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A more comprehensive estimate of the value of water quality ☆

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ABSTRACT

The estimated marginal cost of U.S. water pollution control often exceeds its marginal benefit. We provide intuition, theory and empirical evidence suggesting that the hedonic property model—a common revealed-preference approach to valuing pollution control—may not capture water's recreational benefits. Using the case of Tampa Bay, Florida, we estimate willingness to pay (WTP) for water quality improvements by combining a recreation demand model with a hedonic property model. Results indicate that homeowners have significant WTP for both local and regional recreational water quality improvements and suggest that prior hedonic studies may underestimate the benefits of water pollution control.

1. Introduction

Valuation of non-market environmental amenities such as clean air and water is a long-standing challenge in economics, but the literature (especially for air pollution) has developed significantly over the past few decades. The hedonic property model, a prominent valuation tool attributed to Rosen (1974), monetizes pollution and pollution control impacts via their influence on property prices.

Plausibly causal estimates of the value of environmental amenities and disamenities using hedonics have valued proximity to hazardous waste sites (Greenstone and Gallagher, 2008), shale gas wells (Muehlenbachs et al., 2015), and improvements in air quality under the Clean Air Act (Bento et al., 2015; Bajari et al., 2012). The general approach in contemporary hedonics defines a circle of influence around properties in the sample – for example, assuming that air quality affects property values at some standard radius – usually performing sensitivity analysis around the baseline radius and reporting a range of results. This seems, intuitively, to be good practice when household members tend to be exposed to the environmental condition primarily at or near their home.

Water pollution has also been valued using hedonic property methods using this approach (e.g., Keiser and Shapiro (2019b), Jerch (2021)). The assumption that exposure to water pollution occurs primarily at or near one's property may not be tenable, however. In this paper, we argue for a departure from the long prior literature using hedonics to value water quality changes, based on this premise. Our basic intuition is that, while property owners likely have some marginal willingness to pay (MWTP) for pollution reductions in small creeks, canals, streams, ponds, lakes and other waterbodies near their homes, their MWTP for water quality is likely also influenced by the degree to which water quality affects regional recreational opportunities. For example, a resident of Brooklyn, New York, may value improvements in water quality in the Gowanus Canal if they live nearby; the canal may smell better and be more visually appealing, for example. But Brooklyn residents 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. However, the standard hedonic approach may not capture

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such benefits of improvements in waterbodies that are farther away from the homes of these residents. A more comprehensive economic valuation framework is needed in order to evaluate the benefits of major water quality improvements and compare them with costs.

In this paper, we apply such a framework to the case of water pollution abatement in Tampa Bay, Florida. We show that the recreation benefits of reducing water pollution are substantial, and that excluding them results in dramatic underestimation of benefits. We demonstrate that the hedonic property model may not be well-suited in its basic formulation to capture the recreational benefits of water pollution abatement. The standard hedonic property approach fails in this setting because, unlike air pollution, individuals in high-income countries like the United States are exposed to ambient water pollution via recreation at times and in places of their choice, at locations that may be some distance from where they live. Thus, an accurate estimate of water pollution abatement benefits at recreation sites requires an approach that matches property owners with the sites they frequent.

Theoretically, we are motivated by an integrated, two-stage model of recreation and housing demand developed by Phaneuf et al. (2008). The first stage consists of a random-utility model of recreation demand, with which we estimate Tampa Bay households' indirect utility from recreational fishing trips. The second stage involves a hedonic property model. The time-varying independent variables in the hedonic model include both local ambient water quality very close to each home and estimates of indirect utility from the first-stage recreation demand model, such that our hedonic estimates of MWTP reflect the value of both amenity and recreational improvements due to water pollution abatement. As a result, we are able to estimate separately the portions of property value increases due to water quality improvements that can be attributed to amenity and recreational benefits. In their original application, Phaneuf et al. (2008) used cross-sectional property price and water quality data and assessed recreation behavior with a household survey. We adapt this model in two ways. First, we adopt a panel data approach and exploit variation from repeat home sales using both property fixed effects (FE) models and an innovative long-difference hedonic model. Second, we match households with recreation behavior using a national recreational fishing survey in which visitation is captured at the zip code level, rather than at the household level. The first adaptation is an improvement over prior work with respect to identification. The second is done out of necessity; because household surveys are costly, the approach we take to dealing with measurement error in attributing zip-code-level average recreation behavior to individual households may be useful in other applications.[1]

Given data limitations, our recreation demand models capture only recreational fishing, and not boating for other purposes, beach attendance, wildlife watching or other aquatic activities in the Tampa Bay region. While the impacts of water quality on fishing recreation and property values may be correlated with these other activities, their omission represents a shortcoming of our work. Nonetheless, recreational fishing is an economically important activity in the region, and it provides both a feasible and salient place to start with our proposed approach, which could be extended to other regions with richer aquatic recreation data. The Florida Fish and Wildlife Conservation Commission estimates that recreational fishing comprises about one-third of the annual combined economic impact of fishing, hunting, boating and wildlife-viewing in Florida (Florida Fish and Wildlife Conservation Commission, 2021).[2]

In addition, note that while our two-stage hedonic models provide more comprehensive estimates of the value of water quality improvement than prior work, hedonic estimates quantify benefits of pollution control to local property owners, omitting benefits to the estimated 5 million tourists per year who visit Tampa Bay, its beaches and surrounding islands (Tampa Bay Estuary Program, 2021), who likely also value reductions in water pollution. Habitat and other ecosystem service improvements, which may have both use value (e.g., reduced drinking water treatment costs) and non-use value (e.g., existence value for species such as manatees and shorebirds) are also omitted from our estimates. We return to these limitations of the hedonic approach in our discussion of benefits and costs at the end of the paper.

The water pollution problem we examine in Tampa Bay is nutrient over-enrichment and eutrophication, a common water quality problem, especially in coastal areas. During our study period, 1998 to 2014, the region successfully reduced nutrient pollution in the watershed and experienced notable improvements in water quality. We find significant household MWTP for these nutrient pollution reductions driven by both local amenity benefits and improved recreation opportunities; both factors are capitalized into housing prices and both are statistically and economically significant. Using our more conservative long-difference approach, for the observed average 10 percent increase in dissolved oxygen (our main indicator of good water quality) in the watershed from 1998 to 2014, our baseline estimates suggest that homeowners' valuation of the marginal improvement in very local water quality—an indicator of amenity values—is about $454 per home. Applied to all the repeat-sale homes in our sample, the total value of the observed improvement in amenity values is about $77 million; applied to all owner-occupied homes in the Tampa metro area, the aggregate value is about $366 million. The Tampa housing market capitalized much larger values for the impact of water quality improvements on regional recreation opportunities over the same time period: about $980 per household, which aggregates to $167 million for our entire repeat-sales sample and $789 million for all owner-occupied homes in the metro area. A comparison of these benefit estimates to a very rough estimate of the costs of obtaining the observed water quality improvements suggests a favorable benefit-cost ratio. Though we focus only on a single coastal city, our results suggest that omission of recreational benefits within a hedonic framework may result in dramatic underestimation of the value of water quality improvements to homeowners. More comprehensive estimates that capture homeowner benefits from both local and regional water quality improvements—like the ones we present in this paper—may serve as counterpoints to the existing lack of evidence that the benefits of water quality exceed the billions of dollars that are spent controlling water pollution in the United States every year.

The rest of the paper proceeds as follows. In Section 2, we review the prior literature on the economic benefits of water quality improvements. Section 3 presents our theoretical model. Our data and study area are described in Section 4, and econometric models are presented in Section 5. Section 6 summarizes the main results and describes a number of robustness checks. In Section 7, we implement our rough benefit-cost analysis and we conclude.

[1] Further research implementing a multi-year household recreation demand survey that can be merged with repeat-sales property transaction data would be a valuable future extension of our work.

[2] Property owners' valuation of improvements in recreational fishing (due to water pollution control) may not necessarily compare with their valuation of improvements in these other activities in the same proportion.

2. Literature review

2.1. Hedonic analysis and water quality

Many hedonic analyses in the prior literature estimate the impacts of one or more water quality parameters on property prices, starting with Epp and Al-Ani (1979) and continuing through Jerch (2021).[3] While all of these published studies find significant positive effects of water quality improvements or, conversely, negative effects of water pollution, on property prices, only one (Mendelsohn et al., 1992) uses property fixed effects to control flexibly and comprehensively for non-time-varying property characteristics.[4] Omitted variables are a significant concern in some of these analyses, given the likely correlation between unobserved drivers of property prices (such as proximity to areas with high runoff or point source emissions) and water pollution. Some of the later papers in this literature use neighborhood fixed effects and difference-in-differences approaches (Horsch and Lewis, 2009; Keiser and Shapiro, 2019b; Jerch, 2021) that can have plausibly-causal interpretations, especially when aggregate rather than property-level data are used. However, given that the repeat-sales approach has become standard in the hedonics literature for non-water-quality applications (Bajari et al., 2012; Muehlenbachs et al., 2015; Walls et al., 2015), applying this approach in an analysis of water pollution is one of our significant contributions. Note that the repeat-sales approach also has a drawback, in that properties that sell more than once in our 18-year sample period may differ from properties in the region as a whole, an issue we discuss further in Section 4.2.

A second critical difference between our paper and prior work is our approach to defining the spatial extent of water quality impacts on property prices. Because the benefits of water quality improvements may vary with distance to the waterbody, some papers only attempt to quantify impacts on waterfront homes (Leggett and Bockstael, 2000; Poor et al., 2001; Gibbs et al., 2002; Zhang and Boyle, 2010). Other papers estimate benefits at different distances from the waterbody (Poor et al., 2007; Walsh et al., 2011; Walsh et al., 2017; Guignet et al., 2017; Keiser and Shapiro, 2019b). In this literature, MWTP for water quality diminishes quickly with distance, generally between 2 and 3 kilometers (km) from the water.

Given a rich literature on recreation demand which establishes that households are willing to drive long distances for aquatic recreation and willing to pay for better environmental amenities (including water quality and related ecosystem services, such as fish catch and wildlife viewing) at distant recreation sites, it seems unlikely that these prior hedonic studies capture the local recreational benefits of water quality. Even in our sample, local recreational anglers' average roundtrip travel time to fishing sites is almost 90 min. Unlike in the case of air quality, where health impacts occur everywhere individuals spend time (e.g., at home or on a commute), individuals generally choose when and where they recreate in or near water (and thus experience water pollution), and examining impacts based on simple spatial criteria of proximity of houses to water is likely misleading.

In theory, hedonic property studies like those cited above can pick up both amenity and recreational benefits of water quality improvements (McConnell, 1990). When economists have looked for effects outside of a very tight radius around properties, however, many have not found such effects (Walsh et al., 2011; Keiser and Shapiro, 2019b). This has been interpreted as evidence that homeowners only value water quality close to their homes. However, the maps in Fig. 1 demonstrate our concern about this interpretation. The red dots at the center of each panel in the figure represent two households in our study area. The house at the center of Fig. 1a is an inland property, and the house in Fig. 1b is located near Tampa Bay. The black dots and triangles indicate the location of water quality monitors. Concentric circles are drawn with radii of 1, 2, 3, and 5 km from the property at the center of each panel. First, consider the property in Fig. 1a. A 2-km circle captures a handful of water quality monitors that, when averaged, may yield a reasonably good representation of water quality very close to the home. If one wanted to capture water quality in waterbodies that this household could use for recreational purposes, drawing increasingly larger circles nets many additional water quality monitors but few, if any, are in locations with which the household has any regular contact. Thus, increasing the assumed "zone of influence" for this household by drawing larger circles will attenuate any impact of willingness to pay for nearby water quality, and it will not capture recreational values.

In a coastal metropolitan area like Tampa Bay, averaging observations from water quality monitors in larger circles for properties closer to the coast like that in Fig. 1b will capture some recreation sites, as the 5-km circle does in Fig. 1b. However, the ability of an econometric model to effectively detect the signal of recreational water quality values from the monitors in the Bay (to the east of the property) will depend on how many irrelevant monitors (i.e., those inland and quite far from the home) are also captured. In addition, the standard hedonic model does not capture households' actual recreation sites—it only links homes to sites by proximity. Given these challenges, it is not surprising that regressing housing prices on average measures of water quality within circles around properties frequently generates null results beyond 2 km.

