Effects of Water Quality Impairment Status on Property Values in Tennessee

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Abstract

Worldwide, highly polluted rivers can reduce regional economic growth by up to a third within a generation. In the United States, many waterbodies fail to meet federal water quality standards despite decades of mitigation efforts. Tennessee has a disproportionately high share of impaired waters relative to the national average, with implications for ecosystems, human health, and recreation. This study examines how water quality impairment status is capitalized into residential property values using parcel-level transaction data from Tennessee between 2010 and 2023. We construct a repeated cross-sectional dataset using the most recent sale of each property and estimate hedonic property value models with census tract and year fixed effects. By comparing properties adjacent to impaired and non-impaired waterbodies with nearby properties located 150–750 meters from a waterbody, we estimate whether water quality impairment alters the property value premium associated with proximity to water. Results indicate that proximity to non-impaired waterbodies is associated with a significant property value premium, while impairment reduces the water proximity premium by approximately 5.4% statewide. The effect is larger in West Tennessee,

where impairment reduces the water proximity premium by approximately 17.4%, although properties adjacent to impaired waterbodies continue to retain a positive premium relative to nearby properties without direct water access. These findings provide evidence that water quality degradation can impose localized economic costs by reducing the value of recreational water amenities and highlight the potential economic benefits of water quality improvement efforts.

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Chapter 1

Introduction

Water quality impairment has significant environmental, economic, and social consequences. Globally, polluted waterways substantially reduce regional economic growth. Russ et al. (2022) estimate that increases in river pollution, measured primarily through biochemical oxygen demand (BOD), are associated with significantly lower downstream economic growth rates relative to regions experiencing lower pollution levels. In Europe, 34% of the 130,000 water bodies surveyed in 2020 failed to achieve "good" chemical status. None of the rivers in England, Germany, Belgium, or Sweden met their standards (Hannah et al., 2022). In the U.S., water pollution contributes to trillions of dollars in economic losses annually, according to a sector-based economic assessment of impacts on agriculture, industry, energy production, ecosystem services, and human health (Fallah, 2023). As shown in Figure 1.1, despite decades of regulation under the Clean Water Act (CWA), many waterbodies still fail

to meet their designated uses, such as for drinking, recreation, or aquatic life support, due to pollution and nutrient loading (US EPA, 2024).

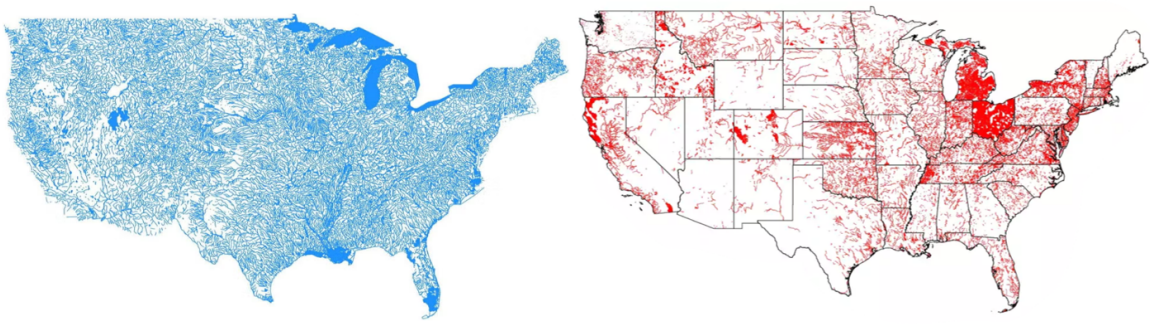

Figure 1.1: Impaired Waterbodies in the United States

Note: The map on the left shows all U.S. waterbodies, while the map on the right shows those labeled impaired by the EPA as of 2015 (U.S. GAO, 2022; U.S. DOI, 2016).

Properties near lakes, rivers, or streams often derive value from environmental amenities, and declines in water quality may reduce their appeal and market value. Estimating these effects is challenging because many benefits of clean water, such as ecosystem health, recreational enjoyment, and aesthetic value, are non-market goods, and information about water quality is not always observable to buyers. Tennessee provides a compelling setting for examining the economic impacts of water quality impairment. The state contains a disproportionately high share of impaired streams compared to the national average (TDEC, 2024), with impairment associated with ecological degradation, public health risks, and reduced recreational opportunities (TDEC, 2023).

Using publicly available water quality impairment data and parcel-level property transaction records spanning 2010 to 2023, we conduct a hedonic property value

analysis to estimate the relationship between waterbody impairment status and residential property values. We hypothesize that properties adjacent to impaired waterbodies sell for lower prices than comparable properties near clean waterbodies.

We find that across Tennessee, proximity to non-impaired waterbodies is associated with a positive and statistically significant price premium. However, this premium is sensitive to water quality conditions. Statewide, water quality impairment reduces the water proximity premium by approximately 5.4%. This effect is larger in West Tennessee, where water quality impairment significantly reduces the premium associated with waterbody adjacency by approximately 17.4%. In contrast, we find no statistically significant evidence that impairment reduces the value of waterbody proximity in East and Middle Tennessee, suggesting that the capitalization of water quality into housing markets varies across regions.

This study contributes to the literature on environmental valuation by providing a hedonic property value analysis on how water quality impairment status affects property values across the entire state of Tennessee. Building on prior studies, we include geographic and temporal fixed effects to estimate both localized and broader impacts of environmental degradation (Kuwayama et al., 2022; Papenfus, 2019; Walsh et al., 2017; Cho et al., 2011; Leggett and Bockstael, 2000). We use regulatory impairment designations, rather than biophysical water quality indicators, applied across a large, geographically diverse, inland state. This reliance on publicly available, administratively defined impairment status enhances the policy relevance of our estimates, as these designations directly govern regulatory and restoration

decisions under the Clean Water Act. By spanning a broad and varied landscape, our findings could offer more generalizable hedonic estimates than those derived from site-specific studies, with direct applicability to benefit–cost analyses of water quality regulations and restoration programs.

A growing body of literature has documented the economic impacts of environmental disamenities, including water quality impairment, through hedonic property value studies. Studies such as Kuwayama et al. (2022), Papenfus (2019), and Leggett and Bockstael (2000) show that property values are sensitive to changes in water quality, particularly for aesthetic, recreational, or health-related uses. However, most research focuses on coastal regions, prominent lakes, or highly visible water features, where degradation is more noticeable and likely to affect market prices (Kuwayama et al., 2022; Papenfus, 2019; Walsh et al., 2017). Less is known about inland contexts, like Tennessee, where water resources vary widely in size, visibility, and recreational use, and where impairment may be less salient but still consequential.

While impairment designations could be less precise than continuous measures, they are systematically maintained, publicly accessible, and policy-relevant. Impairment designations capture both the informational and regulatory dimensions of water quality, reflecting how environmental quality is signaled to the public by government agencies (Papenfus, 2019; Cho et al., 2011). Prior research has noted challenges in incorporating continuous water quality data at the parcel level across a broad geographic area, further underscoring the value of regulatory status as a practical signal in hedonic models (Mamun et al., 2023; Guignet et al., 2022; Papenfus, 2019).

Relatively few studies that do use water quality impairment, or information on water quality, however, examine the effects on property values at a large spatial scale.

Understanding how environmental factors, such as water quality impairment, influence housing prices is critical to motivate future policy. These recurring challenges have shaped the trajectory of the literature and motivate the design of this study.

Chapter 2

Background

The evolution of U.S. water policy provides essential context for this study. The Clean Water Act (CWA), originally passed as the Federal Water Pollution Control Act in 1948, was significantly expanded and reorganized in 1972 to form its current structure (U.S. Congress, 1972). The revised Act established a comprehensive regulatory framework for maintaining and restoring water quality in the nation's surface waters. The EPA serves as the lead agency responsible for implementing the Clean Water Act, including the development of pollutant criteria, issuance of discharge permits, and monitoring of water quality, as illustrated in Figure 2.1.

