is an important area for future work.

water quality.

In Table 3, the observed characteristics of properties in the two groups differ significantly, suggesting that unobserved variables could also differ substantially between the two groups. The property fixed effect model has advantages in controlling for unobservables:

$$ln\text{P}_{ijt} = \beta_0 + \beta_1\text{Age}_{it} + \beta_2 ln\text{WQ}_{ijt} + \beta_3\text{ECS}_{jt} + \gamma_j\text{T}_t + \epsilon_{ijt} \tag{13}$$

The main coefficients of interest are β_2 and β_3. Using dissolved oxygen as the main water quality measure, we expect β_2 to be positive since higher DO means that water quality is better. We also expect β_3 to be positive due the assumption that buyers are willing to pay higher prices for the properties that offer more and better recreation opportunities. Home age is the only time-varying property characteristic in our data.

Using only properties with repeat sales in the estimation, α_i can remove the effects of time-invariant omitted variables and controls for temporal shocks. But the repeat sales model is not without its challenges. First, only a subset of housing units have sold more than once, given the limited market and time period of the study. Second, homes that sold more than once may have unique unobserved attributes compared to properties that sold only once in given study period. Thus, restricting the sample to only repeated sales may reflect a selective implicit price (Freeman et al. 2014). The 300,000 repeated sales in our dataset, and 160,000 sales within 3 km of water bodies account for more than 50 % and 30%, respectively, of qualified sales in our sample, thus they may be reasonably representative of the housing market in the Tampa metropolitan area.

5.3.1 Fixed Effect Model with Proximity

Although Equation (13) captures the overall effect of water quality degradation on property prices, it does not allow us to examine the spatial heterogeneity of water quality impacts on waterfront and near-water properties. Thus, we employ the following specification:

$$\begin{aligned} ln\text{P}_{ijt} = {} & \beta_0 + \beta_1\text{Age}_{it} + \beta_2 ln\text{WQ}_{ijt} + \beta_3 ln\text{WQ}_{ijt} \times \text{ DistancetoWater}_i \\ & + \beta_4\text{ECS}_{jt} + \beta_5\text{ECS}_{jt} \times \text{ DistancetoTampaBay}_i + \alpha_i + \gamma_j\text{T}_t + \epsilon_{ijt} \end{aligned} \tag{14}$$

where DistancetoWater_i captures the remaining proximity effect for non-adjacent properties. Equation 14 allows the impact of DO concentration on the home price to vary with adjacency and distance. Note that the independent effects of distance to water are absorbed in α_i in Equation 14.

Equation (14) is the preferred specification in our study. Ecosystem services could relate to both the selection of a house and neighborhood and the reasons for choosing a recreation site, and policies often affect the quality of local neighborhoods and local recreation sites simultaneously (Phaneuf et al. 2008). Water quality at fishing sites in Tampa Bay, as the main site of recreational use of homeowners in the Tampa region, may impact local housing prices through the recreation opportunity index term ECS_{jt}. $\text{DistancetoTampaBay}_i$ measures the distance of each property to the closest point of Tampa Bay. The key variables of interest are the interactions between time varying water quality measures (both locally and the Bay) and the various water proximity measures.

6 Estimation results

6.1 First Stage Recreational Demand Results

Results for the recreational demand model estimation are reported in Table 4. The estimates are statistically significant and consistent with prior expectations. In general people tend to visit recreational sites that require less travel time, and with better water quality (higher DO value). The coefficient on travel cost shows that as the travel time to a site j increases by 1 minute, the probability of an angler fishing in the site decreases by about 6%. Anglers from the Tampa region are 9% more likely to recreate at a site if the DO level increases by 1 mg/L. The coefficient on seagrass abundance is statistically significant and negative. Though seagrass abundance is an indicator of good water quality in the Tampa Bay, the negative coefficient may be due to the fact that seagrass can be a disamenity to anglers. The presence of seagrass can damage fishing boats, we find that a 1 ha increase in seagrass abundance can lower the probability of fishing at a site by 16%. Using parameters estimated from Equation (6), we then estimated the expected utility from recreation trips initiating from zipcode j following Equation (8) and Equation (9). The average value of expected utility (ECS_{jt}) from the RUM model calculated from trips occurring in each zipcode j year t is 62.61 with a standard deviation of 4.17 (Table 2).

To estimate the marginal effect of DO in Tampa Bay recreational fishing sites, we recalculated the ECS_{jt} using the coefficient estimate from Table 4 following Equation 7 through 9. We estimate that if the DO level in Tampa Bay increased by 1 mg/L, the average ECS_{jt} would increase to 64.08. Given that the mean DO level in Tampa Bay watershed increases by 11 % during 1998-2014 (Table 3), this increase is associated with 1.72% increase in the expected utility of recreation. In the next section, we incorporate the recreational utility index into our hedonic models.

6.2 Basic Hedonic Model and Fixed Effect Model Results

Estimation results for the two base specifications from Equation (12) and Equation (13) are shown in Table 5. The first two columns report estimation results based on Equation (12), Column 3 reports estimation results based on Equation (13).

The coefficients on the house characteristics have largely expected signs. Homeowners in Tampa prefer larger and newer homes with more bathrooms but fewer stories and bedrooms. House prices increase with lot acreage and square footage of heated area. Adding an additional bathroom adds more value to the house than if the space is used for another bedroom. Consumers in Tampa don't seem to value additional bedrooms, but it could be because we are controlling for square footage of the house, and more bedrooms mean smaller bedrooms. Adding an additional story to the house, while holding other things constant, reduces the property price significantly. It may be caused by the additional heating and cooling costs of multistory homes, and the fact that single-story homes are less likely to be damaged by severe storms common to the region (e.g. hurricanes).