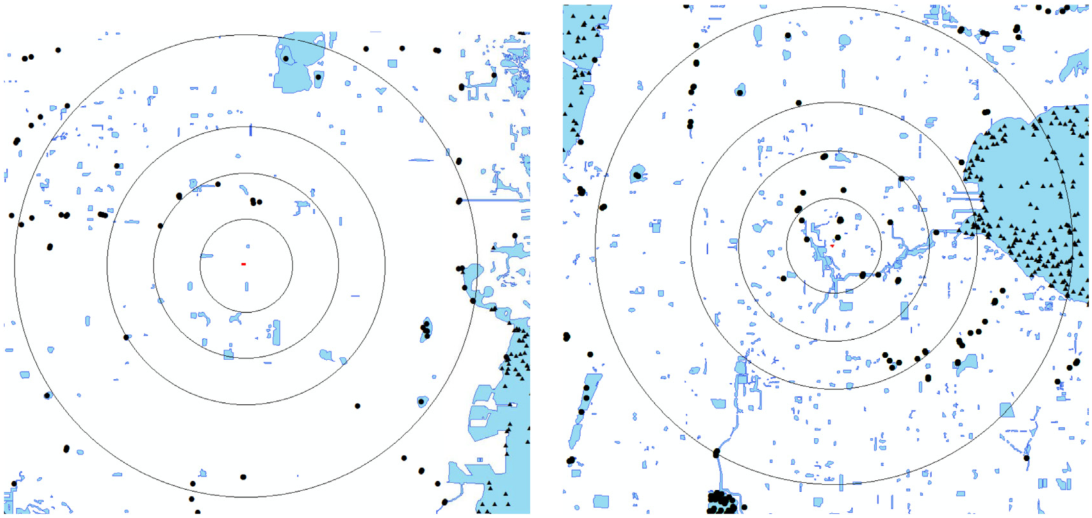
2.2. Recreation demand analysis and water quality

Another commonly used approach to estimate water quality benefits is recreation demand estimation using random utility models (RUMs). We identified 11 papers in the literature that use these models to value water quality changes (Mullen and Menz, 1985; Smith et al., 1986; Bockstael et al., 1987; Bockstael et al., 1989; Phaneuf et al., 2000; Phaneuf, 2002; von Haefen, 2003; Phaneuf et al., 2008; Egan et al., 2009; Abidoye et al., 2012; Abidoye and Herriges, 2012). Similar to the hedonic literature, all but one of these studies finds that water quality improvements increase recreational visitation and willingness to pay, but omitted variables bias is a concern for interpreting these results (Moeltner and von Haefen, 2011; Phaneuf, 2013). Only two of the studies (Abidoye et al., 2012; Abidoye and Herriges, 2012) control comprehensively for both site and visitor characteristics. Three additional papers control for either unobserved site characteristics (Phaneuf et al., 2008) or visitor characteristics (von Haefen, 2003; Egan et al., 2009), but not both.

The recreation demand component of our two-stage approach breaks no new ground. Rather, our contributions lie in: (1) a focus on a large, charismatic waterbody (Tampa Bay) that is the locus of recreational activity in a major coastal metro area and has experienced noticeable water quality improvements over the study period; and (2) integration of a RUM with a hedonic model, which allows us to estimate the value of recreational water quality improvements across the whole metro area housing market, rather than valuing water quality benefits to visitors only at recreation sites.

[3] The full list of hedonic analyses of water quality includes: Epp and Al-Ani (1979), Young (1984), d'Arge and Shogren (1989), Mendelsohn et al. (1992), Steinnes (1992), Boyle et al. (1999), Leggett and Bockstael (2000), Poor et al. (2001), Gibbs et al. (2002), Boyle and Bouchard (2003), Poor et al. (2007), Phaneuf et al. (2008), Horsch and Lewis (2009), Zhang and Boyle (2010), Walsh et al. (2011), Netusil et al. (2014), Wolf and Klaiber (2017), Walsh et al. (2017), Keiser and Shapiro (2019b), Jerch (2021).

[4] Theoretically, hedonic analysis involves two stages. The first stage is the use of property prices and characteristics to obtain a marginal implicit price. The second stage estimates a demand curve for the environmental good or service to use for welfare analysis. Given limitations in data availability, most empirical analyses focus on the first stage.



(a) An inland property (b) A property near Tampa Bay

Fig. 1. Two sample properties in Pinellas County. *Notes:* The red polygons in Panel A and Panel B indicate two properties in Pinellas County. The black dots are local water quality monitors, and the black triangles are recreational water quality monitors in Tampa Bay. The radii of the four circles are 1 km, 2 km, 3 km and 5 km.

2.3. Economic impacts of nutrient pollution

Nutrient over-enrichment is caused by the addition of excess nutrients, primarily nitrogen and phosphorous, to waterbodies via agricultural and urban nonpoint source pollution, which stimulates excessive algae growth. When the algae die, they decay and deplete dissolved oxygen (Morrison and Greening, 2006). Because nitrogen and phosphorous enter waterbodies over a broad catchment area, there are negative impacts not only locally in small streams but also regionally in large streams, rivers, bays and estuaries. Among the serious consequences of eutrophication are hypoxic or dead zones, in which many kinds of marine life cannot be supported. Reported dead zones worldwide doubled between 1995 and 2008 to more than 400 zones, and increased to 515 sites in 2011 (Rabotyagov et al., 2014). Other than Tampa Bay, U.S. waters that experience this phenomenon include other estuaries connected to the Gulf of Mexico, Chesapeake Bay, the Great Lakes (especially Lake Erie), Puget Sound, Long Island Sound, and the North Carolina coast. Economists have estimated significant impacts of eutrophication on commercial and recreational fisheries (Massey et al., 2006; Smith et al., 2017), though other economic damages are largely unknown (Barbier, 2012).[5]

3. Theoretical model

McConnell (1990) may be the earliest paper in the literature to recognize that hedonic estimates can in theory capture both recreational and amenity values of water quality. We essentially follow his advice, recognizing that property owners may obtain surplus from both recreational use and the amenity value of living near the water when water quality improves. However, we introduce the twist that allows households to value different waters for these two different purposes. This allows us to estimate the two values separately, adapting the theoretical model in Phaneuf et al. (2008), which has long-run and short-run decision-making components. In the long run, consumers evaluate neighborhood and property amenities, including pollution, to choose a home. In the short run, once a location is chosen, a household allocates its resources (including time) to market goods and recreation, that is, households evaluate the benefits of outings to recreation sites conditional on residential location. Since short-run recreation decisions are affected by long-run residential location choices, we assume that when making property purchase decisions, consumers will consider each location's accessibility to recreation opportunities.

Let $x(Q)$ represent a household's number of recreation trips, where Q measures water quality at recreation sites in the region. In addition, let p_x be the price of a trip, z be a numeraire good with price equal to 1, and $h(\mathbf{a}, q)$ be the value of housing services which is quasi-fixed in the short run and is a function of a vector of property attributes, $\mathbf{a}$, and water quality close to the home, q (which can differ from regional recreational water quality Q). The household maximizes its utility for recreation trips and market goods conditional on its income after housing expenditures. Thus, the household's short-run maximization problem is:

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

where m is household income net of the property price. Note that this model assumes that households can perceive a change in Q. For instance, if nutrient pollution results in excessive algae in a recreational waterbody, households notice a change in the color of the water, a decline in fish catch, or a beach closure. Solving the problem in (1) yields the household's conditional indirect utility function:

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

where ϵ captures unobserved property heterogeneity.

Suppose that water quality at recreation sites improves from Q_0 to Q_1. A welfare measure for this improvement is compensating surplus (CS), which can be described implicitly by the following equation:

$$V(p_x, m, Q_0, q) = V(p_x, m - CS(m), Q_1, q). \tag{3}$$

That is, CS measures the income that a household is willing to forgo to obtain the improved water quality (Kim et al., 2015).

We can estimate the indirect utility from recreation using a recreation demand model. Let $CS(Q, \epsilon)$ measure the gains to a

[5] Anecdotal evidence suggests that recreational impacts could be significant. In 2005, one of the years included in our study period, Florida's swimming beaches experienced almost 3,500 closures and health advisories due to high levels of bacteria caused by algal blooms, including toxic cyanobacteria blooms (Clean Water Network of Florida, 2008).

household from visiting recreation sites in Tampa Bay with water quality Q. When households make recreation decisions, they consider potential benefits and costs from visiting each possible site. If water quality and recreation costs vary spatially, different neighborhoods will offer different potential net benefits from recreation to households located in those neighborhoods. Thus, we can model expected recreational net benefits as an attribute of location:

$$ECS(Q) = \mathbb{E}[CS(Q, \epsilon)] \quad (4)$$

In long-run equilibrium, housing prices should capitalize the expected benefits from recreation at a given location. Since recreation decisions are made conditional on residential location decisions, we replace the $x(Q)$ in Eq. (1) with $ECS(Q)$ as defined in Eq. (4). The long-run utility maximization problem is thus:

$$\max_{\mathbf{a},q} \quad U(ECS(Q), h(\mathbf{a}, q), z) \quad s.t. \quad m^* = p_h(\mathbf{a}, q) + p_x\tilde{x} + z. \quad (5)$$

Households choose a residential location such that the sum of their expected marginal benefit from recreation and from services directly available from the property (including environmental services) is equal to the marginal property purchase price.

Hedonic models rely on some assumptions worthy of discussion. Property buyers and sellers must be aware of water quality changes (particularly those associated with the water quality parameters in our models), and the extent of the market for water quality improvements should be correctly defined. Households should be able to choose from a set of properties containing all potential combinations of characteristics (e.g., good water quality and good schools) and should face low moving costs. The model can only estimate the value of water quality to property owners, and not to local renters or out-of-town visitors. Some of these issues are discussed at greater length in our discussion of data and models, in sensitivity analyses, or in the interpretation of results. Others cannot be directly tested using our data. Although the hedonic model is a useful tool for valuing water quality, these caveats should be kept in mind.

4. Study area and data

The Tampa Bay watershed (Fig. 2) covers more than 400 square miles. It contains Florida's largest open-water estuary and second-largest metropolitan area and is the second-largest city on the Gulf of Mexico. The Bay provides important social value through species habitat and other ecosystem services, recreational use such as boating and fishing, power plant heat exchange, and commercial ports. Our study area comprises three counties within this watershed—Hillsborough, Pinellas, and Manatee counties—in which more than 2.3 million people live. Almost 90 percent of the total employment within the three counties is located in the watershed (Tampa Bay Estuary Program, 2014).

Nutrient loading to the Bay originates from a variety of sources including agricultural runoff, phosphate mining, fertilizer production, urban stormwater runoff, municipal sewage treatment discharges, industrial point sources, and atmospheric deposition from power plants (Greening et al., 2014; Sherwood et al., 2016). Paired with other aspects of urbanization (for example, construction of causeways that modified the Bay's hydrology), nutrient loading between the 1950s and the 1980s caused a dramatic shift from a "clear-water, seagrass-based system" to a "turbid, phytoplankton-based system" in which blooms of harmful phytoplankton were common and macroalgae mats covered large portions of open water, tidal flats, and seawalls (Greening et al., 2014). One impact of this water quality shift was an estimated 50 percent decline in seagrass coverage, an important indicator of the health of aquatic ecosystems (Greening et al., 2014).

Beginning in the late 1970s, citizens pressured the Florida legislature to impose advanced wastewater treatment standards on municipal sewage treatment plants discharging to Tampa Bay, and the resulting changes in point source emissions have been statistically associated with water quality improvements in Tampa Bay (Beck et al., 2019).[6] This legislation was followed by new regulations and practices including statewide permitting requirements for urban stormwater systems, coastal habitat acquisition and restoration projects, fuel-switching and nitrogen oxide (NOx) abatement technology upgrades by local power plants that reduced atmospheric deposition of nitrogen, and residential fertilizer use ordinances (Beck et al., 2019). These actions led to a recovery from widespread, frequent eutrophic conditions. Tampa Bay's seagrass coverage in 2016 exceeded that observed in 1950—considered by local recovery proponents to be the "reference state" for the Bay (Greening et al., 2014). Other water quality measures are also approaching the conditions last observed in the pre-disturbance 1950s (Greening et al., 2014).

Tampa Bay's recovery and the existence of rich long-term monitoring data documenting that recovery motivate our work in this region. While we do not observe property transactions during the entire recovery period, water quality improves noticeably over our study period, 1998–2014. In addition, the region's recreation opportunities, rapid growth and active housing market make it an ideal place for this study.

At the beginning of our study period, the U.S. Environmental Protection Agency (EPA) developed a Total Maximum Daily Load (TMDL) pollution budget for Tampa Bay covering 189 different sources, based on management targets set by the Tampa Bay Estuary Program. The Tampa Bay Nitrogen Management Council (TBNMC), a public/private partnership of local governments, agencies, and industries, developed an action plan for TMDL compliance and for supporting the Bay's continued recovery. From 1998 to 2014, the TBNMC implemented more than 600 projects to reduce nitrogen loading to the Bay (Beck et al., 2019).[7] While we cannot causally link the observed improvements in water quality to these projects, at the end of the paper, we compare our water quality benefit estimates to a rough estimate of the costs of these nutrient removal projects over our study period.

4.1. Recreation demand data

For the recreation demand model, we use angler data from the Marine Recreational Fisheries Statistics Survey (MRFSS) and the Marine Recreational Information Program (MRIP) produced by the National Ocean and Atmospheric Administration (NOAA) (NOAA Fisheries, 2008). The MRIP surveys a random sample of U. S. recreational anglers (Fisheries, 2013).[8] From the MRIP, we are able to obtain the year, month and time that each interview takes place, the zip code of each angler's residential address, fishing site locations, the number of people in each fishing group, and other visit characteristics.[9]

[6] The literature demonstrate that wastewater treatment upgrades elsewhere have improved water quality as well (Keiser and Shapiro, 2019a; Jerch, 2021; Earnhart, 2004).