Two key aspects of the CWA are Section 303(d), which mandates states to identify impaired waters, and Section 305(b), which requires biennial reporting on the status of water quality (U.S. Congress, 1972). Section 303(d) obliges each state to submit a list of waterbodies that fail to meet designated uses to the EPA every two years. These designated uses include protection and propagation of aquatic life, recreation,

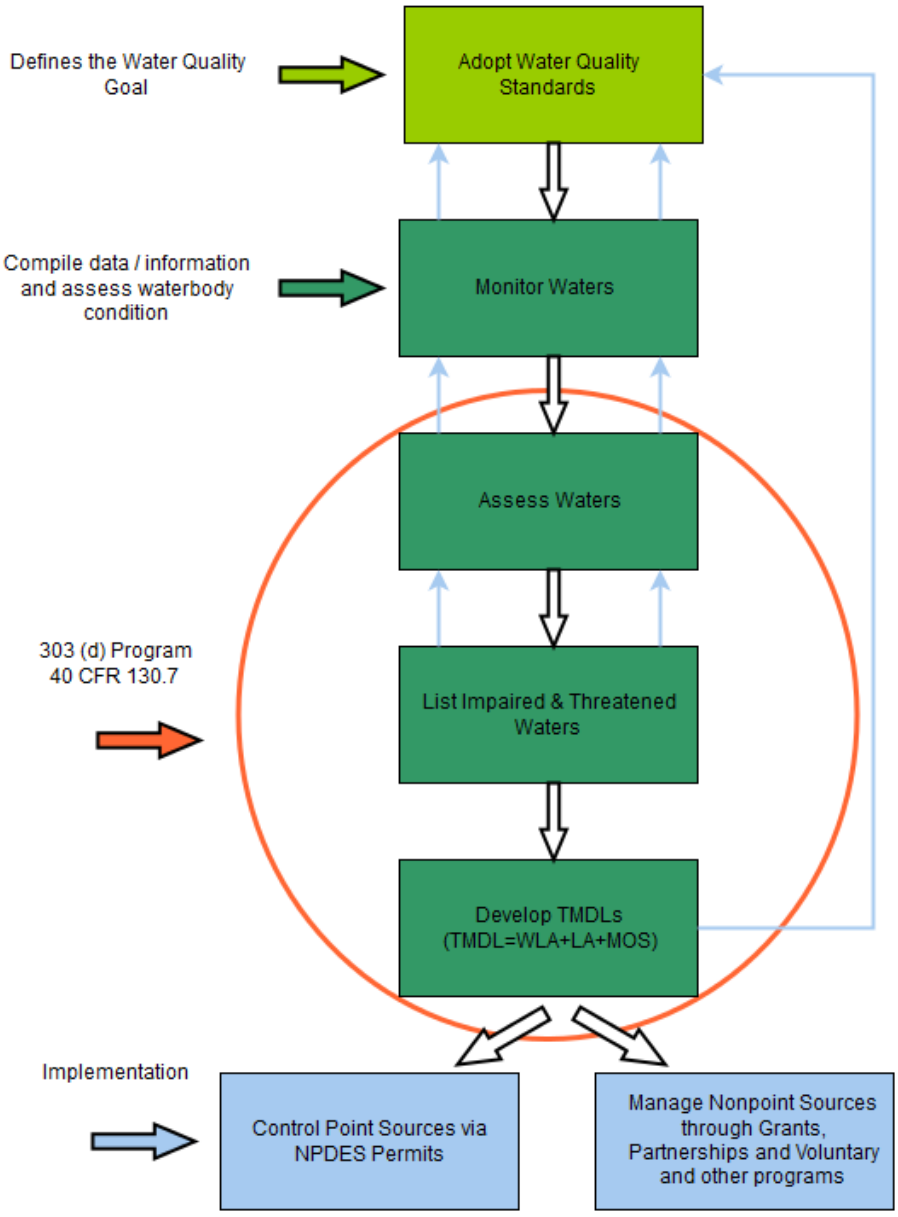

Figure 2.1: Water Quality-Based Approach of the Clean Water Act

Note: Overview of the EPA's process for identifying and managing impaired waters under the Clean Water Act (US EPA, 2023).

public water supply, agriculture, industry, or navigation. These uses reflect water quality standards defined under the CWA and include water quality criteria and antidegradation policies.

The EPA employs a Use Attainability Analysis (UAA) to evaluate the factors affecting each designated use of a waterbody. The UAA is a scientific evaluation of these factors. For example, these factors include pollutants, flow conditions, human-caused conditions, economic and social impacts, hydrologic modifications, and physical conditions of the waterbody (US EPA, 2026). Although the EPA provides the regulatory framework and guidance, individual states are responsible for evaluating waterbodies and identifying factors that may impair attainment of designated uses.

A waterbody is deemed impaired when it does not meet one or more of its designated uses. Once a state determines that a waterbody is impaired, it must develop a Total Maximum Daily Load (TMDL), which establishes the maximum amount of a pollutant that can enter a waterbody while still allowing it to meet and maintain applicable water-quality standards (US EPA, 2025a). Once a TMDL is created, the waterbody is removed from the 303(d) list. Federally, however, there is no policy requiring that a TMDL actually be implemented, so the timeline of developing and overall implementation is up to each state.

In Tennessee, the Department of Environment and Conservation (TDEC) manages water quality programs and prioritizes TMDL development based on internal protocols outlined in their Consolidated Assessment and Listing Methodology (CALM) document (TDEC, 2024). Tennessee follows a rotating five-year cycle across

its five designated watershed groups. Impaired waterbodies are generally sampled at least once per cycle, ideally three times, particularly if used for recreation or showing signs of improvement (TDEC, 2023). However, there is also no federal requirement for minimum monitoring frequency. Monitoring intensity is ultimately determined by the state (TDEC, 2024). Tennessee assigns impairment priorities as high (H), medium (M), low (L), or not applicable (NA), depending on factors, such as pollutant type and upcoming monitoring schedules (TDEC, 2023). High-priority impairments are scheduled for TMDL development within two years. For some high-priority waterbodies impaired for recreational use, sampling for E. coli is often performed monthly (TDEC, 2023). Low-priority impairments, on the other hand, may remain unaddressed for over a decade. As a result, some impaired waters remain on the list for extended periods.

Section 305(b) complements 303(d) by requiring states to report on water quality progress, including updates on TMDL development and implementation (US EPA, 2025a,b). The Assessment, Total Maximum Daily Load (TMDL) Tracking and Implementation System (ATTAINS) platform enables public access to this information. Sections 303(d) and 305(b) of the CWA represent the assessment component of the process. Then, once this information is reported to the EPA by each state, it is made available by ATTAINS. This database categorizes waterbodies by whether they are fully supporting vs. not supporting the CWA's pollution standards, what their designated uses are, and whether a TMDL exists. Contrary to the 303(d) list of impaired waters, ATTAINS delists a waterbody to become fully supporting only

whenever the waterbody fully meets water quality standards, not when a TMDL is made. Importantly, the 303(d) list alone only includes impaired waters that still require a TMDL, whereas the ATTAINS database gives a comprehensive report and includes information on whether a waterbody fulfills the CWA's pollution criteria no matter if there is a TMDL or not.

The EPA or state agencies issue National Pollutant Discharge Elimination System (NPDES) permits to point source dischargers, and when a TMDL has been established for a pollutant, the permit limits must align with the TMDL's wasteload allocation (US EPA, 2025b). Although nonpoint sources are not regulated through NPDES, TMDLs also assign them load allocations, which serve as targets for managing diffuse pollution from sources, such as agricultural or urban runoff. However, these efforts often depend on the voluntary cooperation of landowners and local stakeholders, supported by federal and state grant programs. Even with the permits, impairment persists. Past contamination in sediments, groundwater, or soil could continue releasing pollutants long after discharges are controlled. Nonpoint source pollution is also not regulated, which could make up a large share of impairment depending on the area. For example, the EPA notes that thousands of waterbodies are impaired from stormwater sources. Together, these factors highlight that regulatory compliance does not necessarily translate into improved water quality, allowing impairment to persist even in the presence of permitting and TMDL systems (US EPA, 2025b).

Although the public has access to the 303(d) list and impairment maps via the TDEC website and the EPA, public awareness may be limited. The EPA's "How's

My Waterway" tool, connected to ATTAINS impairment designations, provides more user-friendly access to localized water quality information (US EPA, 2024). However, public notification in Tennessee is not routine unless a formal water quality advisory is issued. Figure 2.2 displays an advisory sign posted in Knoxville, Tennessee, warning visitors to avoid contact with the water. Such advisories are posted only when bacteria levels or fish tissue contaminants exceed health-based thresholds (TDEC, 2019). Thus, many impaired waterbodies may go unnoticed by the general public. There is no database outlining the waterbodies in Tennessee that have advisories.