The classic hedonic models provide counter-intuitive results for both log-transformed dissolved oxygen and the dissolved oxygen dummy. Column 1 and Column 2 from Table 5 show the results using the classic hedonic model based on Equation (12). Column 1 results imply that as the dissolved oxygen level increases by 1 percent, the mean property price is reduced by about 0.027%. Column 2 results indicate that when the DO level in nearby local water is above 5 mg/L, the mean property price decreases by 0.024%. The coefficient on the recreation utility index shows that with one unit increase in Recreation Utility Index (ECS_{jt}), the average property price drops by 7.51%. This is likely due to omitted variable bias. Lower DO and better recreation opportunities are likely to occur in areas with more economic activity, easier access to water and more runoff; home values may also be higher in these areas. While we can only control for a short list of house attributes, even an extensive list of attributes may not eliminate this problem.

Turning to the property fixed effect specifications, Column 3 shows that a 10 percent increase in DO leads to 0.101% increase in mean property prices. This is consistent with findings in other studies that estimate the impacts of dissolved oxygen on housing prices (Netusil et al. 2014).

We find both continuous and discrete representations of DO provide important information on how residents in Tampa value water quality. The significant positive result from Column (3) shows the marginal implicit price for DO is 0.0101% of the mean property price in Tampa. Given the average price of properties, consumers' marginal willingness-to-pay for DO is $230 for a 10% increase in DO. There are 55,687 properties near polluted water (DO $<$ 5mg/L) from 1998-2014, and the mean DO level in their nearby water bodies is about 4 mg/L. If the mean DO level in all those local waters is increased to 5 mg/L, the economic benefits would be more than $32 million, or about $575 per household.

While we are still working to refine and interpret our estimates, the economic benefit from improved recreation opportunity may exceed the benefit from improving local water quality.

6.3 Hedonic Estimation with Proximity

Accounting for proximity to local waters and distinguishing waterfront properties from nearby properties appears to be important, based on results reported in Table 6. The proximity variables are converted from meters to thousands of meters. Results from both Model 1 and Model 2 (Table 6) show that more DO leads to higher property prices, but the positive impacts diminish as properties move away from the water. The further the distance of a property from a local water body, the lower is the impact of local water quality on the property sale prices. But the negative distance results are not robust to the inclusion of more detailed location of polluted local water bodies as shown in Model 3 and Model 4.

Table 7 reports results from the estimation of Equation (14). In both the model with continuous DO concentrations (Model 1) and the model with the 5 mg/L DO thresholds, we see positive and significant effects of property prices, positive and significant effects of improved recreational opportunities on property prices, and the tendency of both effects to decrease with distance from the relevant water bodies.

6.4 Robustness Checks

We first compare our hedonic fixed effect models with and without the recreation utility index (ECS_{jt}). Table 8 shows that the sign and magnitude of coefficients of lnDO and the DO dummy are consistent across specifications. That is, the magnitude of the estimated impact of local water quality on property prices does not change when we include the recreational index in the regressions. This suggests that the two parameters are, in fact, picking up different aspects of MWTP for water quality improvements. It also suggests that, prior hedonic estimates of the annually value of local water quality improvements may not be biased – they are simply not inclusive of recreational benefits to homeowners. Thus, we are safe to exclude the ECS_{jt} in the following robustness checks for simplification.

As discussed, our main models take the average of all monitors within a 3 km radius of a property to represent the water quality of local water bodies. Though based on prior literature (Keiser & Shapiro 2017), this is a somewhat arbitrary choice. To test the robustness of our results, we estimate the property fixed effect models using alternative radii to link properties with water quality monitors nearby: 1 km, 500 m and 300 m. We also try linking properties with the average annual water quality at the nearest monitor. We exclude the waterfront and bayfront dummies in these specifications to simplify the estimation. Table 9 shows the results of these robustness checks, which indicate that our findings are robust to these alternative methods. The signs of the coefficients for the DO dummy are all positive. In addition, the property value effects of local water quality get larger as the radius gets tighter, consistent with previous literature (Walsh et al. 2011, 2017, Wolf & Klaiber 2017), though the effects eventually lose significance due to small numbers of observations for homes within 300 m of one or more monitors [9].

The closest monitors also report positive but insignificant results (Row 5). This is the method widely used in existing literature to link property sales with water quality data. One reason for our insignificant result could be that we do not restrict our sample to properties near water. Thus, the closest monitor method links some properties to monitors relatively far away. While the existing literature takes advantage of the closest monitors

[9]When we spatially join properties with monitors within a 300 m radius, we end up with only 1873 property sales locate near water bodies with DO readings. This is one of the challenges in applying a fixed effect model in hedonic analysis. The limited number of repeat sales in the three counties restricts our ability in to focus on the local water quality in a smaller area around each property.

method by limiting the sales to properties within 1 km from water bodies, they also end up with smaller sample sizes that are not suitable for fixed-effect models. Thus, there is a trade-off between the use of fixed effect models in correcting for omitted variable bias, and spatial precision in identifying the impacts of local water quality.