[7] Hundreds of additional projects also preceded the TMDL.

[8] The MRIP survey we use is the Access Point Angler Intercept Survey (APAIS), an in-person intercept survey that collects information from anglers as they complete their fishing trips. Trained enumerators conduct the survey at marinas, boat ramps, beaches, fishing piers, and other publicly accessible fishing sites.

[9] One disadvantage of the MRIP data is that they do not track the same anglers over time. Such a data structure would have allowed us to control more comprehensively for unobservable characteristics of anglers. In the context of quantifying the benefits of ambient water quality improvements, we see this as a priority for future angler surveys.

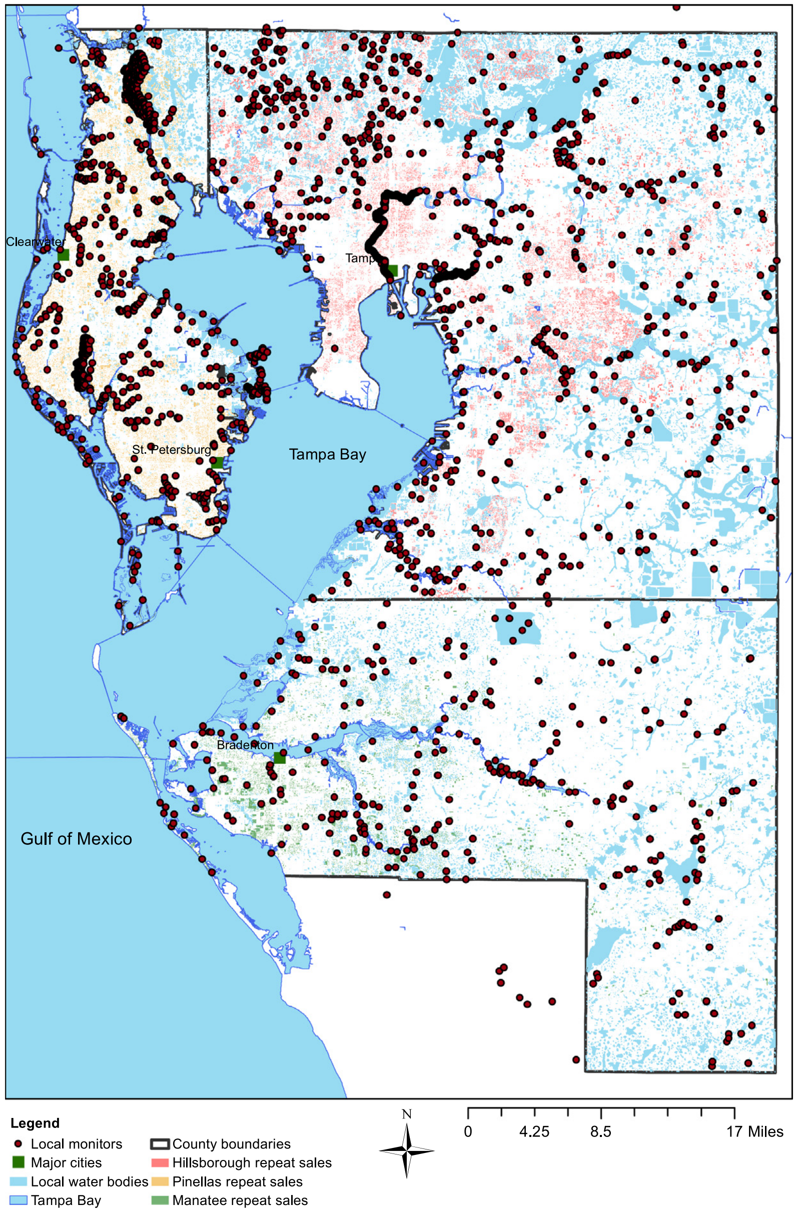


Fig. 2. Map of study area: Tampa Bay watershed, Florida.

Since the MRIP data do not have anglers' full address or self-reported travel cost, we use latitude and longitude information for fishing sites and anglers' residential zip codes to estimate travel costs for each trip. We use the 2010 Census Bureau zip code tabulation area (ZCTA) maps and population data to create a population-weighted center for each zip code in the three counties using ArcGIS, and assume that all anglers live in the population-weighted center of their zip code.[10] We then use the Open Source Routing Machine API to calculate round-trip travel time from the zip code-weighted population centers to fishing sites (Luxen and Vetter, 2011). Our travel cost estimate has two components: the value of this estimated travel time and the operational cost of travel. The value of travel time is estimated at 1/3 of visitors' forgone wages, using the mean hourly wage in the Tampa-St.Petersburg-Clearwater Metropolitan Statistical Area from the Occupational Employment Statistics (OES) Survey (U.S. Bureau of Labor Statistics, 2018).[11] For the operational cost of travel, we multiply the round-trip distance by the driving cost per mile reported by the American Automobile Association (AAA, 2019). Both the wage and the cost-per-mile estimates vary over time. Table 1 reports summary statistics for our estimated travel times and costs. The mean

[10] Figure A.1 in the Online Appendix shows the locations of fishing sites, along with recreational water quality monitors and geographic boundaries in the region. The Census Bureau generates ZCTAs to represent the United States Postal Service (USPS) zip code service areas. Going forward, we refer to the US Census ZCTAs as zip codes given the fact that, in most instances, they are the same.

[11] Recent work on best practices in recreation demand estimation recommends valuing travel time in such models at a fraction of the average wage rate that is less than one and checking the sensitivity of results with respect to this parameter, noting that valuing time at 1/3 of the wage is the most common approach in the literature (Lupi et al., 2021). Heeding this advice, we vary the value of travel time from 1/6 to 2/3 of the average wage and find no significant difference in our main coefficient estimates.

round-trip travel time in our angler data is 87.24 min, or about an hour and a half, and the average trip costs $43.12.[12]

4.2. Property transaction data

We collect property sales data from the property appraiser's offices in Hillsborough, Manatee and Pinellas Counties. In order to better identify the effect of water quality on residential property prices and maintain consistency with prior hedonic analyses, we restrict the sample to single-family homes. Sales dates, dates of construction, parcel size, and transaction prices are available for all three counties. The Hillsborough County Property Appraiser's Office provided additional information, including dates of major improvements, size of living spaces, number of stories, and number of bedrooms and bathrooms. Our sample includes only homes sold at least twice between 1998 and 2014, given our desire to include property fixed effects in our hedonic specifications (Manatee County data are only available from 2005–2014).

One drawback of the repeat-sales approach is that properties that exchanged hands at least twice from 1998 to 2014 may differ from the set of all properties that includes those that sold only once or not at all during the study period. Thus, restricting the sample to repeat sales may yield a selected implicit price (Freeman et al., 2014). The 300,207 repeat sales in our data, and the 146,903 repeat sales in the sample for our property FE model, account for more than 50 percent and more than 25 percent of qualified sales in our original data, respectively.[13] Thus, they may be reasonably representative of the housing market in the Tampa metropolitan area. Fig. 3 shows that average repeat-sales prices (red line) and average prices for all observed property transactions (blue line) in the three counties during the study period have very similar trends over time. Table A.2 compares property characteristics for repeat-sale properties in Hillsborough County (where property characteristics data are available) with those of all properties that sold at least once from 1998 to 2014. The repeat-sales sample includes properties that are, on average, older, about 5.5 percent cheaper, about 6.7 percent smaller, have slightly fewer bedrooms, bathrooms and stories, and slightly smaller lots.

We geocode the sales records and relate them in ArcGIS with shapefiles of house locations and characteristics. We then relate these property data with water quality data, also using ArcGIS. For each model we estimate, we use only properties that have at least one water quality monitor within the relevant distance and time window prior to a transaction. For example, our baseline models use monitors within 3 km of a home to capture local water quality and use water quality observations in the calendar year of each property transaction. Thus, for this model, we drop the 153,304 repeat sales in our data that lack water quality monitors within 3 km in the calendar year of the sale.[14]

We also link properties with the zip code-year level recreational index we create, resulting in additional narrowing of the sample (in our property FE model, this requires dropping 14,482 properties). The remaining 146,903 properties comprise our full sample for the property FE model—65,301 in Hillsborough County, 66,926 in Pinellas County, and 14,676 in Manatee County. The mean property price in the sample is about $230,000 (Table 1).[15] Properties in our sample were sold on average three times from 1998 to 2014 (with an average of 4.5 years between sales) and were about 33 years old when a transaction occurred.

One caveat of our property transaction data is that we do not observe changes in property characteristics over time (except age, which we construct from the year each home was built). If the likelihood of renovation is correlated with either local water quality improvements or the recreational benefits of regional water quality improvements, this omission could bias our estimates (Billings, 2015). If households substitute structural improvements for neighborhood quality, this bias would be negative. If neighborhood quality spurs home improvements (for example, if water quality improvements lead to gentrification), the bias would be upward.[16] Incorporating renovation information, for example from residential construction permitting data, into hedonic analyses that value environmental amenities is an important area for future work.

4.3. Water quality data

4.3.1. Local water quality data

We obtained waterbody shapefiles from the Tampa Bay Water Atlas (University of South Florida Water Institute, 2017), which is derived from the 1:24,000 USGS National Hydrography Dataset (NHD) and contains 749 water resources, including 12 bays, 506 lakes, 230 rivers and the Gulf of Mexico. We define ponds, lakes, wetlands, rivers, swamps, reservoirs and canals as local waterbodies and refer to water quality monitors in these waterbodies as "local water quality monitors." Water quality measures at these monitors are obtained from EPA's STOrage and RETrieval (STORET) data warehouse, which includes water quality monitoring data collected by states, tribes, watershed groups, federal agencies, volunteer groups, and universities. We keep all observations for which monitoring date, station latitude, and station longitude are reported. The resulting sample includes 209,336 water quality observations collected 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 (see Table A.1 in the Online Appendix for descriptive statistics on water quality sampling).[17]

There is no single accepted best indicator for water quality in hedonic and recreation demand analysis. Water quality measures used in past hedonic studies include dissolved oxygen (DO), fecal coliform, total suspended solids, dissolved inorganic nitrogen, pH, Secchi depth and harmful algal concentrations. We use DO, one of the most common measures of water quality in research on water pollution's economic impacts (Keiser and Shapiro, 2019b), and a key indicator of nutrient pollution. Higher DO levels indicate better water quality. DO is critical for fish survival, and water quality that meets the criteria for fish survival also meets criteria for most other beneficial water uses and is often of good ecological status (U.S. Environmental Protection Agency, 2001). DO is also a good indicator of water quality conditions that are noticed by people, and are thus likely to correlate with property prices. Noticeable impacts of low DO include reduced fish catch and the presence of algae mats.

[12] As noted earlier, data on other aquatic recreation trips, such as those for beach attendance and boating, are not available at a fine enough spatial and inter-temporal scale to allow the construction of recreation demand models for these activities in the Tampa Bay area.

[13] Hillsborough County has 186,289 repeat property sales that occurred during this period, Pinellas County has 107,701 repeat sales, and Manatee county has 20,699 repeat sales. Repeat sales represent 63.2 percent of all sales in Hillsborough County (1998–2014), 59.7 percent of all sales in Pinellas County (1998–2014) and 44.9 percent of all sales in Manatee County (2005–2014).

[14] 35.1 percent of repeat sales in Hillsborough (1998–2014), 62.1 percent of repeat sales in Pinellas (1998–2014) and 70.9 percent of repeat sales in Manatee (2005–2014) have reporting water quality monitors within 3 km in the calendar year of the sale.

[15] All prices are in 2014 dollars. Table A.3 in the Online Appendix lists summary statistics for the additional property attributes available for Hillsborough County.

[16] For example, Billings (2015) finds that failure to control for renovation biases repeat-sales hedonic estimates of the impact of transit access on home appreciation in Charlotte, NC by +0.05 to +0.11 percentage points annually.

[17] Some monitors change names slightly, and monitor identification numbers are not unique across counties. Following Keiser and Shapiro (2019b), we define a station as a unique latitude-longitude pair when we link properties with nearby monitors.

Table 1
Descriptive statistics.