Figure 2.2: Water Quality Advisory Sign

Note: The City of Knoxville posted this sign advising the public about contaminated waters.

These institutional features shape both the availability and interpretation of water quality information. Variation in monitoring frequency, impairment designation and

remediation, and public notification may generate substantial heterogeneity in how water quality conditions are perceived by households. Consequently, the extent to which water quality impairment is capitalized in property values is likely to depend not only on environmental conditions but also on the timing, visibility, and credibility of regulatory information.

Chapter 3

Literature Review

Water quality is not traded in markets and therefore lacks an explicit price. To estimate its value, researchers rely on non-market valuation methods, including revealed preference approaches. Among these, the hedonic property model has become a central tool, as it exploits variation in housing prices to infer the value of localized amenities and disamenities, such as environmental quality. The underlying theory assumes that housing is a differentiated good composed of a bundle of characteristics, including structural attributes, neighborhood features, and public goods, and that observed market prices for housing reflect the implicit value of these attributes. Building on this framework, Rosen (1974) formalized the hedonic pricing model as a method for estimating the marginal willingness to pay (MWTP) for individual characteristics, including environmental amenities such as water quality.

While Rosen (1974) proposes a two-stage model to recover full demand functions, most studies only estimate the first stage of the model, yielding MWTP at observed

equilibria rather than recovering full demand functions (Bishop et al., 2020). This approach also relies on the assumption that housing transactions occur within a single market in which households face similar housing price structures. Violations of this assumption, such as analyzing housing transactions across multiple geographic markets, can complicate the identification and interpretation of MWTP estimates. The hedonic property model provides a powerful tool for RP valuation of water quality, but its application requires careful attention to issues of observability, market definition, econometric identification, and welfare interpretation.

3.1 Water Quality as a Valued Attribute

Hedonic pricing models have been used to value many different environmental goods, such as clean air, (Kim et al., 2010; Olmstead, 2010; Chay and Greenstone, 2005, 2003), urban trees Li (2023), public goods (Albouy et al., 2020; Kuminoff and Pope, 2014), and hazardous waste damages (Mendelsohn et al., 1992). This approach is also commonly used to value water quality (Kuwayama et al., 2022; Moore et al., 2020; Papenfus, 2019; Cho et al., 2011; Leggett and Bockstael, 2000). In one of the earliest hedonic water quality valuation studies, David (1968) examined property values in Wisconsin. Since then, there have been many hedonic studies focusing on water quality. A large amount of these earlier studies focus on lake waterfront homes in the Northeastern U.S. (Poor et al., 2007; Gibbs et al., 2002; Poor et al., 2001; Leggett and Bockstael, 2000). Other studies have expanded to different areas of the U.S.,

like Florida (Kuwayama et al., 2022), Washington (Papenfus, 2019), Oregon (Netusil, 2014), and Tennessee (Cho et al., 2011; Cho, 2006). More recent studies also focus on applying hedonic methods to broader geographic areas, such as statewide Walsh et al. (2017) and nationwide (Moore et al., 2020). International research has also been brought to light by Nicholls and Crompton (2018), including studies in China by Yao and Cao (2025) and Chen (2017). These studies commonly report a relationship between the quality of local waterbodies and nearby or adjacent property values.

While there are two studies using the hedonic property value model to value water quality in Tennessee, they are both focused on two small, localized areas (Cho et al., 2011; Cho, 2006). Cho et al. (2011) analyze pollution from a North Carolina paper mill affecting the Pigeon River watershed along the North Carolina–Tennessee border. Cho (2006) uses a hedonic model to estimate the effects of proximity to waterbodies and parks on property values in Knox County, Tennessee. Between these two studies, only Cho et al. (2011) uses impairment designations as a measure of water quality.

3.2 Housing Market Context and Regional Heterogeneity

Beyond direct waterfront effects, households also value access to nearby recreational water resources. Kung et al. (2017) and Kuwayama et al. (2022) show that water quality at recreational beaches influences surrounding housing markets, indicating

that capitalization effects extend beyond properties immediately adjacent to waterbodies. The type of waterbody and the way water quality is measured also play an important role in shaping estimated effects. Much of the existing literature focuses on lakes, 57% according to Heberling et al. (2020), often using measures such as Secchi depth, chlorophyll-*a*, or mercury concentrations (Mamun et al., 2023; Walsh et al., 2017; Tuttle and Heintzelman, 2015). In contrast, relatively fewer studies examine rivers and streams, particularly using policy-relevant measures such as impairment designations.

These studies, among others, are often more localized due to limitations in large-scale water quality or property transaction data availability. This highlights an important tradeoff within hedonic studies. Narrowly focused studies (e.g., Papenfus, 2019; Poor et al., 2007; Leggett and Bockstael, 2000) preserve the single-market assumption but may lack variation in water quality, while broader studies (e.g., Moore et al., 2020; Walsh et al., 2017) introduce variation at the risk of violating this assumption.

Additionally, the value of water quality may vary across regions due to differences in household preferences, recreational opportunities, and local economic conditions. These sources of heterogeneity suggest that estimates from one geographic context may not generalize to others, highlighting the need for region-specific analyses such as the present study. Heberling et al. (2020) highlights how attributes of the housing market could lead to variation in the significance and estimated sign of the coefficients.

However, they further find that variation is driven more strongly by methodological decisions related to model specification and the treatment of empirical challenges.

3.3 Methodological Characteristics and Challenges

While hedonic models are widely used to value environmental amenities, they present several econometric and conceptual challenges. Palmquist (1989) highlights key concerns, including omitted variable bias, spatial dependence, and the identification of marginal willingness to pay (MWTP). A central issue is that unobserved neighborhood and environmental characteristics may be correlated with both housing prices and water quality, leading to biased estimates. For example, if cleaner waterbodies are located in higher-income areas with better schools or public services, then failing to account for these other public goods and neighborhood demographic effects in the hedonic model can distort MWTP estimates.

The empirical literature has developed several strategies to address these challenges, including fixed effects, spatial econometric models, and quasi-experimental designs (Kuminoff et al., 2010). Panel data with repeated sales allow researchers to control for time-invariant property characteristics using fixed effects (Buck et al., 2014; Mendelsohn et al., 1992). However, such approaches are less common in the water quality literature due to data limitations and the difficulty of consistently measuring water quality over time (Heberling et al., 2020). Spatial dependence is often addressed using spatial lag models or distance-based weighting schemes to account

for correlation in housing prices across nearby properties (Bishop et al., 2020; Cho, 2006; Palmquist, 1989).

Beyond identification challenges, interpreting hedonic estimates also requires caution. Kuminoff and Pope (2014) emphasize that changes in property values reflect capitalization effects rather than direct measures of willingness to pay. These equilibrium outcomes are shaped by marginal buyers and sellers in the housing market, and the resulting hedonic estimates may not be representative of the preferences for all households in the market. As a result, hedonic estimates should be interpreted as bounds on willingness to pay rather than precise measures. Additionally, ignoring shifts in the hedonic price function over time may bias MWTP estimates (Bishop et al., 2020).

Several challenges are particularly important in the context of water quality. First, water quality is often imperfectly observed by homeowners. Unless changes are highly visible or accompanied by public advisories, variations in water quality may not significantly affect perceived amenities, limiting the extent to which they are capitalized into housing prices (Leggett and Bockstael, 2000). Second, the limited spatial variation in water quality within localized systems such as lakes or river segments often constrains identification, creating a tradeoff between exploiting broader variation and maintaining a well-defined housing market (Bishop et al., 2020; Leggett and Bockstael, 2000).

Chapter 4

Conceptual Framework

The hedonic pricing model has a long history of application in valuation studies (Ridker and Henning, 1967; Court, 1939). Early applications in the 1950s and 1960s helped popularize the approach (Berndt and Triplett, 1997), while Rosen (1974) later provided its formal theoretical foundation through a two-stage framework that explains how product attributes influence consumer choices. In this framework, the relationship between the price of a good and its attributes is expressed through the hedonic pricing function:

$$P = f(X_1, X_2, \ldots, X_n) \tag{4.1}$$

where P denotes the price of the good (e.g., a property), and X_i represents its attributes, such as parcel size, number of bedrooms, proximity to schools, and environmental quality.

We assume households derive utility from general consumption, housing attributes, and access to local environmental amenities, specifically, opportunities provided by nearby waterbodies. The amenity of waterbodies depends on both the proximity to the waterbody and its environmental quality, which may be diminished when the waterbody is impaired.