The past literature presents several options to represent the impact of the inter-temporal variation in water quality on home-buyers' decisions. The popular approach is to use the average over the year the home was sold, and it is the approach we take in the main analysis (Gibbs et al. 2002, Leggett & Bockstael 2000, Poor et al. 2007, Walsh et al. 2011). Netusil et al. (2014) use wet season and dry season indicators and find that dry season (summer) water quality is more relevant to homeowners since residents are more likely to recreate in summer (Netusil et al. 2014). Walsh et al. (2017) compare the average water clarity of spring and summer in the years of and prior to the home sale (Walsh et al. 2017). They also compare 1 year and 3 year averages and find that the 3 year average generally has a larger implicit price, but the longer temporal window may capture more than just the impact of water quality. When we substitute spring and summer water quality for our annual averages, we find that the signs, significance levels and magnitudes of the main coefficients are almost identical to our main estimates. These results may be caused by the fact that weather in Florida is warm for most of the year, so residents may recreate year-round. These results are not included in the tables, but are available on request.

7 Conclusion

Taken together, our integrated two stage model and robustness checks suggest that water quality improvements indicated by increases in DO, improve both recreational amenities and aesthetic amenities, and that homeowners in Tampa Bay have significant MWTP for both of these improvements. Over 1998-2014, the average DO level in the Tampa Bay watershed increased by 11%. From the first stage estimation, an 11% increase in DO level in Tampa Bay is associated with a 1.72% rise in the expected utility of recreation living in neighborhood j in year t. From the second stage estimation, the 1.72% increase in recreation utility index is associated with about 22.45% rise in the average property price. Improvement of recreational water quality in Tampa Bay over this period may create a high economic benefit, but we are still working on refine and interpret our results.

For the 11% local water quality increase observed between 1998-2014, willingness-to-pay is \$253 per property. Applying these findings to a larger-scale improvements in local water quality could have large economic benefit. There are total of 55,687 property sales near polluted water (DO $<$ 5 mg/L) from 1998-2014, the 11% increase in mean DO level since 1998 yields a economic benefit of $14 million for these households. The mean DO level in their nearby water bodies is about 4 mg/L. Improving the mean DO levels of these waters from 4 mg/L to 5 mg/L could result in over $32 million in economic benefit.

Though our results are preliminary, homeowners appear to value recreational benefits of pollution reductions more than local amenity benefits. Consistent with the existing literature, we also find that water quality impacts on nearby property prices diminish with distance from the polluted water, whether through recreational amenities or aesthetic amenities.

When applying hedonic analysis to evaluate water quality to inform cost-benefit analysis, excluding the MWTP for recreational benefits of water quality improvements would lead to an underestimate the value of water quality improvements to homeowners. The two effects appear to be separable in Tampa Bay, suggesting prior hedonic estimates of the value of water quality may be unbiased estimates of local amenity values, but that they exclude the potentially much larger regional recreational values expressed in housing prices.

Further work on our agenda includes using a residential sorting model, rather than a RUM, in the first stage to account for potential endogeneity in recreation demand model. Similar to the endogeneous congestion analysis in Timmins & Murdock (2007), water quality in recreation sites can also endogenously affect recreation demand. We also plan to test the more flexible quadratic Box-Cox functional form to the hedonic model and compare it with the log-log form presented in this paper. Kuminoff et al. (2010) find that the Box-Cox form outperforms the linear, log-linear, and log-log specifications. Third, STORET has many water quality indicators, such as fecal coliform, chlorophyll a, turbidity, total nitrogen and total phosphorous. We will explore the possibility that homeowners value indicators other than DO, including the Water Quality Index used by the EPA.

This work adds to the literature on understanding how people value water quality improvements, especially nutrient pollution abatement. Dead zones, as consequences of nutrient pollution, cause large amounts of economic damages each year in the United States and elsewhere, and many federal and state regulations have been implemented to tackle this problem. Further work to help policymakers better understand how people value nutrient pollution abatement can contribute to more comprehensive evaluation of these regulations.