Variable	N	Mean	Std. dev.	Min	Max
Water quality measures					
Local dissolved oxygen (DO) (mg/L)	146,903	5.79	4.07	0.20	104.00
Average local DO 1998–2003 (mg/L)	14,390	5.88	8.42	0.61	104.00
Average local DO 2009–2014 (mg/L)	14,390	5.89	1.40	1.04	12.37
Change in average DO (mg/L)	14,390	0.01	8.45	−100.22	7.99
Tampa Bay DO (mg/L)	146,903	6.40	0.83	3.16	10.53
Seagrass abundance (index)	146,903	2.35	0.91	0.00	4.79
Recreation demand					
Travel cost ($)	146,903	43.12	20.64	0.34	152.33
Travel time (minutes)	146,903	87.24	34.95	1.64	267.06
Distance to water					
Distance to Tampa Bay (m)	146,903	15,317.35	15,212.89	0.00	120,557.70
Distance to local waters (m)	146,903	2,796.27	1,742.42	0.00	11,372.92
Property characteristics					
Repeat-sales sample sale price (2014$)	146,903	229,306.50	154,742.5	5,262.23	1,541,511.00
Long-diff. sample sale price (2014$)	37,513	213,269.50	145,852.90	6,873.87	1,395,970.00
Average sale price 1998–2003 (2014$)	14,390	204,674.30	137,652.90	6,873.87	1,395,970.00
Average sale price 2009–2014 (2014$)	14,390	195,782.90	140,483.20	7,724.32	1,097,957.00
Change in average price (2014$)	14,390	−8,891.35	63,111.49	−581,720.80	684,031.80
Year	146,903	2005.76	4.44	1998.00	2014.00
Property age (years)	146,903	32.99	21.07	1.00	133.00

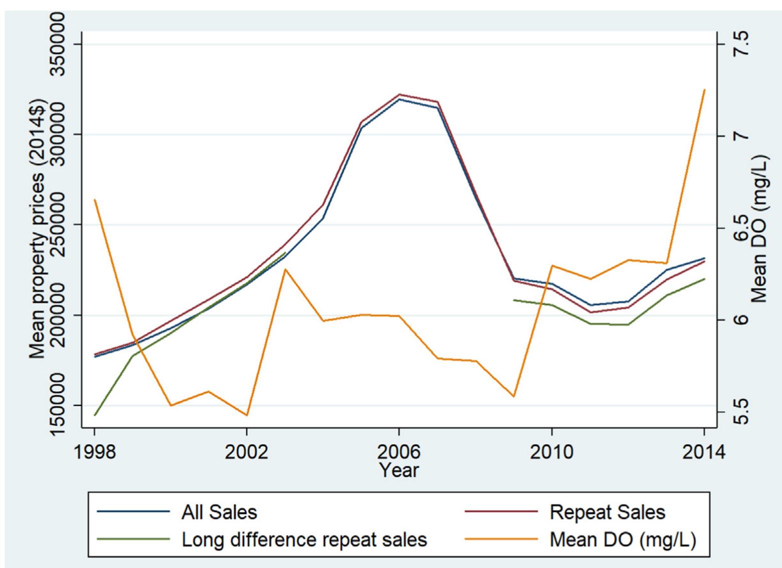


Fig. 3. Average property prices in the three counties and average DO concentration among all water quality monitors, 1998–2014. *Notes:* "All sales" averages annual property transaction prices across the 241,909 properties sold in Hillsborough, Pinellas and Manatee Counties at least once, 1998–2014. "Repeat sales" averages annual prices across the 170,192 properties sold at least twice, 1998–2014. "Long difference repeat sales" averages prices across the 14,390 properties sold at least once during 1998–2003, and at least once during 2010–2014. Mean DO is the average dissolved oxygen concentration observed at all local and recreational water quality monitors each year.

The large red dots in Fig. 2 depict the location of the STORET local water quality monitors and the smaller dots in pink, yellow, and green show the locations of repeat-sales properties in our sample. We calculate the mean DO concentration of all the monitors within varying radii in the calendar year of a property sale to generate the local water quality measure for each property. For our baseline model, we choose a 3-km radius, based on existing evidence that nationwide water pollution impacts are capitalized for homes within 3 km (Keiser and Shapiro, 2019b; Walsh et al., 2017). We also test the robustness of our results to other radii, from 300 meters (m) to 5 km, and to varying time windows around the date of a property sale.

We also create a dummy variable indicating whether the DO level for any given observation is above 5 milligrams per liter (mg/L); a DO concentration of 5 mg/L is a critical value for fish survival and may capture a threshold for detectable impacts (U.S. Environmental Protection Agency, 1994). Table 1 shows that the mean DO value in our sample is 5.79 mg/L, with about 36 percent of properties near waters having less than 5 mg/L DO, on average. We use the continuous DO concentration in all models in the paper, reporting the 5 mg/L threshold results in the Online Appendix.

Table A.3 in the Online Appendix lists summary statistics for properties categorized by our principal independent variable, the DO level in local waterbodies. Properties near polluted waterbodies

[18] We exclude seagrass transects more than 11,000 m from each fishing site in order to avoid spatially joining fishing sites located along the west coast of Pinellas County with seagrass transects in Tampa Bay, which lie across the peninsula formed by Pinellas County (Figure A.1).

are older and are located further from nearby waterbodies and from Tampa Bay. In Hillsborough County, where we have additional information on property characteristics, properties near polluted waterbodies are smaller and have fewer bedrooms, bathrooms, and stories on average. These differences highlight the importance of controlling comprehensively for property characteristics when estimating the impact of water pollution on property prices.

The water quality data comprise a collection of readings that vary in terms of the time of year and weather conditions under which a reading is taken, type of water body, and depth at which a sample is taken. As noted above, our DO estimates aggregate readings from multiple monitors to describe water quality near each property, in most models over a period of one year. If the accuracy of our DO averages varies systematically with water quality and/or property prices, non-classical measurement error could be a source of bias. Model controls such as calendar month fixed effects eliminate some, but not all, of this concern.

4.3.2. Recreational water quality data

For the recreation demand model, we use DO values from STORET monitors near fishing locations in Tampa Bay, which we refer to as "recreational water quality monitors," mapped in Figure A.1 in the Online Appendix. Consistent with the methods we use to define water quality in local waterbodies, we spatially join all monitors within a 3-km radius of each of our 85 fishing sites and calculate the annual mean DO. The mean DO level at recreational water quality monitors is 6.40 mg/L (Table 1).

In addition to observations from water quality monitors, we rely on seagrass acreage measurements from the Tampa Bay Estuary Program (TBEP) (Johansson, 2016). The health of Tampa Bay seagrass meadows has become an important issue in recent decades as scientists and environmental managers have worked to reverse the effects of nutrient pollution in the Bay. In 1997, the TBEP coordinated the creation of a Bay-wide seagrass monitoring program to document temporal and spatial changes in seagrass species composition, abundance, and distribution. Currently, 62 locations are monitored (Florida Fish and Wildlife Conservation Commission, 2003). The TBEP's seagrass abundance data are reported as an index, with higher values representing greater abundance. We match fishing sites with their closest seagrass transects.[18] Average seagrass coverage (converted from the TBEP index) is about 29,920 hectares (ha) from 1998 to 2014 (Table 1). While seagrass coverage is an important positive indicator of ecosystem health and fish abundance, it may also be a disamenity for anglers because these plants can get caught on fishing lines and boat propellers (Guignet et al., 2017), and boaters can be fined for scarring seagrass beds with their motors.

The yellow line in Fig. 3 shows the trend in the average annual DO concentration over time, using all of the local and recreational water quality monitors in the data. While the year-to-year variation can be substantial, the trend is increasing, reflecting the regional water quality improvements described in the literature. The annual average DO concentration in 2014 is 11 percent higher than in 1998. Similarly, the average DO increase over the earliest six years (1998–2003) and latest six years (2009–2014)—the periods we will use to calculate long-run changes in some of our models—is 10 percent. Thus, throughout the discussion of results in Section 6, we use a 10 percent improvement in average DO concentrations over the 16-year study period to interpret coefficient estimates and compare them across models.

4.3.3. Possibility of endogenous monitor placement

The literature suggests that the placement of air quality monitors in the United States may be statistically associated with the level of air quality (Muller and Ruud, 2018). If monitors are placed (or monitoring frequency occurs) differentially in areas with either higher or lower water pollution, this could introduce bias in our estimates of the impact of water quality on property values. To explore this question, we examined whether the intensity of water quality monitoring is correlated with water quality over time in several ways.

We first estimate the mean DO concentration by census block for the six-year periods at the start and end of our sample, which coincide with the two time periods we use in our main long difference model (1998–2003 and 2009–2014). We then sort census blocks into DO quintiles for each time period. We do the same for the number of water quality monitors, sorting each census block into quintiles of monitoring intensity by time period. Then we calculate directional changes in quintiles for both DO concentrations and monitoring intensity from time period 1 (1998–2003) to time period 2 (2009–2014). For example, if a census block was in DO quintile 1 from 1998–2003 and DO quintile 3 from 2009–2014, the change is positive (water quality improves). Because on average our water quality monitors report DO concentration for only 8 years, out of 708 census blocks, only 313 census blocks have DO concentration data that can be used to calculate a mean for both time periods. Thus, we restrict this analysis to these 313 blocks. We then calculate the correlation coefficient for the change in DO quintile and the change in monitoring intensity quintile from the two time periods. The overall correlation (0.011) is small, positive, and statistically insignificant. Conditional on water quality improvement, the correlation is 0.066 and also insignificant.

Given that the above tests look only at monitors present in both the first and last six years of the sample, and monitor entry and exit could be endogenous, we perform some additional tests. First, we calculate the correlation between the linear trend in DO readings of a monitor in time period 1 (1998–2003) and the probability that the monitor reports any DO readings in time period 2 (2009–2014). Because we need at least 2 readings on two separate days in period 1 to estimate a DO trend, we have 1,030 monitors (out of 3,278) that can be used for this purpose. The correlation between the DO trend in time period 1 and the probability of a monitor showing up in time period 2 is 0.0301 and statistically insignificant.

Next, we estimate the average trend in DO readings in the 12 months prior to a monitor exiting the data. Using all the monitors that report DO readings in the three counties from 1998–2014, we regress DO on a linear time trend and station FEs. The coefficient on the time trend is small, positive, and statistically insignificant, suggesting that DO is not trending upward or downward systematically before monitors exit.

Finally, we look for a systematic trend in the first 12 months after a monitor enters, using the same approach described above. The coefficient on the linear time trend is small, positive and statistically insignificant, suggesting that DO is not trending upward or downward systematically after monitors enter. Taking all of these results together, we are not concerned about endogenous placement of water quality monitors during our sample period in the Tampa Bay region.

[19] A useful attribute for a RUM specification would be the ability to add time fixed effects, which would allow us to control more comprehensively for time-varying factors that are constant across fishing sites. However, we are not aware of the existence of discrete choice models that allow for estimation using time fixed effects as well ACSs.

5. Methods

5.1. Random utility specification for recreation demand

In the random utility model, properties in Tampa Bay are located in J zip codes, and anglers can choose to fish at K recreation sites in the region. Each recreation site $k \in K$ has an observable level of water quality, WQ_{kt}, which can vary over time. The literature recognizes the need to control for unobserved site characteristics in random utility models (Moeltner and von Haefen, 2011; Phaneuf, 2013). One strategy is the use of Alternative Specific Constants (ASCs)–equivalent to site fixed effects–in the basic RUM model. Following Phaneuf et al. (2008), we assume the indirect utility for a visit to site k by individual i in year t is a linear function. The RUM specification is:

$$V_{ikt} = \alpha_0 + \alpha_1 Travel_{ikt} + \alpha_2 WQ_{kt} + \eta_k + v_{ikt}, \tag{6}$$

where V_{ikt} represents indirect utility of fishing trips and $Travel_{ikt}$ denotes the round-trip travel cost. η_k is an ASC that captures time-invariant site characteristics, such as the number of boat ramps or slips, whether the fishing site has lodges, and other attributes we assume remain constant over time.[19] We use a conditional logit model, so v_{ikt} is an error term distributed Type-I Extreme Value.

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

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

where $\widehat{V}_{ikt}$ is the observed element of utility, and C is an unknown constant indicating that the absolute level of utility cannot be measured. Because the term C in Eq. (7) does not affect utility differences, we drop it in the remaining equations (Haab and McConnell, 2002). The average compensating surplus per trip is thus given by:

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

We divide EV_{it} by the coefficient on the travel cost variable, interpreted as the marginal utility of income, to obtain a monetary measure of $\mathbb{E}(CS)_{it}$. If water quality improves from WQ_0 to WQ_1, indirect utility rises from $\widehat{V}^0_{ikt}$ to $\widehat{V}^1_{ikt}$ (per Eq. (6)) and the change in average compensating surplus per trip then is given as:

$$\Delta\mathbb{E}(CS)_{it} = \frac{1}{\hat{\alpha}_1}\left\{\ln\left[\sum_{k=1}^{K} exp\left(\hat{V}^1_{ikt}\right)\right] - \ln\left[\sum_{k=1}^{K} exp\left(\hat{V}^0_{ikt}\right)\right]\right\}. \tag{9}$$

Our estimate of $\mathbb{E}(CS)_{it}$ varies across zip codes and over time. The average recreational compensating surplus in zip code j in year t can be expressed as the average utility of all person-trips (N_{jt}) originating from the zip code in that year:

$$ECS_{jt} = N_{jt}^{-1}\sum_{i=1}^{N_{jt}} \mathbb{E}(CS)_{it} \ . \tag{10}$$

We incorporate this estimated ECS_{jt} into our hedonic model to capture how recreational impacts of water quality improvements may be capitalized in housing prices.