Household utility is represented as:

$$U = U(C, \mathbf{Z}, R(d, q)) \tag{4.2}$$

where C is the numeraire good used to define all other prices in the model, $\mathbf{Z}$ is a vector of housing attributes (e.g., square footage, number of bedrooms, age), and $R(d, q)$ denotes recreational utility derived from the nearest waterbody. Recreational utility depends on the distance d to the waterbody and the water quality q, with impairment reducing q.

Households face the budget constraint:

$$Y = C + P(\mathbf{Z}, d, q) \tag{4.3}$$

where Y denotes household income, and $P(\cdot)$ is the property price depending on housing attributes $\mathbf{Z}$, location (through d), and environmental quality q.

Following Rosen (1974), households select properties such that their marginal willingness to pay for attributes equals the implicit market price of those attributes. They choose C, $\mathbf{Z}$, and a location (determining d and q) to maximize utility

subject to their budget constraint. In equilibrium, impairment-induced reductions in water quality decrease value and thus willingness to pay, leading to lower prices for properties near impaired waterbodies.

While Rosen (1974) provides the theoretical foundation for hedonic valuation, subsequent research has highlighted limitations of the single-market assumption underlying the original framework. Leggett and Bockstael (2000) discuss this assumption, noting that expanding the geographic scope of a study may introduce multiple housing markets with different implicit prices for environmental amenities, making it more difficult to identify the value of an environmental good. Differences in household preferences, income levels, housing market conditions, and available substitutes may result in heterogeneous valuations of environmental attributes across locations. Therefore, empirical applications should account for spatial heterogeneity when estimating the capitalization of environmental amenities, particularly when the study area extends beyond a single housing market.

As discussed in Chapter 3, capitalization of environmental amenities also depends on whether households observe and value information about environmental quality. This framework assumes that waterbody impairment status is at least partially observable to market participants and therefore incorporated into housing prices, although actual buyer awareness may vary. When households respond to available information about environmental conditions, differences in perceived water quality should be reflected in their willingness to pay for nearby properties.

Consistent with this framework, proximity to clean water represents a positive environmental amenity, while impairment of the nearby waterbody reduces the recreational value associated with water access. Changes in perceived water quality are therefore expected to be capitalized into property prices. This relationship is also consistent with rational expectations theory Laidler (2024); Muth (1961), which suggests that consumers incorporate publicly available information, such as impairment listings, into their decisions and adjust willingness to pay according to expected environmental quality.

Chapter 5

Data and Empirical Strategy

5.1 Data

5.1.1 Property Transaction Data

Our primary dataset originates from the Tennessee Comptroller of the Treasury and the Tennessee Property Assessors, consisting of transaction-level records for land parcels in 86 of Tennessee's 95 counties from 2010 to 2023. These records include detailed information on the most recent sale price, sales history, parcel location, land use type, number of buildings, and other structural and site characteristics. We construct a cross-sectional dataset using the most recent sale for each parcel. We begin by restricting the sample to residential land use and single-family homes, excluding condominiums and multi-family properties to better isolate the effect of water quality on housing values (Kuwayama et al., 2022; Papenfus, 2019). We

further restrict the sample to transactions occurring after 2009 to align with the availability of water quality impairment data from the EPA's ATTAINS database. We also exclude parcels that are located near multiple waterbodies. Although the number of such observations is small, including them could introduce ambiguity in defining attainment (or impairment) status, as these parcels may be influenced by more than one waterbody with potentially different impairment conditions. To avoid confounding effects and ensure a clear interpretation of adjacency and impairment status, these parcels are removed from the analysis.

All property sale prices are adjusted for inflation to 2023 dollars using the Consumer Price Index (CPI) for All Urban Consumers. To reduce the influence of extreme values, we exclude observations below the 1st percentile and above the 99th percentile of the sale price distribution (Bishop et al., 2020). Extreme sale prices may reflect atypical transactions, data errors, or properties with characteristics that differ substantially from the typical residential market. Removing these observations reduces the potential for outliers to disproportionately influence coefficient estimates and improves the model's ability to capture the relationship between water quality impairment and residential property values. We also remove parcels with missing or invalid spatial geometries, which are parcels lacking usable geographic coordinates or containing misshapen spatial features that prevent accurate spatial operations, such as calculating proximity to impaired waterbodies. These exclusions result in the removal of two counties and approximately 6% of the original sample.

Nine additional counties are not included due to independent reporting systems (Chester, Davidson, Hamilton, Hickman, Knox, Montgomery, Rutherford, Shelby, and Williamson), leaving a final set of 84 counties. These excluded counties are among the most urban in Tennessee, with higher population densities and more developed housing markets relative to the rest of the state. Davidson, Knox, Shelby, and Hamilton are particularly important, as they contain the state's largest metropolitan areas, Nashville, Knoxville, Memphis, and Chattanooga, respectively. As a result, the analysis primarily reflects property markets in less urban and rural counties, which may limit the generalizability of results to highly urban settings. Figure 5.1 illustrates the geographic coverage of the sample.

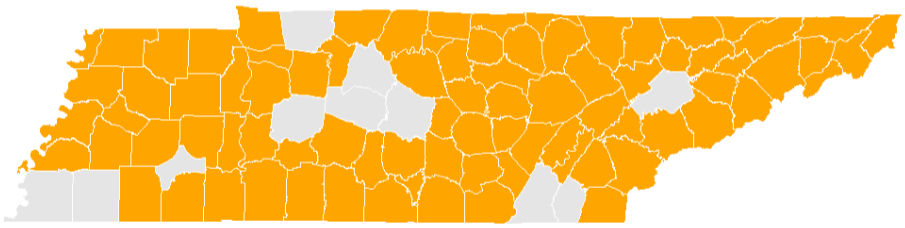

Figure 5.1: Counties Included in the Study Sample

Note: Counties shaded orange are included in the study, and counties shaded gray are not.

We then divide the sample into comparison groups based on parcel proximity to a waterbody. Specifically, we compare parcels located within 150 meters of an impaired waterbody to parcels located between 150 and 750 meters away. These distance thresholds follow the general approach of Papenfus (2019), who uses properties within 500 meters as a comparison group. However, we extend the outer comparison radius to 750 meters in the Tennessee context because parcels within 500 meters may still

include waterfront properties, particularly in areas with irregular parcel shapes or dense waterbody networks. By comparing parcels immediately adjacent to impaired waterbodies with parcels located farther from the shoreline, we reduce the likelihood that the comparison group receives direct waterfront amenities. This approach allows for a cleaner comparison that better isolates neighborhood-level effects of proximity to impaired waterbodies rather than direct frontage effects.

In addition, to avoid omitted variable bias, we include as many property-specific characteristics that might affect the home's sale price as the data allows. We create three dummy variables categorizing the material that a home is made out of into a high, mid, and low quality group. We use a similar approach for the grade of a home, which gives a letter grade to a house based on the quality of the structure. We divide it into four categories on if the grade is below average, average, above average, and excellent. We also include the square footage of the home, the age in years, number of stories, the distance in kilometers to the nearest major road, and the distance to the nearest urban cluster. Commonly, studies control for the number of bedrooms and bathrooms, but we do not have access to that data (Papenfus, 2019).

To calculate the distance to the nearest major road, we import data on all roads across the state of Tennessee from Tennessee's Department of Transportation (TDOT). We classify major road types as urban interstate, rural interstate, urban freeway, expressway, rural/freeway or expressway, urban other principal arterial, and rural other principal arterial. We use each parcel's centroid to find the nearest major roadway for each parcel and calculate the distance from each parcel to that roadway.

Using a similar approach, we also assign a distance for each parcel to the nearest urban cluster, meaning a densely settled area of at least 5,000 people (U.S. Census Bureau, nd). We use data from Topologically Integrated Geographic Encoding and Referencing (TIGER), which reports census data from 2020. We find the nearest urban polygon to each parcel's centroid and calculate the distance in kilometers. We also assign each parcel to its school district and census tract, both using TIGER, to implement time and spatial fixed effects.