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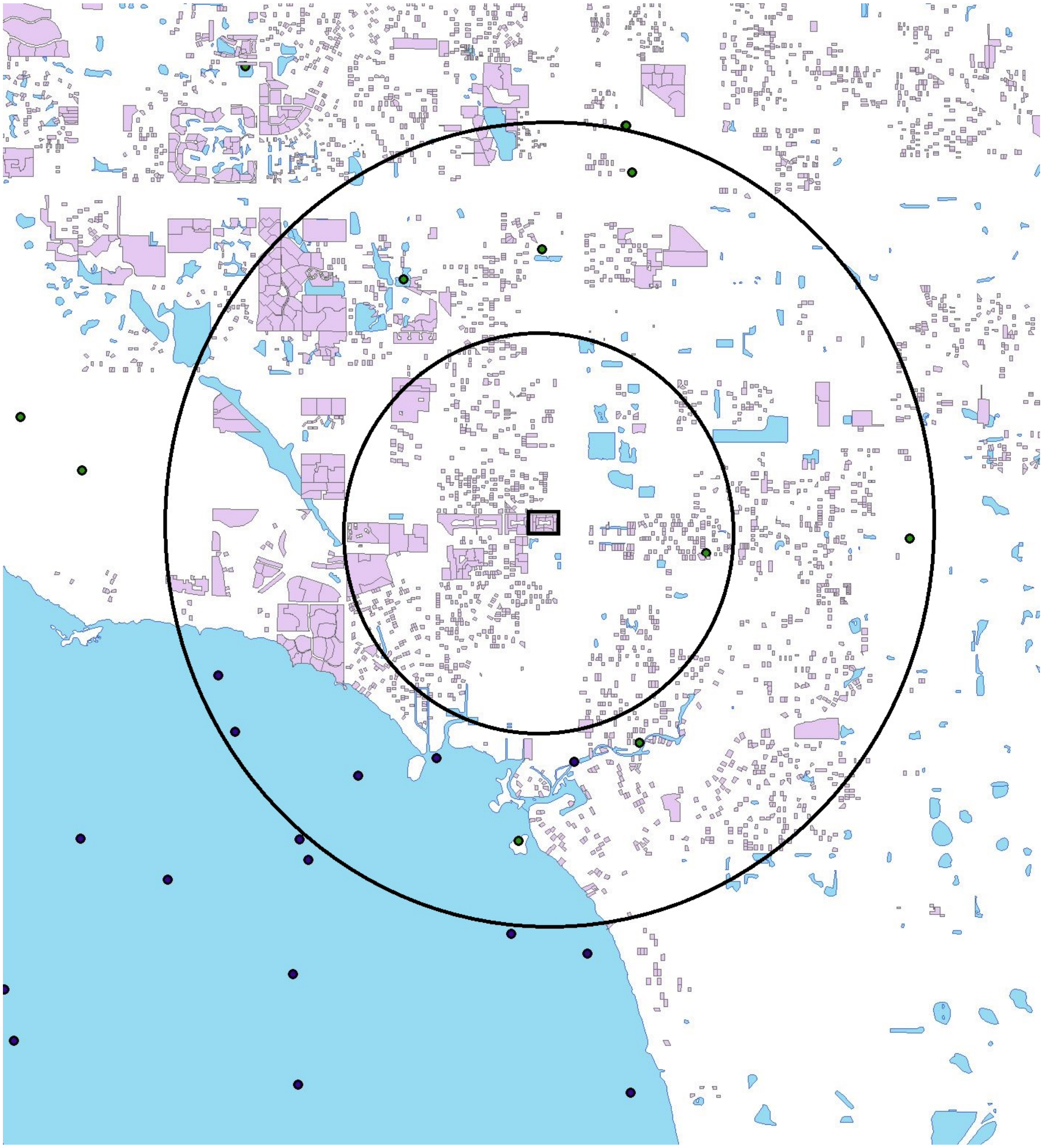