5.2. Hedonic specification

Our hedonic specifications control for observable and unobservable property attributes by exploiting only price changes within a property over time (Palmquist, 1982). We use two approaches: a standard property fixed-effects model and an innovative model using long differences. Further extensions to both of these basic models are discussed in Section 6.

5.2.1. Property fixed effects model

Using a log-log specification in line with the previous literature, the basic property fixed-effects model is as follows:

$$lnP_{ijt} = \beta_0 + \beta_1 Age_{it} + \beta_2 lnWQ_{it} + \beta_3 \widehat{ECS}_{jt} + \alpha_i + \gamma_t + \omega_m + \epsilon_{ijt}. \tag{11}$$

Home age is the only time-varying property characteristic in our data. The main coefficients of interest are β_2 and β_3. Using DO as the main local water quality measure, we expect β_2>0 since higher DO represents better water quality. We also expect β_3>0 if buyers are willing to pay higher prices for properties that offer more and better recreation opportunities. We interpret β_2 as homeowners' MWTP for an increase in DO within waterbodies close to homes. We use β_3 and Eqs. (7)–(10) to estimate MWTP for an increase in DO in the regional recreational waters frequented by residents of homeowners' zip codes. The property fixed effect, α_i, removes the effects of time-invariant omitted variables. We also include a year fixed effect, γ_t, and a calendar-month fixed effect, ω_m, (January-December) to account for seasonal and year-to-year patterns in home sales.

As noted in Section 4.1, the MRIP data include anglers' zip codes, but not their street addresses. Thus, our estimate of ECS_{jt} is a zip-code-level average measure of recreational utility in each year. The sample of anglers in the MRIP data in any individual household's zip code in a given year is small, and different households have different numbers of fellow anglers from the same zip code who are surveyed in the MRIP. In estimating Eq. (11), we treat the resulting potential bias from heteroskedastic measurement error as a partial missing-data problem, using multiple imputation (Blackwell et al., 2017). We first generate 250 stand-alone recreational demand datasets—representing what could have been observed if there were no measurement error—randomly drawing (with replacement) 20 percent of anglers (10,373 individuals) from the full MRIP sample each time. We estimate Eq. (6), and then use each set of coefficients and Eqs. (7)–(10) to estimate ECS_{jt}. On average across the 250 replications, we obtain 1,790 estimates of ECS_{jt}.[20] We then merge the ECS_{jt} estimates with the hedonic data, creating 250 datasets with which to estimate Eq. (11). We combine the estimates from these regressions using Rubin's Rule (Rubin, 1987), reporting the mean of each resulting vector of coefficient estimates in the results tables.

To calculate the standard errors, we first estimate the within imputation variance as $\text{Var}_{\text{within}} = \sum_{k=1}^{250} SE_k^2/250$ and between imputation variance as $\text{Var}_{\text{between}} = \sum_{k=1}^{250}(\beta_k - \bar{\beta})^2/(250-1)$, where k indexes the individual replication sample. We then calculate the total variance as $\text{Var}_{\text{total}} = \text{Var}_{\text{within}} + \text{Var}_{\text{between}} + \text{Var}_{\text{between}}/250$.The standard error is the square root of total variance. The individual replication standard errors are clustered by property or zip code, depending on the model.

5.2.2. Long-difference model

Although the property fixed-effects model represents an advance over the cross-sectional approaches in the literature on water quality, we make an additional modification in the interest of better matching the econometric approach with the theoretical model in Section 3. Recall that in that model, households make short-run recreation decisions, conditional on home location, based on water quality at recreation sites. Thus, the impacts of recreational water quality on visitation are identified

[20] There are 2,083 zip-code-years in the data with some visitation, but our data-generating process excludes some zip-code-years from each replication dataset.

from short-run variation. The home purchase decision, however, is a long-run choice, and home prices should capitalize the expected long-run benefits from recreation and amenity value of water quality. In our view, a long-difference hedonic model may better fit this theory than the standard fixed-effects approach described above.

Ex ante, we do not have a clear reason to expect that the long-difference model will necessarily yield the same results as the property fixed effects model. Our property fixed effects model exploits year-to-year variation in local and regional water quality for identification, whereas our long-difference model exploits longer-run variation with water quality observations that are anywhere between 6 to 16 years apart. As a result, coefficient estimates from the two models are likely to capture relevant benefits of water quality improvements at different time scales. The fact that long-difference approaches may yield different results from annual panel data approaches is acknowledged in the climate-economy literature, which has implemented long-difference models with the goal of identifying medium-term climate adaptation benefits that might not be captured by annual variation in weather (Burke and Emerick, 2016; Dell et al., 2012; Dell et al., 2014; Kolstad and Moore, 2020), as well as in the urban economics literature, which uses long differences to capture longer-term neighborhood and community dynamics (Baum-Snow, 2007; Kahn, 2007). Similarly, the practice of pairing panel fixed-effects models with long-difference models to explore policy impacts at different time scales has been increasingly adopted for examining other environmental issues such as agricultural pollution (Paudel and Crago, 2021), wetland protection (Taylor and Druckenmiller, 2022), and certification of green buildings (Qiu and Kahn, 2019).

Following the climate-economy literature, we construct our long-difference model using average long-run housing price changes, average local water quality changes, and average recreational utility index changes in two time periods for the same property. The two time periods in our main long-difference specification are 1998–2003 and 2009–2014, which we refer to as period a and period b, respectively. We choose these two periods because they represent the earliest and latest six-year periods in our data, and because doing so allows us to avoid the unusual property price changes during the housing boom and bust, evident in Fig. 3. Our long-difference sample is very small because inclusion in the sample requires that a property sell at least once in *both* the early and late time periods, so that we can take differences, instead of at least twice in the full sample (the inclusion constraint in the property fixed-effects model). In addition, we only observe Manatee County transactions beginning in 2005, so properties in this county drop out entirely. In Fig. 3, we can see that the average price in the long-difference sample (green lines) starts out somewhat lower than the full and repeat-sales samples in 1998, but then tracks very closely with the larger groups through 2003 (the pre-housing crisis, early period used for differencing). Post-housing crisis, the price level for this small sub-sample is again slightly lower than the larger groups, but the trends over time are very similar.

Our approach estimates the average price of property i during time period a as:

$$\overline{P_{ija}} = \frac{1}{n}\sum_{t \in a} P_{ijt}, \tag{12}$$

where n is the number of times the property sold in time period a. We then construct the following equation:

$$ln\overline{P_{ija}} = \theta_0 + \theta_1 \overline{Age_{ija}} + \theta_2 ln\overline{WQ_{ija}} + \theta_3 \overline{ECS_{ja}} + \alpha_i + \overline{\omega_m} + \epsilon_{ija}, \tag{13}$$

where $\overline{WQ_{ija}}, \overline{Age_{ija}}, \overline{ECS_{ja}}$, and $\bar{\omega}_m$ measure the average local water quality, average property age, average recreational utility index, and average calendar month of sale of property i in zip code j during period a. An analogous equation can be written for period b, in which the subscript a in Eq. (13) is replaced with the subscript b.

Differencing the two time periods drops the time-invariant property fixed effect α_i and results in:

$$\Delta lnP_{ij} = \theta_0 + \theta_1 \Delta Age_{ij} + \theta_2 \Delta lnWQ_{ij} + \theta_3 \Delta \widehat{ECS_j} + \Delta\omega_m + \Delta\epsilon_{ij}, \tag{14}$$

where ΔlnP_{ij} is the change in the log housing price of property i in zip code j between period a and period b. The independent variables are interpreted in a similar way.

The coefficients of interest are θ_2 and θ_3, which measure how long-run changes in local water quality and recreational opportunities affect the housing price. Similar to β_2 and β_3 in Eq. (11), we expect θ_2 and θ_3 to be positive. The interpretation of θ_2 and θ_3 is complicated by the fact that the dependent variable is the difference in log prices, and our independent variables are differences in log water quality and average ECS. We interpret the coefficients as marginal effects, instead of actual MWTP estimates. For instance, we interpret θ_2 as the marginal effect of the average water quality increase from period a to period b on the average housing price in period b, holding constant the average housing price and water quality in period a.

As we did for the property fixed-effects models, we use multiple imputation to obtain coefficient estimates and associated standard errors for Eq. (14), in order to address potential measurement error from estimating ECS_j at the zip code, rather than the property level, following the procedure described in Section 5.2.1.

One important feature of the two-stage approach, which applies to both the property FE models and the long-difference models, is the ability to control for potential correlations between regional and local water quality. This is because the *ECS* variable in the hedonic specifications is a function of predicted indirect utility of fishing trips (V_{ikt}) estimated in the first stage, which in turn is a function of regional water quality (WQ_{kt}) as shown in Eq. (6). Thus, by nesting the recreational demand model into the hedonic regression equation, our two-stage approach controls for both local and regional water quality, so correlation between the two should not bias our coefficient estimates.[21]

5.2.3. Interpreting hedonic estimates as MWTP

Because all of our hedonic models (both the property FE models and the long-difference models) exploit panel data over a 17-year period, the possibility that the hedonic housing price function may shift over time suggests that the capitalization effects we estimate could differ from true MWTP (Kuminoff and Pope, 2014). In Appen-

[21] While the recreational demand model only includes regional water quality at recreational sites, it is unlikely that the coefficient on regional water quality (α_2) would suffer from omitted variable bias. The Estimate of α_2 will be biased only if (a) water quality at sites is correlated with water quality in the zip codes from which people make trips to those sites, and (b) water quality in the zip codes from which people make trips to those sites is correlated with the probability of making a visit to the site, controlling for water quality at the site. Tampa residents in our data travel an average of almost 90 min roundtrip to fish at recreational sites; not surprisingly, the correlations between water quality at sites and water quality at the most common trip-originating zip codes for a site are all small and statistically insignificant: −0.019 using the most frequent originating zip code, −0.024 using the top three originating zip codes, and 0.018 using the top five originating zip codes. In addition, we find no significant correlations between the change in average DO levels between the two long-difference periods at each fishing site and its paired single- and three-most common originating zip codes. We find a small, negative, and weakly significant correlation (at the 10% level) between changes in water quality at fishing sites and their paired five-most common originating zip codes. These tests do not suggest that bias from correlated water quality at fishing sites and properties from which anglers travel is an important concern in our case, though it may be in other applications.

dix B, we perform several different tests to examine this possibility, and the results are not consistent with a hedonic price function that is shifting systematically over time during the sample period, at least for water quality. Thus, our discussion of results refers to our estimates as MWTP. However, the possibility that the effects we estimate may not equate perfectly to MWTP is an important caveat to our work.

6. Results

6.1. Demonstration of the typical hedonic approach

Before estimating our preferred two-stage model, we start with a demonstration of the typical hedonic approach, providing some analysis to support the heuristic critique we developed around Fig. 1. We estimate Eq. (11), leaving out the recreational utility component (ECS_{jt}), and assigning water quality monitors to properties as long as they are within a specified radius of the home—defined at 1, 2, 3, 5, and 10 km—ignoring actual recreation behavior. We do this, first, using only the local water quality monitors, and leaving out the recreational water quality monitors in Tampa Bay. Next, we run the same set of regressions using all (local and recreational) water quality monitors within the specified radii, so that the contribution of recreational waters to homeowners' MWTP for pollution abatement can be captured within the five different radii.

Coefficient estimates and their 95 percent confidence intervals, measured against the lower horizontal axis, are reported in Fig. 4, with the local-monitor results in blue and the all-monitor results in red. The sample size for each regression is reported above each estimate; sample size grows with the specified radius for the "zone of influence" because there are many fewer properties with reporting water quality monitors a short distance away, so the number of property transactions with reporting monitors grows as we draw larger circles. To ease interpretation, the implied MWTP for the observed average 10 percent increase in DO in the Tampa Bay watershed from 1998–2014 can be read from the upper horizontal axis.

Several insights arise from Fig. 4. First, estimated coefficients for the local measures of DO are mostly small and positive, hovering around 0.01, for an implied MWTP for the average water quality improvement in the watershed during the study period of $100-$300. Second, once we include the recreational monitors, the estimated coefficients increase appreciably. For the smallest radii, the red coefficient estimates in Fig. 4 imply a MWTP for the average water quality improvement from 1998 to 2014 of between $2,500 and $3,000 per property—an order of magnitude larger than those without the recreational waters included. Third, the all-monitor coefficients decrease in magnitude as we draw larger and larger circles around Tampa Bay homes to describe water quality, until the estimates at 10 km are in the range of the local-monitor-only estimates. This is consistent with the issue we raised in the heuristic discussion of Fig. 1; it may be the case that the larger "zones of influence" capture so many irrelevant water quality monitors (those that describe water quality in locations that a household does not value) that the signal of pollution abatement's value at key sites gets lost in the noise from the sites with little or no value.