5.1.2 Water Quality Impairment Data

The ATTAINS data we use in this study provides a summary of each waterbody in Tennessee from 2010 through 2024, with a unique assessment ID assigned to each segment of a larger waterbody. Each waterbody is assessed based on different assessment types that are associated with a designated use and reported every two years. These assessment types include biology, habitat, physical/chemical, and pathogens. Within each assessment type, one or more specific parameters are measured to determine attainment of water quality standards. For example, the pathogen assessment type means that it is monitored for E. coli, which is the parameter. From this, each segment is assigned an overall status, indicating whether it is fully supporting or not supporting at least one designated use. For example, if a waterbody is impaired for recreation but not impaired for any of the other designated uses, the overall status will be "Not Supporting" because it is impaired for at least one use. In this study, we define impairment as a waterbody's overall use being "Not

Supporting". This is the definition of impairment according to the CWA and reflects the 303(d) list that states report.

The only difference is that, as mentioned in Section 2,when a TMDL is created, the 303(d) list deems a waterbody no longer impaired. This means that some waterbodies that are not on Tennessee's 303(d) list due to a TMDL being created for it are considered impaired in our study. We keep a waterbody labeled as impaired until it actually meets the pollution standards put in place by the CWA rather than following TMDL creation[1]. This approach allows us to focus on the actual restoration of waterbodies rather than TMDLs that are unclear as to whether they are implemented or not. Figure 5.2 shows the average number of waterbodies classified as "Not Supporting" in each county in Tennessee during the 2010-2022 reporting cycles. 84% of waterbodies do not change status at all between 2010–2022.

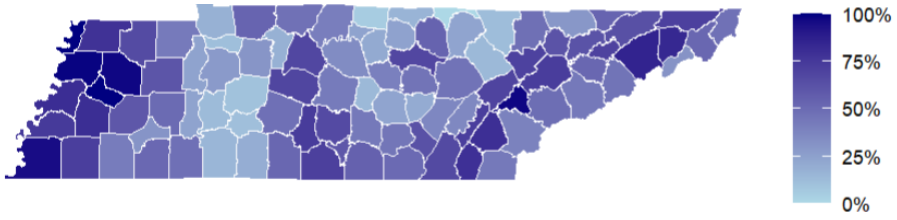

Figure 5.2: Rate of Impairment Per County in Tennessee

Note: Average proportion of impaired waterbodies in each county across all available reporting cycles (2010–2022).

More recent data from 2018–2022 includes the specific parameter causing impairment if the status is "Not Supporting", but this is largely incomplete with the majority of observations being NA. These data also include whether a TMDL has been

[1]We discussed this with a TDEC expert who confirms that TMDL implementation is not common in Tennessee.

developed, if the waterbody has subsequently been removed from the 303(d) list, and impairment by designated uses. Due to these not being available across all years of data and incomplete for specific parameters, we do not consider these variables in our study. The impairment data before 2018 are also not disaggregated by designated use, so we only consider whether a waterbody is impaired or not, irrespective of designated use. Many waterbodies are impaired for multiple designated uses, so we do not expect that using impairment as a general label rather than using a specific designated use will affect results[2].

Based on this map, there are more impaired waterbodies in highly populated areas, like Nashville and Memphis. The Northeastern region of Tennessee also has a high concentration of impaired waterbodies, likely influenced by downstream pollution from a Superfund site where a chemical plant in Saltville, Virginia, discharged waste into the Holston River (Haywood, 2003).

Tennessee defines a waterbody as "any public or private water on or beneath the ground surface that flows through, borders, or is within the state" (TDEC, 2020). Waterbodies that are fully contained within private, single-ownership property that do not connect to natural surface or underground waters are excluded from what Tennessee defines as a waterbody. In ATTAINS, rivers and streams are grouped within a single waterbody category, and assessment units may include multiple stream reaches and tributaries based on underlying hydrographic datasets. As a

[2]Using ATTAINS 2018–2022, we find that if a waterbody is impaired for any one designated use, it's overall status is "Not Supporting."

result, smaller tributaries and drainage features are often incorporated into broader river classifications (TDEC, 2023). This leads to a noisy dataset of waterbodies not observed by homebuyers.

To overcome this limitation, we use the National Hydrography Dataset (NHD) to define the waterbodies used in this study. This dataset follows the Strahler stream order, which is a method that classifies the hierarchy of channels within a watershed (US EPA, 2004). More specifically, the Strahler stream order assigns each stream or river a number based on its branching complexity, with higher-order streams representing larger and more prominent waterbodies. By using this classification, we focus on the waterbodies that are most likely to influence nearby property values and exclude minor channels that may have little economic impact. Therefore, we reduce the number of less economically relevant waterbodies in the final sample by restricting our sample to those with a stream order of four or higher and filtering lakes and reservoirs to have an area greater than or equal to 25 acres. This allows us to filter out waterbodies that buyers may not acknowledge are present and pay a premium for.

We also filter for assessed waterbodies, meaning that they are monitored within that reporting cycle. As noted in Section 2 Tennessee follows a cycle that prioritizes which waterbodies to assess based on factors like pollution and public need. We do not have an impairment status if a waterbody is not assessed, so we exclude any waterbodies that are not assessed within a given cycle. Figure 5.3 illustrates

the distribution of impaired and non-impaired waterbodies in 2010, while Figure 5.4 presents the corresponding distribution in 2022.[3]

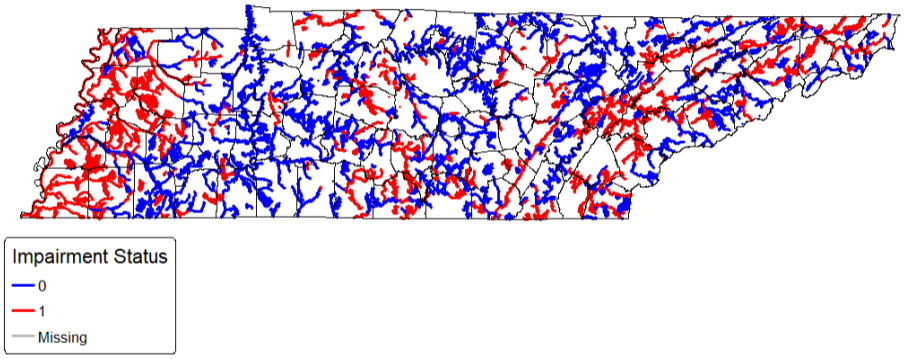

Figure 5.3: Impairment Distribution in 2010

Note: Red lines indicate impaired waterbodies; blue lines indicate non-impaired waterbodies.

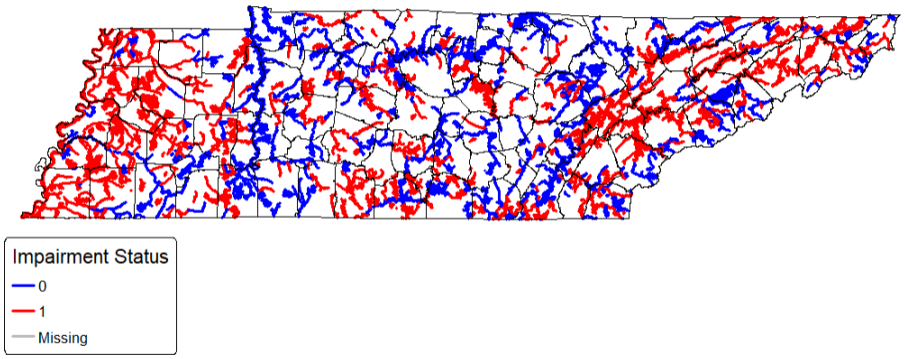

Figure 5.4: Impairment Distribution in 2022

Note: Red lines indicate impaired waterbodies; blue lines indicate non-impaired waterbodies.

5.1.3 Linking Residential Properties to Water Quality Data

We link our parcel-level data with water quality data from ATTAINS by obtaining spatially explicit information on each waterbody's location and overlapping the layers using GIS. We use 2023 boundary lines, given it was the data available, for each

[3]Approximately 84% of waterbodies do not change impairment status between 2010 and 2022.

parcel to account for potential divisions within a piece of land or property. There are very few parcels within 750m of multiple waterbodies, so we drop those parcels to avoid confounding effects from proximity to multiple waterbodies. We merge these shapefiles to our property transaction data using a shared GIS link. To align property sales with the biennial reporting cycle of the impairment data, we group sale years into two-year intervals. For instance, sales from 2019–2020 are linked to the 2018 reporting cycle, 2021–2022 sales to the 2020 cycle, and so on. We exclude the 2024 reporting cycle due to lack of parcel data. Figure 5.5 illustrates the spatial linkage and visualization of parcels in proximity to waterbodies.