Figure 1: Properties and Water Quality Monitors in Manatee County

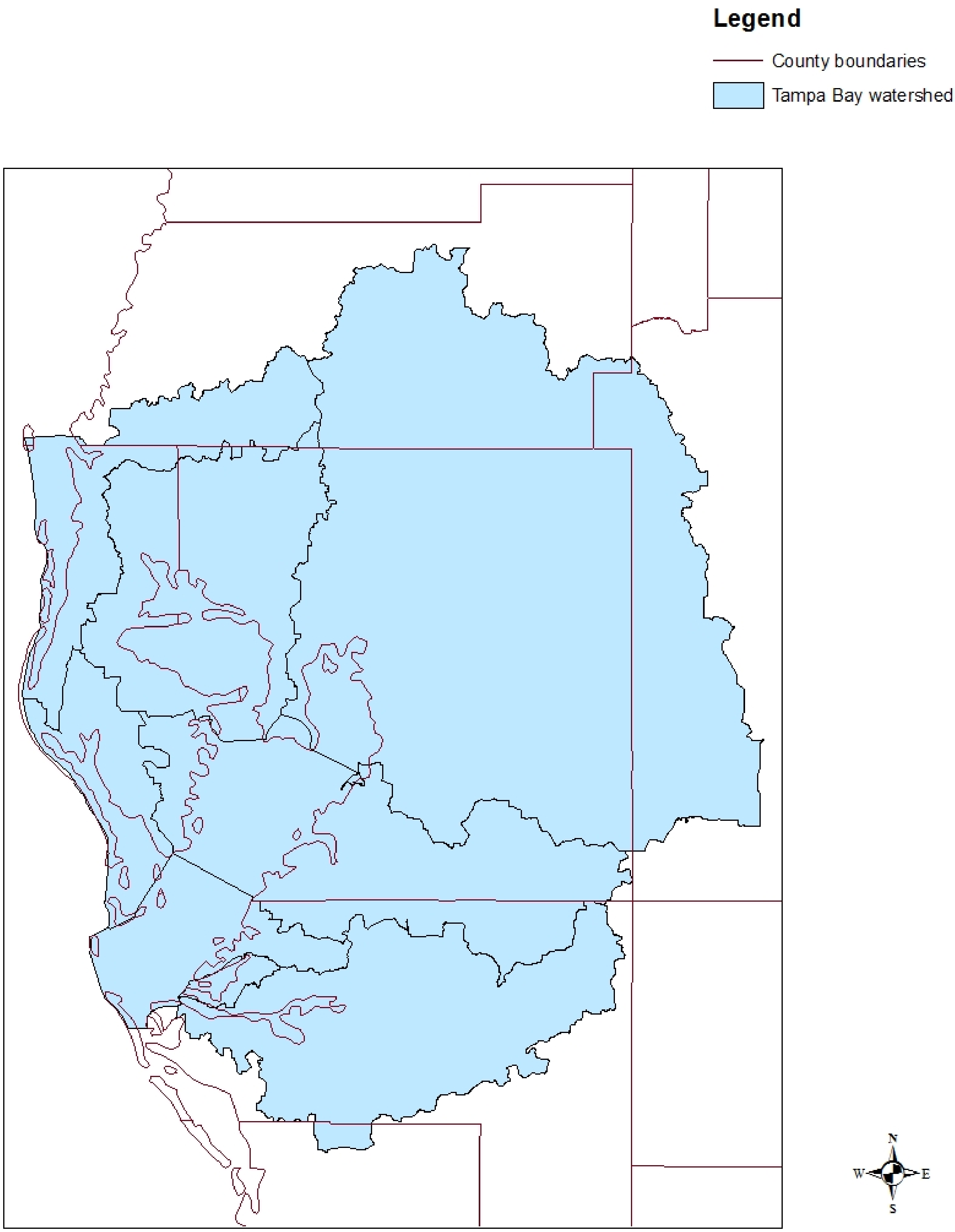

Figure 2: Map of Study Area is Tampa Bay watershed, Florida

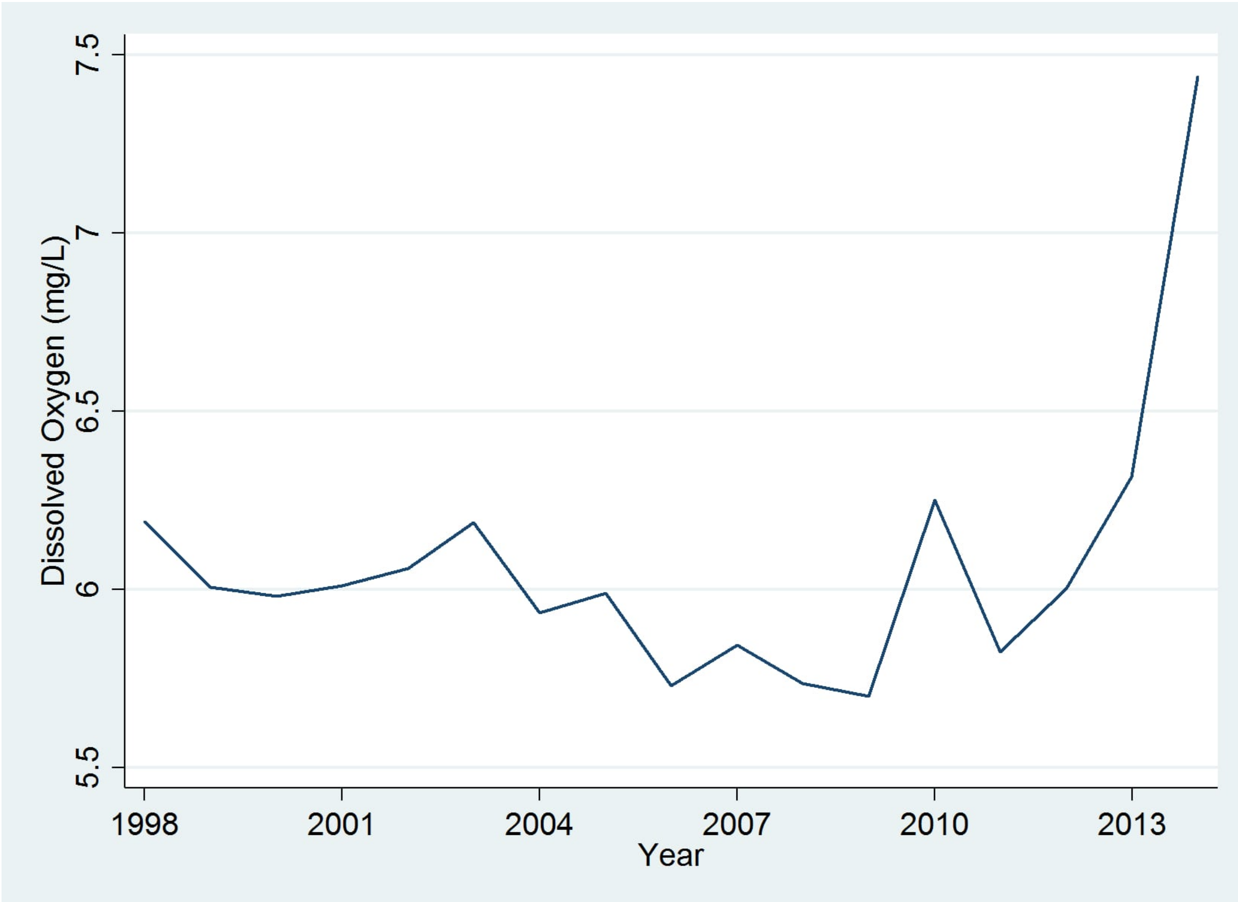

Figure 3: Dissolved Oxygen Trend 1998-2014

Notes: Graphs show the linear dissolved oxygen trend which also controls for year fixed effects and monitoring site fixed effects. Standard errors are robust.