This last insight is also consistent with households further from water having systematically lower MWTP for water quality improvements. As we allow monitors at increasing distances from

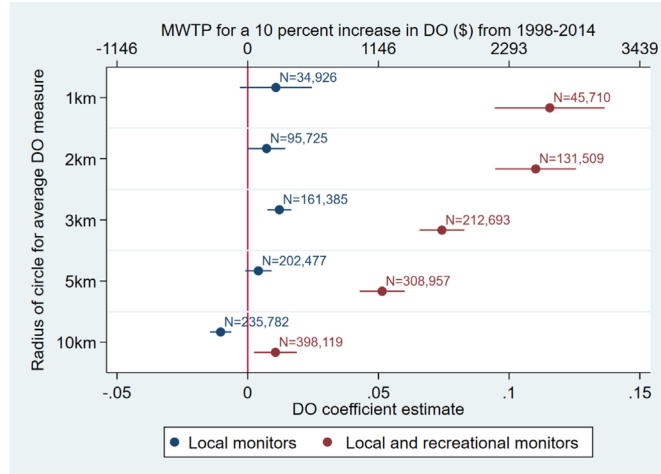


Fig. 4. Coefficient estimates and MWTP for DO from a typical hedonic approach when water quality measurements are averaged for monitors within varying radii of properties. *Notes:* Blue point estimates and confidence intervals are from regressions using only local water quality monitors. Red point estimates and confidence intervals are from regressions using all (local and Tampa Bay) water quality monitors. Sample sizes for each regression are reported above each estimate.

each property to influence our coefficient estimates, we are also able to include homes in the sample that are further and further from any water quality monitor and are thus further from water altogether. If heterogeneity in MWTP among property-owners depending on water proximity explains the observed pattern of decreasing "all-monitor" coefficient estimates, then it is a real phenomenon that one would want to capture in any estimate of the monetized benefits of water pollution abatement. We do not observe this pattern consistently in the local-monitor results, however. The value of local water pollution abatement is quite similar when we use monitors between 1 km and 10 km.

Though this analysis—comparable to the standard hedonic approach when valuing changes in pollution—points to the importance of recreational benefits in estimating MWTP for water pollution abatement, it is naïve relative to actual recreation behavior. A different approach is needed to match homes with the recreation sites that individuals living in those homes typically visit. Thus, we implement the two-stage approach described in Sections 3 and 5.

6.2. First-stage recreation demand results

Results from the recreation demand model are reported in Table 2. Column 1 defines water quality as the average DO at recreational water quality monitors in Tampa Bay within 3 km of each fishing site in a given year; Column 2 uses a 5-km radius to define average water quality in a site-year. We find that results are robust to these differences in specification. The logit coefficient estimates can also be expressed in terms of marginal effects in order to pro-

[22] We take caution in interpreting the marginal effects associated with coefficients estimated using conditional logit. The implementation of conditional logit in Stata assumes that the fixed effect is equal to zero, which can be problematic. For more discussion on this issue see, Kemp et al. (2016).

[23] Damaging seagrass beds in Florida can result in a fine of up to $1,000 (see: https://www.flseagrant.org/news/2016/07/savanna-barry-smart-boating-seagrasses-important/).

[24] Results using the 5 mg/L DO dummy at a 3-km radius are similarly positive and significant (see Online Appendix, Table A.6).

[25] If we estimate the typical hedonic model using a vector of property characteristics instead of property fixed effects, we obtain intuitive results for property characteristics, and counter-intuitive results for water quality—better water quality has a negative, insignificant effect on property values. Results are reported in the Online Appendix, Table A.5. This underscores the importance of controlling comprehensively for property characteristics when estimating MWTP for water pollution abatement.

Table 2
First-stage recreation demand model.

	(1) RUM (3 km)	(2) RUM (5 km)
Travel cost (US dollars)	−0.110***	−0.113***
	(0.00078)	(0.00080)
DO (mg/L)	0.0722***	0.0663***
	(0.0089)	(0.0114)
Seagrass abundance	−0.170***	−0.141***
	(0.0104)	(0.0104)
Alternative-specific constants	Yes	Yes
Observations	1,765,796	1,801,615

Standard errors in parentheses.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$
Notes: Models are estimated using conditional logit, with a choice set of 85 fishing sites visited during the study period. Column 1 links fishing sites to recreational water quality monitors within 3 km. Column 2 links sites to monitors within 5 km. Travel cost is estimated as the sum of the value of travel time (1/3 of foregone wages times round-trip travel time) and the operational cost of travel (AAA's driving cost times round-trip distance).

vide a more intuitive interpretation.[22] Specifically, as travel cost to a site increases by \$1, the probability of an angler fishing at the site decreases by about 0.6 percent. The coefficient on travel cost can be interpreted as the marginal utility of income, and our estimate is similar to others in the literature (von Haefen, 2003).

The effect of DO on visitation is positive, significant, and very similar across the two models. Anglers from the three counties in our study are 0.3 to 0.4 percent more likely to recreate at a site if the DO level increases by 1 mg/L, equivalent to a 16 percent increase from mean DO at the Bay monitors in our sample. The coefficient on seagrass abundance is statistically significant and negative in both specifications. A 1-unit increase in seagrass abundance (a 43 percent increase over the mean) lowers the probability of fishing at a site by 0.7 to 1 percent. Though seagrass abundance is correlated with higher water quality in Tampa Bay, the negative coefficient may be due to the fact that seagrass can be a disamenity to anglers. For example, anglers in shallow water must take care not to scar seagrass beds with a boat motor's propeller, and seagrass can catch and tangle fishing lines.[23]

In the Online Appendix, we re-estimate the recreation demand model using the 5 mg/L DO threshold instead of the continuous DO concentration (Table A.4). Results are similar, except that the DO coefficient is not significantly different from zero in the model using a 5-km radius to describe water quality at fishing sites.

Using the estimated parameters in Table 2, we then estimate the expected utility from recreation trips initiating from each zip code j in each year following Eqs. (8)–(10). In Table 3, we present descriptive statistics for this estimated value of expected utility (ECS_{jt}); the average value across all years and zip codes is \$35.98. In addition, in Fig. 5, we map the mean values of ECS_{jt} over the study period by zip code, as well as mean DO values at each recreational fishing site. The heat map of ECS_{jt} quintile by zip code shows some predictable results. For example, values are high in Pinellas County (the peninsula that separates the Bay from the Gulf). Some other coastal zip codes, especially those in southern Hillsborough County, also have high average recreational utility. Fig. 5 also shows, however, that residents of the region's less densely-populated zip codes further from the coast (e.g., in northern Hillsborough and eastern Manatee Counties) also obtain high utility from recreational fishing in the Bay. This is not surprising, given the relatively high average travel time (about 90 min round trip) to fishing sites in the MRIP sample. It does support our contention, however, that accounting for actual recreation behavior may paint a different picture of the value of recreational water quality than approaches that proxy for behavior using proximity.

To estimate the marginal effect of DO increases at Tampa Bay recreational fishing sites using the RUM model, we can recalculate the ECS_{jt} using the DO coefficient estimate from Column 1 of Table 2 and use Eqs. (7)–(10). Given that the mean DO level in the Tampa Bay watershed increases by about 10 percent from 1998 to 2014, we use Eq. (9) to estimate the change in ECS_{jt} associated with this increase in water quality. The increase in ECS_{jt} is \$0.42 per trip on average, which is about a 1.2 percent increase over the mean in the expected utility of recreation.

6.3. Second-stage hedonic results: The property FE model

Results from estimating Eq. (11) are reported in Table 4. In Column 1, which lists results from our baseline property FE model, a 10 percent increase in local DO is associated with a 0.116 percent increase in mean property prices.[24] Households' MWTP for local DO is about \$266 per property for the observed 10 percent increase in DO from 1998 to 2014. This is in line with the previous literature's small, positive estimates of MWTP for local water quality improvements.[25]

The recreational utility index coefficient in Column 1 of Table 4 is positive and statistically significant. It is also large in magnitude. Recall from the previous section that a 10 percent increase in DO is associated with a \$0.42 increase in ECS_{jt}. Based on the second-stage results in Column 1 of Table 4, a \$1 increase in ECS_{jt} is associated with a 25.1 percent increase in the housing price. Thus, the \$0.42 increase in ECS_{jt} is associated with a 10.54 percent increase in the average housing price, or about \$24,172 per property—almost two orders of magnitude larger than our estimated MWTP for local water quality improvements.

One test of whether our amenity and recreational estimates are really separable is to observe what happens to our estimates of the amenity value of local water quality improvements when the recreational utility index is omitted from the model. Column 2 of Table 4 shows that the local DO coefficient is insensitive to the exclusion of the ECS_{jt} variable. This suggests that the two parameters are, in fact, picking up different aspects of MWTP for water quality improvements.

In Column 3, we repeat the model from Column 1 but instead using a 5-km radius to characterize water quality at local waterbodies and Bay recreational fishing sites. The sample size grows for this model, because we can now include repeat-sales properties that are located between 3 and 5 km from at least one local water quality monitor. In Column 3, the local DO coefficient is statistically significant and slightly larger than for the 3-km radius, but the ECS_{jt} coefficient is not statistically different from zero.

In the Online Appendix (Table A.6), we re-estimate the property FE models in Table 4 using the 5 mg/L DO threshold instead of the continuous DO measure. Results are qualitatively similar and perhaps a bit stronger. The coefficients on local DO are positive and significant using both the 3-km and 5-km radii, and are slightly smaller than the coefficients on local DO that are estimated using the continuous DO measure. Again, the coefficient on ECS_{jt} is large, positive, and significant in the specification using a 3-km radius but is small and insignificant when using a 5-km radius.

6.3.1. Models with interactions between time trends and spatial controls

One threat to identification in our baseline model is that we do not control for factors influencing housing prices that vary over both time and space that could be correlated with water quality.

[26] There are 138 zip codes in the data (66 in Hillsborough County, 26 in Manatee County, and 46 in Pinellas County). There are 16 census subdivisions in the three counties: 7 in Hillsborough, 4 in Manatee, and 5 in Pinellas.

Table 3
Descriptive statistics for ECS_{jt}.

Variable	N	Mean	Std. dev.	Min	Max
Estimated ECS ($)	146,903	35.98	2.42	29.28	38.67
Average ECS 1998–2003 ($)	14,390	35.30	1.56	29.28	37.40
Average ECS 2009–2014 ($)	14,390	34.35	2.46	30.69	38.15
Change in average ECS ($)	14,390	−0.95	2.89	−6.54	8.80

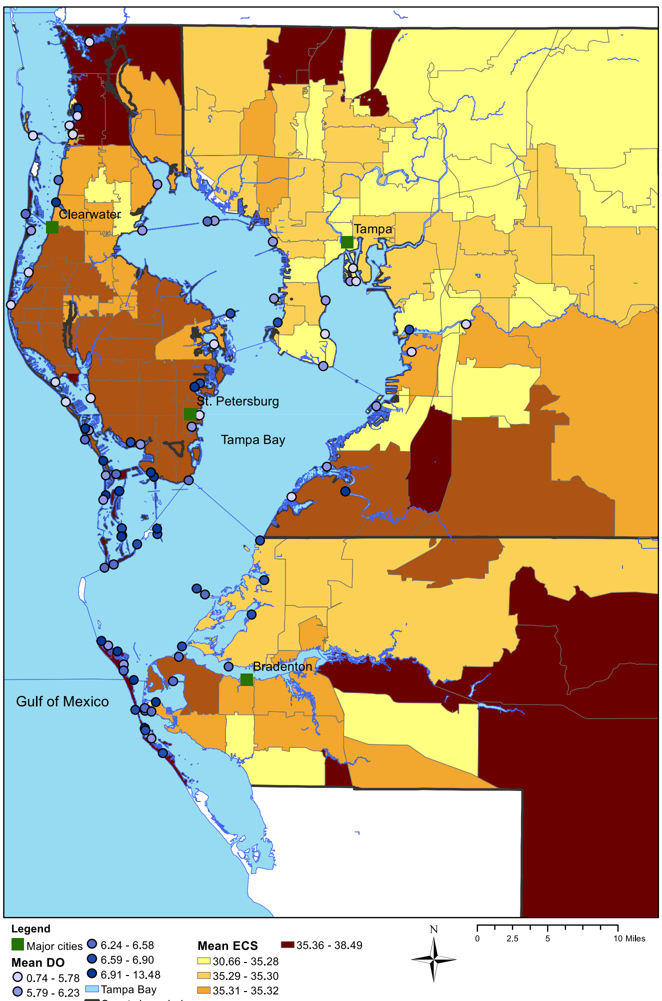


Fig. 5. Average ECS and average DO (mg/L), 1998–2014. *Notes:* This figure maps average ECS and average DO for all zip codes and recreational fishing sites, respectively, associated with properties in the repeat-sales sample.

For example, the economic recession and housing crisis that occurred during our sample period and are visible in Fig. 3 may have had heterogeneous effects by county or neighborhood, and those effects could be correlated with water quality and recreational utility. This would bias our coefficient estimates. The most comprehensive approach to this challenge would interact our year fixed effects with geographic controls at a higher spatial scale than the property. However, given that recreational utility is estimated at the zip code level, and there are only a small number of zip codes in the data (and even fewer counties, subdivisions, or other levels of spatial aggregation), this approach leaves too few repeat sales to identify the effect of recreational utility on property prices.[26] We estimate two alternative models that include different levels of interactions between a time trend and geographic controls, as well as year fixed effects, as in Eq. (15):

$$lnP_{ijct} = \beta_0 + \beta_1 Age_{it} + \beta_2 lnWQ_{it} + \beta_3 \widehat{ECS}_{jt} + \alpha_i + \gamma_t + \omega_m + \lambda_c * T + \epsilon_{ijct} \quad (15)$$

where λ_c indicates that a property is located in county or census subdivision c, and T is a linear time trend. Results are presented in Table 4, Columns 4 and 5.