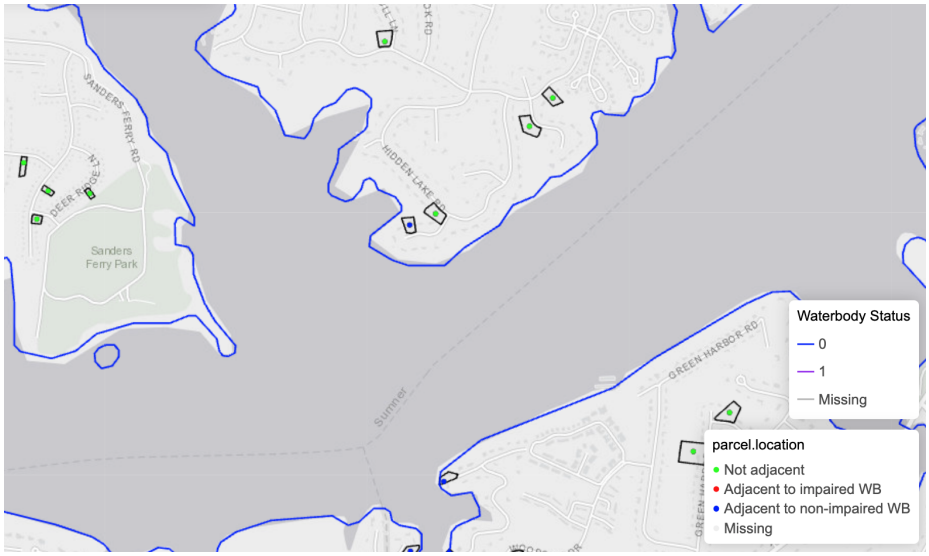

Figure 5.5: Property Distance to Waterbodies

Note: Sample includes parcels located $\leq$ 150 m from impaired waterbodies, $\leq$ 150 m from non-impaired waterbodies, and $\leq$ 750 m from any waterbody. A value of 1 indicates an impaired waterbody, and 0 indicates a non-impaired waterbody.

To measure parcel proximity, we first calculate a centroid for each parcel, ensuring the point falls inside the parcel polygon. We then compute the straight-line

(Euclidean) distance from each centroid to the nearest assessed waterbody within the same reporting cycle. This allows us to assign each parcel a distance to the closest waterbody and determine its impairment exposure.

Based on these distances, we construct treatment and control groups that distinguish between proximity to water and water quality. Parcels are first classified by their proximity to the nearest waterbody, where parcels within 150 meters are considered adjacent. Among these parcels, the treatment group consists of properties located near impaired waterbodies, while the control group consists of properties located near non-impaired waterbodies. Parcels located farther from waterbodies (e.g., beyond 750 meters) serve as an additional comparison group to capture baseline property values unrelated to water proximity.

This framework allows us to separately identify the effect of proximity to water and the disamenity associated with water quality impairment. Additionally, we classify parcels by Tennessee's three legally defined Grand Divisions—East, Middle, and West Tennessee—to account for geographic variation and to maintain the single-market assumption in hedonic models (Leggett and Bockstael, 2000). Figure 5.6 shows these divisions.

East Tennessee is mountainous, including the Great Smoky Mountains, and contains the Tennessee River Valley with soils less suited for large-scale agriculture (Tennessee Historical Society, 2020). Middle Tennessee features rolling hills and valleys, including most of the Cumberland Plateau and Central Basin, which are

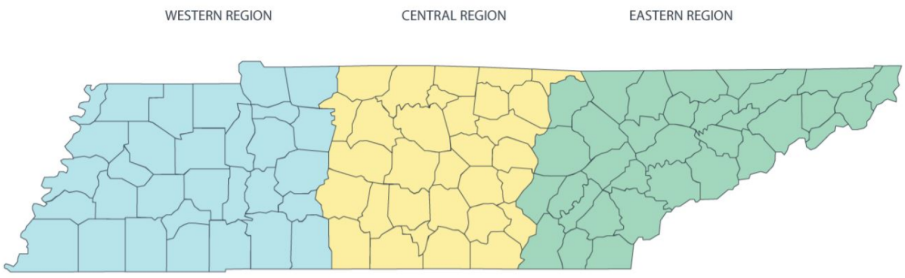

Figure 5.6: Tennessee's Grand Divisions

Note: Map accessed from UT Institute of Agriculture (Tennessee Association of Agricultural Agents and Specialists, 2020).

suitable for larger farms but prone to flooding. West Tennessee is the flattest region, bounded by the Mississippi River and Western Tennessee River valley.

We also explore alternative geographic classifications, such as Metropolitan Statistical Areas (MSAs) and USDA urban/rural zones, but these approaches resulted in too few parcels in Tennessee's most urban counties and often led to unstable estimates. Finally, we test alternative proximity measures to provide additional insight into the effect of distance on property values. These include parcels directly on the waterfront and successive buffers of 500 meters up to 1000 meters (Papenfus, 2019; Walsh et al., 2017). Our preferred model captures the contrast between parcels directly adjacent to a waterbody versus those close enough to receive neighborhood amenities. Table 5.1 presents summary statistics for variables in our preferred specification across each of the three regions, with a total sample of 36,320 property transactions across Tennessee [4].

[4]Summary statistics for the state of Tennessee are reported in Table A.1 of the Supplementary Appendix.

Table 5.1: Summary Statistics by Tennessee Region

Panel A: East Tennessee

Statistic	N	Mean	St. Dev.	Min	Max
Property Price (USD 2023)	15,236	238,771.10	152,393.10	13,014.54	857,674.60
Log Property Price (USD 2023)	15,236	12.16	0.72	9.47	13.66
Adjacent to Waterbody	15,236	0.18	0.38	0	1
Adjacent × Impaired	15,236	0.12	0.33	0	1
Non-Adjacent × Impaired	15,236	0.61	0.49	0	1
Stories	15,236	1.24	0.43	1	4
Age of Building	15,236	35.80	28.76	0	217
Buildings	15,236	1.03	0.18	1	6
Distance to Urban Area (km)	15,236	7.52	15.40	0.00	123.58
Distance to Highway (km)	15,236	3.25	4.08	0.02	41.62
Log Base Area	15,236	7.16	0.34	3.26	8.98

Panel B: Middle Tennessee

Statistic	N	Mean	St. Dev.	Min	Max
Property Price (USD 2023)	11,689	245,592.40	155,306.90	13,019.29	858,959.80
Log Property Price (USD 2023)	11,689	12.18	0.75	9.47	13.66
Adjacent to Waterbody	11,689	0.12	0.32	0	1
Adjacent × Impaired	11,689	0.04	0.20	0	1
Non-Adjacent × Impaired	11,689	0.35	0.48	0	1
Stories	11,689	1.33	0.47	1	4
Age of Building	11,689	30.69	29.22	0	186
Buildings	11,689	1.01	0.14	0	6
Distance to Urban Area (km)	11,689	11.55	20.59	0.00	121.48
Distance to Highway (km)	11,689	3.16	3.80	0.02	24.53
Log Base Area	11,689	7.18	0.33	5.28	8.49

Panel C: West Tennessee

Statistic	N	Mean	St. Dev.	Min	Max
Property Price (USD 2023)	9,395	199,835.90	147,609.60	13,014.54	858,263.60
Log Property Price (USD 2023)	9,395	11.92	0.81	9.47	13.66
Adjacent to Waterbody	9,395	0.16	0.37	0	1
Adjacent × Impaired	9,395	0.09	0.28	0	1
Non-Adjacent × Impaired	9,395	0.51	0.50	0	1
Stories	9,395	1.23	0.42	1	3
Age of Building	9,395	35.87	25.89	0	157
Buildings	9,395	1.02	0.14	1	4
Distance to Urban Area (km)	9,395	15.44	25.96	0.00	131.63
Distance to Highway (km)	9,395	4.57	6.10	0.02	34.51
Log Base Area	9,395	7.22	0.33	5.08	8.66

Notes: Summary statistics are for residential parcels within 750 meters of a waterbody in Tennessee. Sale prices are adjusted to 2023 USD using CPI. Observations below the 1st percentile and above the 99th percentile of sale price are excluded. Distances to urban clusters and highways are measured in kilometers.