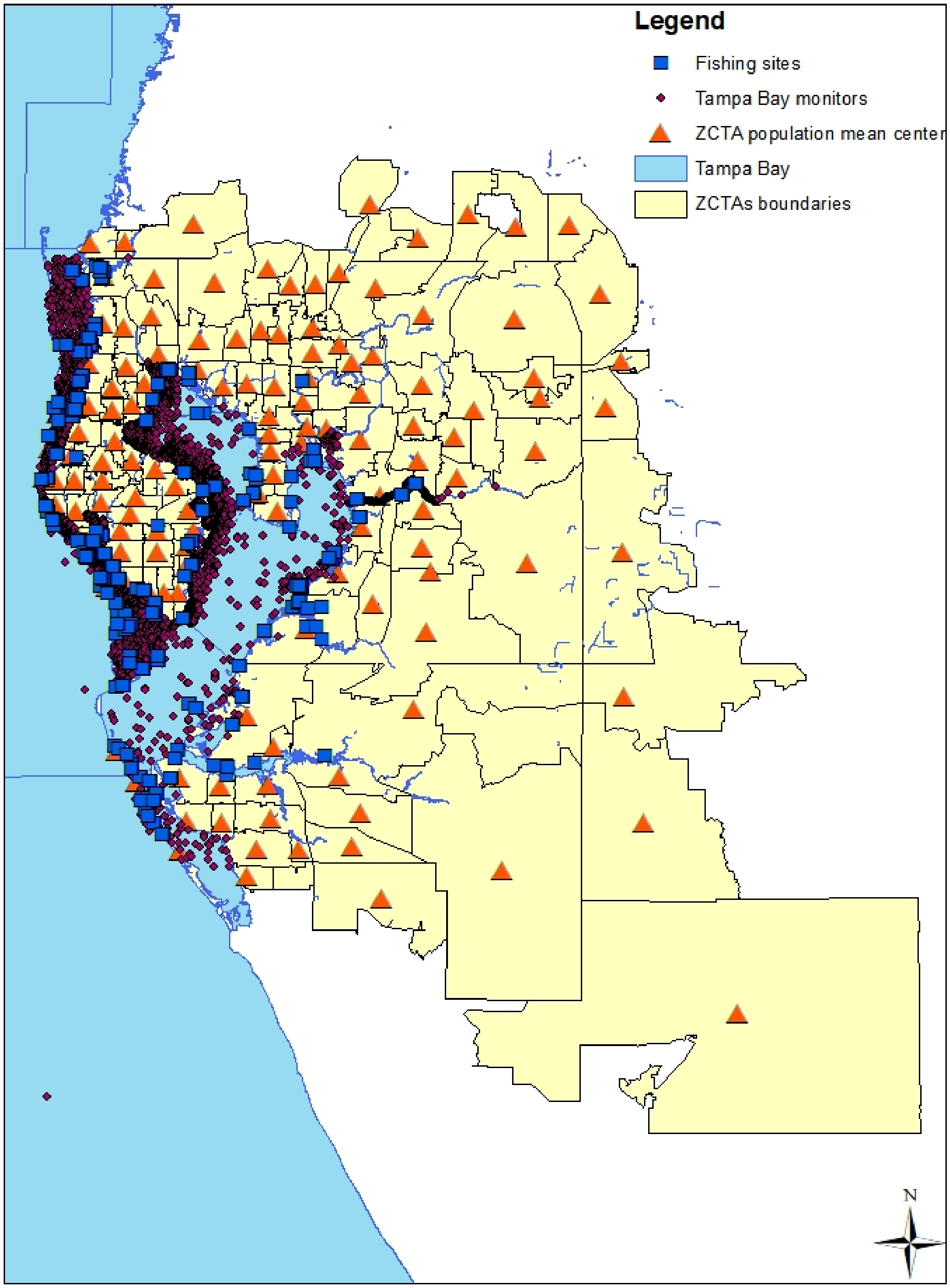

Figure 4: Map of Fishing Sites and Population Center of ZCTAs

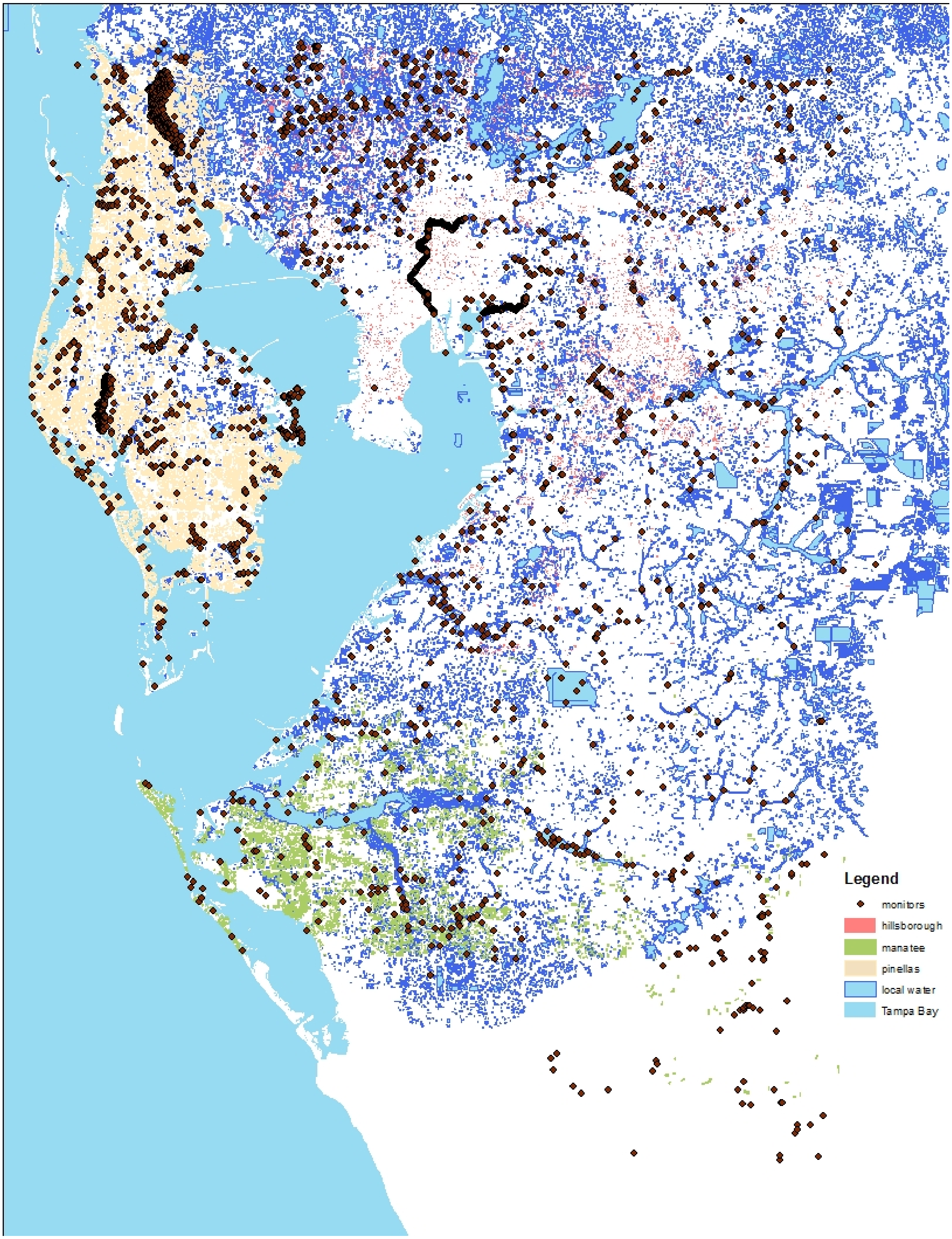

Figure 5: Map of Water Quality and Repeated Property Transactions Data

Table 1: Water Pollution Basic Descriptive Statistics

	Dissolved Oxygen
mean	5.94026
min	0
5th percentile	1.68
95th	8.89
max	28740
# of	
obs (without missing)	209336
monitoring sites	5913
mean readings per monitor per year	53
mean readings per monitoring site	443
mean years per monitoring site	8
missing	44
yearly average	
# of obs	22714
mean	5.92772
min	0
5th percentile	2.5265
95th percentile	8.725
max	10.8

Table 2: Descriptive Statistics

Variable	N	Mean	Standard Deviation	Min	Max
Water quality measures					
Local dissolved oxygen (DO)	161388	5.82	3.95	0.18	104.00
Tampa Bay DO	161388	6.38	0.97	3.74	9.02
Dummy for local DO	161388	0.35	0.48	0.00	1.00
Seagrass acreage	161388	29920.58	4418.42	24843.00	40297.00
Recreation demand					
Travel time	161388	57.22	35.31	1.64	261.34
Estimated recreation demand index	149542	62.61	4.17	51.35	67.01
Distance to water					
Distance to Tampa Bay	161388	15348.79	15356.15	0.00	120557.70
Distance to water bodies	161388	917.11	1077.42	0.00	38217.63
Property properties					
Sale price (2014 dollar)	161388	230561.50	154648.10	5262.23	1541511.00
Number of repeat sales	161388	2.56	0.76	2.00	7.00
Repeat sales – Hillsborough	76846	2.62	0.79	2.00	7.00
Repeat sales – Pinellas	68846	2.56	0.76	2.00	6.00
Repeat sales – Manatee	15696	2.31	0.56	2.00	6.00
Year	161388	2005.79	4.44	1998.00	2014.00
Property age	161385	31.86	21.22	1.00	133.00
Number of bedrooms	76846	3.21	0.81	0.00	8.00
Number of bathrooms	76846	2.09	0.68	0.50	6.50