The effect of local DO on property prices, identified using variation in water quality over time within 3 km of a property, and within a year, is relatively insensitive to the inclusion of these additional controls. The estimated effect of recreational utility on property prices changes substantially, however. The coefficient on ECS_{jt} in Column 4 is about one-fourth the magnitude of that in our baseline model in Column 1 and not statistically significant. In Column 5, when we include the subdivision-specific trends, it is even smaller and also statistically insignificant.

The identifying variation for the recreational utility index coefficient comes from changes in recreation within zip codes over time. In Column 4, the trend in recreational utility (which may be more important to property owners than periodic departures from the trend) at the county level is removed from the identifying variation for the recreational utility index. After removing property fixed effects and county-specific trends, the remaining variance in *ECS* pertains only to within-county deviations from zip code means relative to the county-specific trend. The model in Column 5 is even more restrictive. In our view, the variation in recreational utility across census subdivisions and counties is important variation to capture in the coefficient on *ECS*; thus, the Column 1 model is preferred to those with the county-specific trend and subdivision-specific trend controls. However, concerns about identification in that model provide additional support for our long-difference approach, the results for which we describe next.

6.4. Second-stage hedonic results: The long-difference model

Table 5 reports results from the long-difference models. Column 1 reports results from our baseline long-difference model, with standard errors clustered by property. In the baseline model, if we hold average property price and average local DO in period *a* (1998–2003) constant, a 1 percent increase in average local DO in period *b* (2009–2014) is associated with a 0.0233 percent increase in the average second-period property price. If the average second-period local DO increases by 10 percent (the average change observed in the data between period *a* and period *b*), the average property price increases by 0.233 percent. From Table 1, the average property price from 2009 to 2014 is about $196,000. Thus, the marginal effect of a 10 percent increase in average local DO from the first to the second period is about $454 per property, a 71 percent increase over the $266 estimate using Column 1 of Table 4.

Recall again that a 10 percent increase in DO is associated with a $0.42 increase in *ECS*. From Column 1 of Table 5, a $1 increase in ECS_j is associated with a 1.19 percent increase in property prices. Thus, the $0.42 increase in *ECS* is associated with a 0.5 percent increase in the average housing price, or about $1,000 per property. Property markets appear to have capitalized a value of regional recreational fishing benefits from water quality improvements in

Table 4
Second-stage hedonic regression results for the property fixed effects model.

	(1) Basic 3 km	(2) No ECS_{jt} 3 km	(3) Basic 5 km	(4) County time trend	(5) Subdiv. time trend
ln(DO)	0.0116***	0.0113***	0.0129***	0.0111***	0.00967***
	(0.00306)	(0.00306)	(0.00442)	(0.00318)	(0.00340)
ECS_{jt}	0.251***		0.0165	0.0609	0.0272
	(0.0814)		(0.0771)	(0.0795)	(0.0846)
Property age	−0.0123***	−0.0123***	0.0112	−0.0135***	−0.0139***
	(0.00328)	(0.00328)	(0.00822)	(0.00326)	(0.00336)
Property FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Sale month FE	Yes	Yes	Yes	Yes	Yes
County-year trend	No	No	No	Yes	No
Subdivision-year trend	No	No	No	No	Yes
Observations	146,903	146,903	166,706	146,903	125,276
R-squared	0.627	0.627	0.661	0.633	0.632
MWTP for 1 mg/L local DO ($)	459	448	516	440	383
MWTP for 1 mg/L Tampa Bay DO ($)	37,769	N/A	2,483	9,164	4,093

Estimated standard errors in parentheses are clustered by property.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$
Notes: The dependent variable is the log property transaction price. Column 1 uses a 3-km radius to define average water quality around properties. Column 2 drops the recreational utility index, ECS_{jt}. Column 3 repeats Column 1, using a 5-km instead of a 3-km radius to define average water quality around properties. N rises in Column 3 because more repeat sales are located within 5 km of at least one water quality monitor than within 3 km. Column 4 includes county-specific trends as additional controls. Column 5 includes census subdivision-specific trends. Reported coefficient estimates and standard errors are obtained using multiple imputation, using methods described in detail in Section 5.2.1.

Table 5
Second-stage hedonic regression results for long-difference and property fixed effects models.

	(1) Long diff. SE property	(2) Long diff. SE zip code	(3) Long diff. No ECS_{jt}	(4) Long diff. County × time period	(5) Long diff. Subdiv. × time period	(6) Property FE SE property	(7) Property FE SE zip code
$\Delta ln(DO)$	0.0233***	0.0233	0.0189***	0.0234***	0.0368***		
	(0.00642)	(0.0210)	(0.00639)	(0.00643)	(0.00768)		
ΔECS_j	0.0119***	0.0119***		0.0118***	0.0157***		
	(0.00130)	(0.00329)		(0.00130)	(0.00141)		
Δ Property age	0.0350***	0.0350***	0.0308***	0.0350***	0.0383***		
	(0.00177)	(0.00315)	(0.00173)	(0.00177)	(0.00189)		
ln(DO)						0.00707	0.00707
						(0.00494)	(0.0154)
ECS_{jt}						0.329**	0.329
						(0.131)	(0.288)
Property age						−0.0219*	−0.0219
						(0.0131)	(0.0296)
Property FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	Yes	Yes
Δ sale month	Yes	Yes	Yes	Yes	Yes	No	No
Sale month FE	No	No	No	No	No	Yes	Yes
County-time period dummy	No	No	No	Yes	No	No	No
Subdivision-time period dummy	No	No	No	No	Yes	No	No
Cluster SE level	Property	Zip code	Property	Property	Property	Sales	Zip code
N	14,390	14,390	14,390	14,390	12,219	37,513	37,513
R-squared	0.052	0.052	0.043	0.052	0.064	0.530	0.530
MWTP for 1 mg/L local DO ($)	774	774	628	778	1,223	0	0
MWTP for 1 mg/L Tampa Bay DO ($)	1,529	1,529	N/A	1,516	2,017	49,506	0

Standard errors in parentheses are clustered by property unless otherwise noted.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$
Notes: Columns 1–5 report results from long-difference models, using a 3-km radius to characterize water quality and clustering standard errors by property. Column 2 clusters standard errors by zip code. Column 3 drops the recreational utility index, ECS_j. Column 4 includes county*time period (a and b) dummies as additional controls. Column 5 includes census subdivision*time period controls. Columns 6 and 7 show results from property FE models estimated using the long-difference sample and clustering standard errors by property and zip code, respectively. Reported coefficient estimates and standard errors are obtained using multiple imputation, using methods described in detail in Section 5.2.1.

Tampa over two decades that is more than twice the size of the value of improvements in ambient water quality very near to properties. Again, we note that the *ECS* coefficients in the property FE and long-difference models measure different things. But if we compare the two qualitatively, the recreational utility component of the estimated value of water quality improvements in the long-difference models is much smaller than in the property FE models.

In Column 2 of Table 5, we estimate the same long-difference model (Eq. (14)), clustering standard errors by zip code rather than by property. While we measure property-specific local DO, the

[27] A larger number of observations are available for these robustness checks than for the long-difference specifications because we include all transactions between 1998 and 2014 as long as the properties appear in the long-difference sample.

recreation demand index is constructed by zip code, so it may be more appropriate to cluster at this higher level of aggregation (Cameron and Miller, 2015). Our estimate of the marginal effect of local DO is no longer significant, but the *ECS* coefficient remains significant.

As we did for the property FE models, we also try dropping ECS_j from the long-difference model and present the coefficient estimates in Column 3. The effect of improved local DO on property prices is slightly smaller, but not different enough to raise concerns that the two variables are not identifying different contributions of water quality improvements to property values.

In the next two columns of Table 5, we include a set of interactions between counties and the two time periods (Column 4) and a set of interactions between census subdivisions and the two time periods (Column 5). Our reasoning is similar to that in Eq. (15); if inter-temporal shocks common to counties or neighborhoods are correlated with water quality improvements from period a to period b, this could bias our estimates of the effects of water quality on property prices. The inclusion of these additional covariates does not change our estimates much compared to Column 1. If anything, the magnitudes of the estimated effects increase in the model with subdivision-specific trends (Column 5).

In Table A.7 of the Online Appendix, we also test the robustness of the long-difference results to different definitions of period a and period b: allowing the period a sample to extend to just before the recession and housing crisis (i.e., period a: 1998–2006 and period b: 2009–2014), and splitting the full time period in half (i.e., period a: 1998–2007 and period b: 2008–2014). In both cases, the marginal effects of both local DO and recreational utility are quite a bit larger than our estimates in Table 5. The sample sizes are also about twice as large. As in Column 2 of Table 5, when we cluster standard errors by zip code in these models, the marginal effect of local DO (a small share of our total estimated value of water quality improvement) is not statistically significant. Both of these alternative specifications include transactions during the housing boom, and the second specification also includes the subsequent bust. Thus, we report the Table 5 results as the main long-difference results.

Given its comportment with the theoretical model and ability to control comprehensively for unobservables, the long-difference model may be the preferred approach to valuing water quality improvements. However, the choice between long differences and property FEs creates a stark tradeoff in sample size (and possible selection). The long-difference repeat-sales sample is less than one-tenth the size of the full sample, because we must observe properties sold at least once in each time period, as well as recreation at fishing sites from each zip code in each time period, in order for those properties and zip codes to be included in the models. Fig. 3 suggests that the trends in property prices in the long-difference sample are similar to those for all sales and repeat sales in both periods, with the exception of a low start in 1998 for the long-difference sample. However, Fig. 6 shows that the long-difference sample drops many zip codes entirely, including all zip codes in Manatee County, many of which have high average recreational utility from fishing in the Bay (mapped in Fig. 5). As noted earlier, Manatee County drops out because we only observe transactions there from 2005 to 2014. Fig. 5 also shows that average

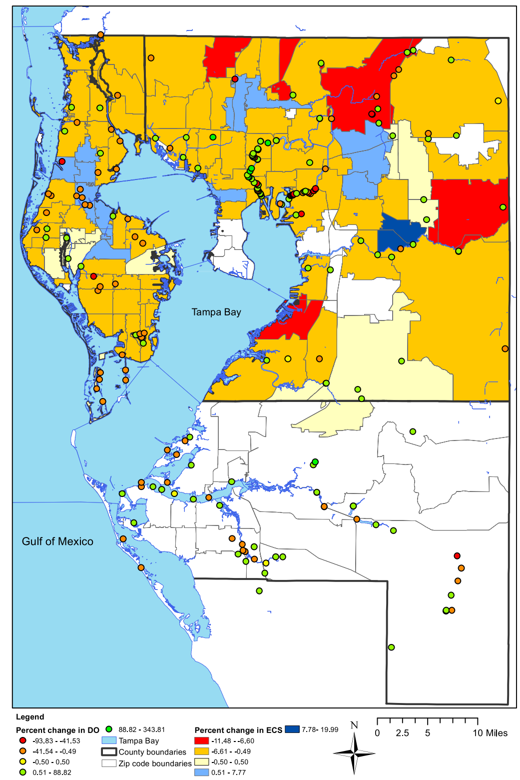


Fig. 6. Percent change in average ECS and percent change in average DO, 1998–2003 to 2009–2014. *Notes:* This figure maps the change in average ECS and the change in local ambient DO for all zip codes associated with properties in the long-difference repeat-sales sample.

water quality at coastal fishing sites in Manatee County are among the highest in our sample.

To get a sense of the extent to which differences in results between the property FE model and the long-difference model are driven by differences in samples, in the final two columns of Table 5, we re-estimate the basic property FE model from Table 4, restricting the sample to the same properties that appear in the long-difference sample, and clustering standard errors at two levels—property and zip code.[27] We note that when using the long-difference sample with the property FE approach, the DO coefficient is not statistically significant and the coefficient on *ECS* is larger than when the property FE model is estimated with the full sample of repeat sales. This suggests that differences between estimates in our long-difference and property FE models are driven by difference in specification as well as by difference in samples. More generally, the long-difference sample may not be representative of Tampa area property owners' willingness to pay for water quality improvements, especially in recreational waters. For these reasons, in the benefit-cost analysis in Section 7, we use both the property FE and the long-difference results, reporting a range of estimates.