Properties vary in both structural and locational characteristics but are relatively similar across each region. Middle Tennessee has the highest average property price with West Tennessee being the lowest by about 39,000. Approximately 15% of homes are adjacent to a waterbody across all of the regions, but East Tennessee, on average, has more homes adjacent to impaired waterbodies. Middle Tennessee has a low percentage of adjacency to an impaired waterbody with an average of 4% of homes. Other property characteristics are broadly comparable across regions. However, West Tennessee appears to be more rural, as indicated by a higher average distance to the nearest urban cluster and highway. These variables help control for observable differences affecting sale prices.

5.2 Econometric Methods

To examine the benefits of water quality improvements, we use a hedonic valuation approach applied to residential property values in Tennessee. We focus on single-family homes located within 150m of an impaired waterbody. Properties situated between 150m and 750m of any waterbody serve as the comparison group. This empirical approach closely follows the methodology outlined in Papenfus (2019). We use the following log-linear regression model to estimate the relationship between water quality impairment status and property values:

$$\ln(P_{it}) = \beta_0 + \beta_1 Adjacent_i + \beta_2(Adjacent_i \times ImpWB_{it}) + \beta_3(NonAdjacent_i \times ImpWB_{it}) + X'_{it}\theta + \delta_c + \delta_t + \varepsilon_{it}, \tag{5.1}$$

where the outcome variable P_{it} is the log sale price of property i at time t. $Adjacent_i$ is an indicator equal to one for properties located within 150 meters of a non-impaired waterbody. $Adjacent_i \times ImpWB_i$ is an indicator for properties that are both adjacent to a waterbody and whose nearest waterbody is classified as impaired. $NonAdjacent_i \times ImpWB_i$ is an indicator for properties located within the comparison group (150–750 meters from the nearest waterbody) whose nearest waterbody is classified as impaired. The omitted reference group consists of properties that are not adjacent to a waterbody and whose nearest waterbody is classified as non-impaired.

The vector X_{it} includes structural housing characteristics such as square footage, number of buildings, number of stories, housing grade, exterior wall quality, distance to the nearest urban cluster, distance to the nearest major road, and the time-varying age of the home[5]. We include census tract fixed effects, δ_c, which absorb time-invariant differences across census tracts, such as persistent neighborhood characteristics, location-specific amenities, and other unobserved factors that may influence property values. We also include year fixed effects, δ_t, which absorb temporal shocks affecting all properties, such as changes in macroeconomic conditions and broader housing market trends. Standard errors are clustered at the census tract

[5]In the baseline specification, these controls enter additively, which assumes that the effects of water proximity and impairment are constant across properties. In reality, these effects may vary with property quality; however, modeling this heterogeneity is beyond the scope of the current specification.

level to account for spatial correlation in unobserved determinants of housing prices. The logarithmic transformation reduces skewness in the distribution of sale prices and allows estimated coefficients to be interpreted as semi-elasticities. This means that coefficients represent approximate percentage changes in property values. For a more precise interpretation, the exact percentage change associated with a one-unit change in a covariate is calculated as $(e^{\beta} - 1) \times 100$, where β is the estimated coefficient from the regression. We estimate equation 5.1 separately for each of the three regions in Tennessee, East, Middle, and West, to assess whether the relationship between water quality and property values differs across distinct regional housing markets.

Our identification strategy exploits two sources of variation: (1) proximity to a waterbody and (2) the impairment status of that waterbody. Properties located within 150 meters of a waterbody are classified as *Adjacent*, while properties located between 150 and 750 meters from the nearest waterbody serve as the comparison group. Among properties in both groups, we distinguish between those whose nearest waterbody is classified as impaired and those whose nearest waterbody is non-impaired. Under this specification, the coefficient on *Adjacent* (β_1) captures the price premium associated with proximity to a non-impaired waterbody relative to nearby properties whose nearest waterbody is non-impaired but not adjacent. The interaction term (β_2), which is the primary coefficient of interest, captures the additional price effect associated with being adjacent to an impaired waterbody relative to being adjacent to a non-impaired waterbody (the impairment effect for adjacent properties). Finally, the coefficient on $NonadjImpWB$ (β_3) captures the difference in property

values associated with having an impaired nearest waterbody among properties that are not adjacent (the impairment effect for non-adjacent properties).

Thus, β_2 identifies whether the value associated with adjacency to a waterbody differs depending on impairment status. This coefficient is identified from comparisons among adjacent and nearby properties with different waterbody impairment statuses, while controlling for structural characteristics, location characteristics, and fixed effects. The key identifying assumption is that, absent impairment, properties adjacent to impaired and non-impaired waterbodies would exhibit similar price premiums associated with proximity to water. In other words, adjacent and nearby properties must be comparable in unobserved neighborhood characteristics, and impairment status must not be systematically correlated with other determinants of property values within the same proximity band. While the inclusion of census tract and year fixed effects, along with controls for distance to urban clusters and major roads, helps account for observable sources of spatial sorting and temporal changes, we cannot rule out that impaired waterbodies are located in areas that differ from clean waterbodies along unobserved dimensions. Therefore, β_2 should be interpreted as a conditional association between waterbody impairment and adjacent property values rather than a causal estimate.

Chapter 6

Results and Discussion

We estimate equation 5.1 separately for each of Tennessee's three regions and the entire state, and report the results in Table 6.1. Estimating the model separately by region allows us to account for differences in terrain, property density, and local housing market conditions that may influence how property values respond to water quality impairment. While we estimate the model using alternative fixed-effects structures, reported in Table 6.4, our preferred specification includes census tract and year fixed effects. The sample includes residential properties located within 750 meters of the nearest waterbody.

The estimates capture two related components of the water quality amenity: the value associated with proximity to water and the extent to which impairment status alters this value. The coefficient on *Adjacent* reflects the premium associated with proximity to a non-impaired waterbody relative to nearby properties in the comparison group. The interaction term $Adjacent \times ImpWB$, our primary coefficient

of interest, captures whether this proximity premium differs when the adjacent waterbody is impaired. Finally, the coefficient on $NonAdjacent \times ImpWB$ captures whether impairment status is associated with differences in property values among properties located within the comparison group but not directly adjacent to water.

It is important to note that these estimates represent the capitalization of environmental quality into property values rather than direct measures of willingness to pay. As Kuminoff and Pope (2014) emphasize, hedonic price estimates reflect equilibrium outcomes resulting from household sorting across locations rather than individual-level valuations.

We now discuss the results by region, beginning with East Tennessee. In East Tennessee, Table 6.1 shows that proximity to a non-impaired waterbody is associated with a statistically significant premium of 10.7 percent, equivalent to approximately $25,500 relative to the regional mean sale price of $238,771. The estimated coefficient on the interaction between adjacency and impairment is positive but statistically insignificant. The coefficient on $NonAdjacent \times ImpWB$ is positive and significant at the 10% level, suggesting that properties within the comparison group whose nearest waterbody is impaired have slightly higher values than those near non-impaired waterbodies. Although we expected both interaction terms to be negative based on theory and previous literature, the estimated effects are either statistically insignificant or small in magnitude, providing limited evidence that impairment reduces property values in East Tennessee. Overall, East Tennessee exhibits a strong

Table 6.1: Regression Results of Water Quality Impairment on Property Values by Tennessee Region

	East	Middle	West	Statewide
Adjacent	0.102***	0.098***	0.244***	0.142***
	(0.034)	(0.031)	(0.042)	(0.023)
Adjacent × Impaired	0.050	-0.072	-0.191***	-0.055*
	(0.049)	(0.047)	(0.061)	(0.032)
Non-Adjacent × Impaired	0.055*	0.017	-0.025	0.008
	(0.029)	(0.027)	(0.034)	(0.017)
Stories	0.299***	0.261***	0.296***	0.287***
	(0.015)	(0.015)	(0.019)	(0.009)
Age	-0.004***	-0.005***	-0.005***	-0.005***
	(0.0003)	(0.0004)	(0.0006)	(0.0002)
Number of Buildings	0.121***	0.107**	0.030	0.103***
	(0.027)	(0.049)	(0.056)	(0.023)
Distance to Urban Area (km)	0.001	-0.001	0.0004	-0.0007
	(0.001)	(0.001)	(0.002)	(0.0010)
Distance to Highway (km)	0.019***	0.009**	0.005	0.011***
	(0.004)	(0.004)	(0.006)	(0.003)
ExtWall High	0.120***	0.132***	0.105***	0.118***
	(0.014)	(0.013)	(0.015)	(0.008)
ExtWall Low	-0.222***	-0.209***	-0.283***	-0.236***
	(0.032)	(0.043)	(0.045)	(0.023)
Log Base Area	0.532***	0.574***	0.754***	0.594***
	(0.030)	(0.037)	(0.037)	(0.021)
Grade Below	-0.446***	-0.363***	-0.424***	-0.433***
	(0.030)	(0.038)	(0.053)	(0.024)
Grade Above	0.165***	0.045	0.118**	0.125***
	(0.033)	(0.043)	(0.046)	(0.023)
Grade Excellent	0.290*	0.137	-0.291	0.178
	(0.156)	(0.122)	(0.203)	(0.125)
Year FE	Yes	Yes	Yes	Yes
Census Tract FE	Yes	Yes	Yes	Yes
R^2	0.48676	0.60216	0.57539	0.55338
Observations	15,085	11,618	9,338	36,041

Notes: This table uses all parcels ≤ 750m as the comparison group to all parcels adjacent to a waterbody (≤ 150m). All models include year and census tract fixed effects. Standard errors are clustered at the census tract level and are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

positive amenity value associated with proximity to water, with no evidence that impairment reduces this premium.