Number of stories	76846	1.18	0.41	0.00	6.00
Heated area	76846	1756.02	669.49	400.00	6191.00
Lot acreage	92529	0.27	0.41	14.55	24872.22

Table 3: Summary Statistics by DO Level in Nearby Water Bodies

Variable	DO >5mg/L	DO<5mg/L
DO level	6.786488	3.987896***
	(4.557541)	(0.793955)
Seagrass acreage	30600.63	28629.76***
	(4667.104)	(3562.314)
Property age	30.78656	31.5763***
	(20.59694)	(23.18531)
Price in 2014 dollar	236733.3	214490.5***
	(158108.4)	(139122.1)
Distance to local water	884.7475	978.5272***
	(1111.28)	(1007.198)
Distance to Tampa Bay	14370.69	17205.37***
	(13731.78)	(17895.23)
Local water front	0.0480979	0.0470128
	(0.2139742)	(0.2116681)
Tampa Bay front	0.0106432	0.0112055
	(0.102616)	(0.1052622)
N	105,701	55,687
Number of bedrooms	3.261176	3.142298***
	(0.8025294)	(0.8172554)
Number of bathrooms	2.125861	2.050403***
	(0.6617159)	(0.7032632)
Number of stories	1.181847	1.173358***
	(0.4053854)	(0.4065889)
Heated area	1796.238	1707.23***
	(670.4052)	(665.1376)
Lot acreage	0.2791506	0.2304873***
	(0.4192332)	(0.2588822)
N	42,126	34,720

Note: Means, with standard deviations in parentheses, for observations used in regression analysis. Asterisks in column 2 indicate significant difference in means between the two groups, according to t-test for difference in means.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 4: First Stage Recreation Demand Model

	Fishing dummy
Travel cost (minutes)	-0.0635***
	(-133.15)
Dissolved oxygen (mg/l)	0.0900***
	(9.57)
Seagrass abundance	-0.160***
	(-14.79)
Site FE	Yes
Observations	1,738,137

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Second Stage Hedonic Estimations