6.5. Robustness checks

6.5.1. Effects of proximity to water

Although Eqs. (11) and (14) capture the overall effect of water quality on property prices, they do not allow us to examine how this effect varies with proximity to water, as is common in the prior literature. To this end, we also estimate models that interact both local DO and the recreational utility index with a property's distance to water. Table A.8 in the Online Appendix reports results. Results from the property FE model are listed in Column 1, and results from the long-difference model are listed in Column 2. In

[28] The number of observations varies by specification in Table A.10 because the number of repeat sales for which we are able to estimate average water quality in each time window varies. Note that the 12-month moving DO average (Column 1) actually gives us a larger sample than the models in Table 4 (which use average DO in the calendar year of each property transaction). Also, in Table A.10, as the time window for calculating the DO average shrinks, so does the sample. This is due to the fact that some monitors do not report very frequently, and properties are dropped from the sample when there are no DO observations in the relevant time window.

Table 6
Range of monetized benefit estimates for the observed 10 percent increase in average DO concentration in the Tampa Bay watershed, 1998–2014.

Water quality benefit	WTP -sample households only	WTP -all repeat sales, 1998–2014	WTP -Tampa Bay metro area
Panel A: Benefit estimates using coefficient estimates from property fixed-effects model			
Amenity benefit	\$266 × 64,353 = \$17.1 million	\$266 × 170,192 = \$45.3 million	\$266 × 806,000 = \$214.4 million
Recreational benefit	\$24,172 × 64,353 = \$1.56 billion	\$24,172 × 170,192 = \$4.11 billion	\$24,172 × 806,000 = \$19.5 billion
Amenity + recreational benefit	\$24,438 × 64,353 = \$1.57 billion	\$24,438 × 170,192 = \$4.16 billion	\$24,438 × 806,000 = \$19.7 billion
Panel B: Benefit estimates using coefficient estimates from long difference model			
Water quality benefit	WTP -sample households only	WTP -all repeat sales, 1998–2014	WTP -Tampa Bay metro area
Amenity benefit	\$454 × 14,390 = \$6.53 million	\$454 × 170,192 = \$77.3 million	\$454 × 806,000 = \$365.9 million
Recreational benefit	\$979 × 14,390 = \$14.1 million	\$979 × 170,192 = \$167 million	\$979 × 806,000 = \$789 million
Amenity + recreational benefit	\$1,433 × 14,390 = \$20.6 million	\$1,433 × 170,192 = \$244 million	\$1,433 × 806,000 = \$1.15 billion

Notes: Sample households in Panel A, Column 1 are the 64,353 homes sold twice or more in Hillsborough, Pinellas, and Manatee Counties from 1998 to 2014, and for which we also observe water quality variables and estimate the zip code-level annual recreational utility index. Sample households in Panel B, Column 1 are the 14,390 homes sold at least once between 1998 and 2003 and at least once between 2009 and 2014, and for which we also observe water quality variables and estimate the zip code-level recreational utility index. All repeat sales in Column 2 include all 170,192 homes sold twice or more in the three counties, 1998–2014. This includes properties dropped from our sample due to missing water quality or recreational visitation data. All homeowners in the Tampa Bay metro area in Column 3 include the approximately 806,000 owner-occupied households in the 2010 Census in the Tampa-St. Petersburg-Clearwater metro area (U.S. Department of Housing and Urban Development, 2015), which includes Hillsborough and Pinellas counties, as well as two counties excluded from our sample (Hernando and Pasco), and excludes Manatee County (which is in our sample). The amenity and recreational benefit estimates are calculated using the estimated coefficients from models reported in Column 1 of Table 4 for Panel A, and those reported in Column 1 of Table 5 for Panel B.

both models, higher DO in local water is associated with higher property prices, and the effects of recreational utility are also positive and significant. The property FE model suggests that recreational value falls with distance from water, but amenity value does not. The long-difference model indicates no effect of distance on the marginal value of water quality improvements.

6.5.2. Smaller spatial radii for local water quality monitors

Recall that our models take the average of all monitors within a 3-km radius of a property to represent local water quality, with additional results reported for a 5-km radius. To further test the robustness of our results to this choice, we estimate models using radii of 1 km, 500 m and 300 m. We first use the alternate radii to estimate recreational utility. We then incorporate the new recreational indices in the second-stage hedonic model using the same radius for properties as we do for fishing sites in the first stage. Table A.9 in the Online Appendix reports results for both continuous DO and the 5 mg/L threshold variables. We report only the local DO results, with the full set of coefficients available on request. In the property FE models, the effect of improved water quality on property values gets larger as the radius gets smaller, up to 500 m, consistent with previous literature indicating larger effects for properties closer to the water (Walsh et al., 2011; Walsh et al., 2017; Wolf and Klaiber, 2017). The effects lose significance for the smallest radius (300 m), likely due to the very small number of observed repeat sales within that distance of one or more reporting water quality monitors. In the long-difference models, the impacts of local DO are not statistically significant below a 3-km radius; note that these samples of homes sold at least once in each period that are located very close to monitors are very small.

6.5.3. Moving average DO concentrations

While it is common in the literature to use the average water quality measure from the calendar year of a property's sale to represent water quality conditions in hedonic regressions, as we do above, we implement a set of robustness checks using average DO concentrations within a 3-km radius of a property observed over the 3 months, 6 months, and 1 year before each sale date. We report these moving average results in Table A.10 in the Online Appendix.[28] Column 1 uses the mean DO concentration in the 12 months prior to a property's sale date. The magnitude of the coefficient on $ln(DO)$ in this model is very similar to that in our baseline model in Column 1 of Table 4. Results from Columns 2 and 3 of Table A.10 suggest statistically insignificant MWTP for local DO increases 6 and 3 months prior to a sale. Property transactions can take several months to complete, so homeowners may have no or low MWTP for local DO increases while waiting to close transactions. The coefficients on ECS_{jt} in Table A.10 show consistently that homeowners have positive and statistically significant values for recreational utility, and that these values are robust to varying time windows prior to a sale, though they are somewhat larger than in our baseline model.

7. Discussion and conclusions

Our empirical results demonstrate that valuation of water pollution abatement using hedonic analysis is strongly downward-biased if recreational waters are omitted, or if they are included but the analysis ignores actual recreation behavior. Taken together, our integrated two-stage models and robustness checks suggest that increases in dissolved oxygen (DO) improve both regional recreational and local aesthetic amenities and that homeowners in Tampa Bay have significant MWTP for both of these improvements. Our baseline MWTP estimates for recreational water quality improvements in Tampa Bay from 1998 to 2014 are much larger than our estimates of MWTP for local amenity improvements. The two effects appear to be separable in Tampa Bay, suggesting prior hedonic studies of the value of water quality could provide unbiased estimates of local amenity values, but may exclude the potentially much larger regional recreational values.

With the caveat that the capitalization effects we estimate could differ from MWTP (though the tests described in Appendix B give us some confidence that the hedonic price function is not shifting systematically over time), we perform a back-of-the-envelope welfare analysis using our benefit estimates and a rough estimate of the costs of water quality improvement. From 1998 to 2014, the average DO concentration in the Tampa Bay region increased by about 10 percent. Table 6 summarizes our monetized benefit estimates for this water quality improvement. Using the property FE estimates reported in Column 1 of Table 4, Panel A of Table 6 shows that the local amenity benefits from this improvement range from about \$17.1 million if we apply them only to our sample households, to about \$214.4 million if we apply them to all owner-occupied households in the Tampa Bay metro area in the 2010 Census (U.S. Department of Housing and Urban

Development, 2015). In contrast, when we use the two-stage model coefficient estimates to also monetize the recreation benefits from DO improvements over the 16-year study period, our benefit estimates range from \$1.6 to \$19.7 billion, depending on the scope of the property market to which these benefits accrue.

In Panel B of Table 6 we use the long-difference estimates from Table 5 for the same exercise. The monetized estimates of MWTP for a 10 percent local DO improvement range from \$6.53 to \$365.9 million, depending on the geographic scope of homeowners to whom benefits accrue. The MWTP estimates for the combined amenity and recreational improvements are substantially smaller than those estimated from our property FE model (from \$20.6 million considering only our long-difference sample properties to \$1.2 billion for the whole Tampa metro area). Note that the low-end estimate is made smaller due to both a much smaller repeat-sales sample as well as the smaller coefficient estimates, while the high-end estimate is influenced only by differences in coefficient estimates.

How do these benefit estimates compare to the costs that firms, homeowners, governments (taxpayers), and other stakeholders incurred to achieve the water quality gains observed in the Tampa Bay watershed between 1998 and 2014? There are several challenges to answering this question. First, the water pollution control projects that contributed to DO gains over this period were incredibly diverse in scope and type, implemented by dozens of different public and private sector institutions (Beck et al., 2019). Second, the impact of each project has not been rigorously evaluated to determine its causal impact on water quality. One study suggests that some types of projects, particularly point-source nitrogen controls, may be statistically associated with subsequent water quality improvements at downstream water quality monitors over time (Beck et al., 2019). Other approaches (for example, nonpoint source control and habitat restoration projects) may be less strongly associated with water quality improvements (Beck et al., 2019). However, we are not able to determine which projects actually caused the water quality improvements we observe in the data, and for which we estimate Tampa property owners' MWTP.

From the Tampa Bay Estuary Program, we obtained a catalog of the more than 800 projects implemented between 1971 and 2017. If we consider only those 600 projects implemented between 1998 and 2014 (our study period), and only those for which cost estimates exist (311 projects), the costs of these projects sum to about \$585 million, about 14 percent of our estimated benefits for all repeat-sales properties between 1998 and 2014, using the property FE results in panel A of Table 6. Using the long-difference results in panel B, estimated benefits are about 58 percent lower than this very rough cost estimate. If the benefits accrued more broadly—to all owner-occupied single-family homes in the metro area—then the benefits are about twice the costs, even using the long-difference results, which as noted earlier drop transactions for many properties with high average recreational utility. These are very favorable benefit-cost ratios when compared to other water quality benefit-cost analyses in the literature (Keiser and Shapiro, 2019b; Keiser and Shapiro, 2019a; Keiser et al., 2019).

Our coefficient estimates and resulting WTP estimates for water quality improvements are somewhat different for local amenity values between the property FE and long-difference models; results from the two approaches differ much more for recreational water quality improvements. This variation in results is attributable to both sample and specification differences. Because we cannot say which estimates are "best," we use WTP estimates from both approaches in our rough benefit-cost analysis. To our knowledge, we are the first to estimate long-difference hedonic property models, so we cannot lean on prior literature to explain this phenomenon, but we note that a similar problem arises in other parts of the economics literature. As noted earlier, previous studies in climate and urban economics that employ both panel and long difference analyses articulate an *ex ante* expectation that the two approaches will capture different behavioral and environmental responses and also grapple with issues regarding restriction of samples (Baum-Snow, 2007; Eid et al., 2008). Exploring the differences between the two approaches in settings with even richer data is an important area for further research.

Though our benefit estimates are more comprehensive than prior work using hedonics or recreation demand modeling, they are still incomplete. We exclude the recreational fishing benefits that improved water quality has afforded non-residents such as tourists visiting Tampa Bay, as we used only the MRIP survey data for anglers whose trips originated from zip codes in the three sample counties. Mitigating eutrophication also reduces emissions of methane, a greenhouse gas (Beaulieu et al., 2019), which could be valued using estimates of the social costs of GHGs and would almost certainly not be capitalized into local property prices. Moreover, the rebound in seagrass coverage in Tampa Bay results in additional nitrogen removal (as these healthy plants absorb nutrients for growth), generating a positive feedback. Scientists have estimated that the additional nitrogen removal services associated with the rebound in seagrass in Tampa Bay between 1982 and 2010 has, itself, removed enough nitrogen from the Bay to avert more than \$20 million per year in expenditures for additional denitrification by municipal wastewater treatment plants and other sources (Russsell and Greening, 2019). These kinds of avoided costs are also unlikely to be capitalized into local housing prices, as it would be difficult for homeowners to be aware of them. Thus, our benefit estimates are almost surely conservative.

We cannot assess the quality of the 311 available nutrient project cost estimates from the TBEP, or the projects for which costs have not been estimated. In addition, projects implemented before 1998 may contribute to the water quality changes we observe after 1998. Thus, costs may be over- or under-estimated.

This work adds to our understanding of how people value water quality improvements, especially nutrient pollution abatement. Eutrophication, a consequence of nutrient pollution, may cause large economic damages in the United States and elsewhere. Many local, state and federal regulations have been implemented to address this problem. Further work to help policymakers better understand how people value nutrient pollution abatement, and how these values are capitalized in housing markets, can contribute to a more comprehensive evaluation of such regulations.

We also contribute to the literature on hedonic valuation of pollution control, more generally. We estimate a hedonic model valuing water quality that controls comprehensively and flexibly for property characteristics, using two different approaches. Our novel long-difference hedonics approach may comport better with hedonic theory than other approaches in the literature, given that the hedonic model considers the property location decision in long-run equilibrium. Lacking data on recreation site visitation at the property level—likely a problem faced by other researchers examining similar questions, unless they implement a household survey—we use multiple imputation to address the resulting measurement error relative to recreation data observed by property. These innovations may enable future work valuing water pollution and pollution control with a broader geographic scope than we have examined in this paper.

Appendices

Appendices A and B associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jpubeco.2022.104600.

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