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
ln(DO)	-0.0265***		0.0101***	
	(0.00355)		(0.00261)	
DO >5mg/L		-0.0236***		0.00785***
		(0.00312)		(0.00214)
Recreation demand index	-0.0751**	-0.0775**	0.206***	0.203***
	(0.0278)	(0.0278)	(0.0348)	(0.0348)
Property age	-0.00359***	-0.00360***	-0.0108***	-0.0108***
	(0.000143)	(0.000143)	(0.00303)	(0.00303)
Lot acreage	0.0287***	0.0294***		
	(0.00674)	(0.00676)		
Heated area	0.000556***	0.000556***		
	(0.00000619)	(0.00000618)		
Number of bedrooms	-0.0276***	-0.0278***		
	(0.00377)	(0.00377)		
Number of bathrooms	0.0955***	0.0953***		
	(0.00539)	(0.00539)		
Number of stories	-0.0583***	-0.0584***		
	(0.00650)	(0.00650)		
N	65683	65683	144933	144933
R-squared	0.734	0.734	0.931	0.931

Standard errors in parentheses and have been clustered at property level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Hedonic Estimation with Proximity to Local Water

Variable	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
ln(DO)	0.0332***		0.00779	
	(0.00425)		(0.00627)	
ln(DO) $\times$ Distance to local water	-0.000972***			
	(0.000116)			
ln(DO) $\times$ Waterfront	0.0105		0.00518	
	(0.00681)		(0.0117)	
Property age	-0.0116***	-0.0116***	-0.0116***	-0.0116***
	(0.00271)	(0.00272)	(0.00272)	(0.00272)
DO $>$ 5mg/L		0.0231***		0.00555
		(0.00289)		(0.00677)
DO $>$ 5mg/L $\times$ Distance to local water		-0.000990***		
		(0.000102)		
DO $>$ 5mg/L $\times$ Waterfront		0.0159*		0.00773
		(0.00727)		(0.00966)
ln(DO) $\times$ Distance from $0-0.2$km			0.00593	
			(0.0107)	
ln(DO) $\times$ Distance from $0.2-0.4$km			0.0109	
			(0.0107)	
ln(DO) $\times$ Distance from $0.4-0.6$km			-0.00615	
			(0.0113)	
ln(DO) $\times$ Distance from $0.6-0.8$km			0.0133	
			(0.0126)	
ln(DO) $\times$ Distance from $0.8-1$km			0	
			(.)	
ln(DO) $\times$ Distance $>$ 1km			0.0134	
			(0.0118)	
DO $>$ 5mg/L $\times$ Distance from $0-0.2$km				0.000532
				(0.00770)
DO $>$ 5mg/L $\times$ Distance from $0.2-0.4$km				0.00380
				(0.00762)
DO $>$ 5mg/L $\times$ Distance from $0.4-0.6$km				-0.0107
				(0.00811)
DO $>$ 5mg/L $\times$ Distance from $0.6-0.8$km				0.00292
				(0.00871)
DO $>$ 5mg/L $\times$ Distance from $0.8-1$km				0
				(.)
DO $>$ 5mg/L $\times$ Distance $>$ 1km				0.00211
				(0.00770)
Property FE	Yes	Yes	Yes	Yes
Census block * Year FE	Yes	Yes	Yes	Yes
N	159382	159382	159382	159382
R-squared	0.931	0.931	0.931	0.931

Standard errors are in parenthesis and have been clustered at the property level.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 7: Hedonic Estimation with Recreation Utility Index

	(1) Model 1	(2) Model 2
ln(DO)	0.0141**	
	(0.00457)	
ln(DO) × Distance to local water monitors	-0.00168	
	(0.00141)	
DO > 5mg/L		0.00793*
		(0.00371)
DO > 5mg/L × Distance to local water monitors		-0.000197
		(0.00112)
ECS_{jt}	0.249***	0.246***
	(0.0354)	(0.0354)
ECS_{jt} × Distance to Tampa Bay	-0.0000908***	-0.0000904***
	(0.0000118)	(0.0000118)
Property age	-0.0109***	-0.0109***
	(0.00305)	(0.00305)
N	144933	144933
R-squared	0.931	0.931

Standard errors in parentheses and have been clustered at property level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Hedonic Fixed Effect Models With and Without Recreation Utility Index

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
ln(DO)	0.0101***		0.00971***	
	(0.00261)		(0.00242)	
DO >5mg/L		0.00785***		0.00632**
		(0.00214)		(0.00203)
ECS_{jt}	0.206***	0.203***		
	(0.0348)	(0.0348)		
Property age	-0.0108***	-0.0108***	-0.0116***	-0.0116***
	(0.00303)	(0.00303)	(0.00272)	(0.00272)
N	144933	144933	159382	159382
R-squared	0.931	0.931	0.931	0.931

Standard errors in parentheses and have been clustered at property level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Estimated Coefficients on Dissolved Oxygen dummy with Different Methods in Defining Local Water Quality

	(1) Model with No Proximity	(2) Model with WQ and Proximity	(3) Model with Seagrass
3km monitors	0.00632***	0.00291	0.0341
(N=159,382)	(0.00203)	(0.00246)	(0.00246)
1km monitors	0.0187***	0.0226**	0.0229***
(N=33,415)	(0.00541)	(0.00689)	(0.00692)
500m monitors	0.0339***	0.0454***	0.0454***
(N=18,341)	(0.00735)	(0.00989)	(.00989)
300m monitors	0.0226	0.0318	0.0327
(N=1,873)	(0.02409)	(0.03722)	(0.03717)
Closet monitors	0.000363	0.00626	0.00661
(N=15,411)	(0.0114)	(0.0136)	(0.0136)

Standard errors are in parenthesis and have been clustered at the property level.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.