In Middle Tennessee, adjacency to a non-impaired waterbody is associated with a statistically significant price premium of 0.098, corresponding to an approximate 10.3 percent increase in property values, or $25,200 relative to the mean sale price of $245,592. The estimated coefficient on the interaction between adjacency and impairment is negative (-0.072), consistent with the hypothesis that impairment reduces the value associated with proximity to water. However, the estimate is not statistically significant, meaning that we cannot conclude that the water proximity premium differs between impaired and non-impaired waterbodies in Middle Tennessee. The coefficient on $NonAdjacent \times ImpWB$ is small and statistically insignificant, suggesting that impairment does not significantly affect property values among non-adjacent properties.

West Tennessee exhibits the strongest capitalization of both water proximity and impairment status. The coefficient on *Adjacent* is 0.244, corresponding to a 27.6 percent increase in property values, or approximately $55,200 relative to the regional mean sale price of $199,836. The interaction between adjacency and impairment is negative and statistically significant (-0.191), implying that impairment reduces the adjacent waterbody premium by approximately 17.4 percent, or $34,800. These results suggest that although impaired waterbodies retain some amenity value, impairment substantially reduces the premium associated with living in close proximity to water. Similar to Middle Tennessee, the coefficient on $NonAdjacent \times$

$ImpWB$ is statistically insignificant, suggesting limited evidence that impairment affects nearby but non-adjacent properties.

We then estimate the model using the full statewide sample and find results that are broadly consistent with those observed in West Tennessee. Across Tennessee, proximity to a non-impaired waterbody is associated with a positive and statistically significant premium, with the coefficient on $Adjacent$ equal to 0.142. However, the negative and statistically significant coefficient on $Adjacent \times ImpWB$ indicates that impairment reduces the premium associated with proximity to water by 5.4 percent. The coefficient on $NonAdjacent \times ImpWB$ is small and statistically insignificant, providing limited evidence that impairment affects properties located near, but not directly adjacent to, impaired waterbodies.

However, we do not rely on the statewide specification alone, as combining distinct regional housing markets may introduce concerns regarding the single-market assumption required in hedonic models (Leggett and Bockstael, 2000). Therefore, the regional estimates provide the primary basis for interpretation, allowing the capitalization of water quality impairment to be evaluated within more localized housing markets. To further examine potential heterogeneity, we estimate separate models for rivers and lakes, reported in Table A.2 in the Supplementary Appendix. Differences in recreational use, visibility, and the types of amenities provided by rivers and lakes may cause homebuyers to value water quality differently across waterbody types. For both waterbody types, however, the interaction between adjacency and

impairment is negative and statistically significant, suggesting that being adjacent to either waterbody type is associated with a potential decrease in the property value.

In addition to our main specifications, we also conduct several robustness checks to assess the sensitivity of our results. First, we estimate the model using varying distance thresholds in Table 6.2. We use a 500m and a 1000m distance threshold both with adjacency being labeled as homes $\leq$150m from a waterboy and a 750m threshold with adjacency being $\leq$250m and $\leq$500m. we expect that as a parcel gets further away from an impaired waterbody, the price effect will diminish. These results are consistent with our main specification in Table 6.1. In West Tennessee, direct adjacency to an impaired waterbody remains negatively and significantly associated with property values. As the adjacency threshold increases, the estimated effect becomes smaller and less statistically significant, suggesting that the influence of water quality impairment diminishes with distance.

We also conduct a robustness check in Table 6.3 by estimating separate models on subsamples of adjacent and non-adjacent properties. Estimating these models separately reduces concerns that unobserved differences between adjacent and non-adjacent properties may influence the estimated effects in the pooled specification. In these models, the coefficient of waterbody impairment captures the effect of impairment within each subsample and should correspond to the respective interaction terms in equation 5.1. Overall, the results are consistent with the

Table 6.2: Alternative Definitions of Spatial Proximity

Panel A: East Tennessee

	(1)	(2)	(3)	(4)
Adjacent	0.093***	0.107***	0.034	0.035
	(0.034)	(0.036)	(0.029)	(0.023)
Adjacent × Impaired	0.066	0.038	0.064	0.047
	(0.050)	(0.048)	(0.042)	(0.033)
Non-Adjacent × Impaired	0.070**	0.041*	0.043	0.053
	(0.034)	(0.023)	(0.029)	(0.033)
R^2	0.49406	0.47986	0.48532	0.48471
Observations	10,309	19,758	15,085	15,085

Panel B: Middle Tennessee

	(1)	(2)	(3)	(4)
Adjacent	0.098***	0.098***	0.024	0.021
	(0.030)	(0.031)	(0.020)	(0.019)
Adjacent × Impaired	-0.064	-0.062	-0.020	-0.007
	(0.050)	(0.046)	(0.037)	(0.030)
Non-Adjacent × Impaired	0.018	0.019	0.016	0.031
	(0.033)	(0.025)	(0.026)	(0.029)
R^2	0.60870	0.60528	0.60130	0.60131
Observations	7,474	15,360	11,618	11,618

Panel C: West Tennessee

	(1)	(2)	(3)	(4)
Adjacent	0.217***	0.255***	0.163***	0.116***
	(0.040)	(0.044)	(0.034)	(0.030)
Adjacent × Impaired	-0.188***	-0.183***	-0.138***	-0.085**
	(0.064)	(0.064)	(0.051)	(0.040)
Non-Adjacent × Impaired	-0.037	-0.011	-0.018	0.006
	(0.043)	(0.030)	(0.034)	(0.039)
R^2	0.57482	0.58697	0.57323	0.57147
Observations	6,037	12,757	9,338	9,338

Notes: Columns (1) and (2) vary the comparison sample by including properties located within 500 meters and 1000 meters, respectively, while maintaining the baseline adjacent definition of properties located within 150 meters of a waterbody. Columns (3) and (4) maintain the baseline 750-meter comparison sample but redefine adjacent properties as those located within 250 meters and 500 meters of a waterbody, respectively. All models include the same control variables and year and census tract fixed effects as the preferred specification reported in Table 6.1. Standard errors are clustered at the census tract level and reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

main specification in terms of the direction of the estimated effects, although some differences in statistical significance emerge.

In East Tennessee, the coefficient on impairment among adjacent properties is positive and statistically significant, while the corresponding interaction term in the main specification is positive but statistically insignificant. Specifically, the coefficient on $Adjacent \times ImpWB$ is 0.050 in the main specification, compared to 0.074 in the adjacent-property subsample, where it is statistically significant at the 10% level. For non-adjacent properties, the estimated coefficient has the same sign as the main specification, although it shows stronger statistical significance in the subsample analysis. In Middle Tennessee, impairment among adjacent properties has a negative and statistically significant effect, consistent with the sign of the interaction term in the main specification, although the main specification does not achieve statistical significance. The results for non-adjacent properties are consistent across both specifications. In West Tennessee, the impairment coefficient for adjacent properties is negative but statistically insignificant, matching the sign of the main specification but differing in statistical significance. The estimated effect for non-adjacent properties has the same sign as the main specification and is more statistically significant in the subsample analysis. These differences in statistical significance may be driven by reduced statistical power in the separate subsample models due to smaller sample sizes and lower within-group variation.

Table 6.3: Subsample Estimation by Proximity to Waterbody

	East Tennessee		Middle Tennessee		West Tennessee	
	Adjacent	Non-Adjacent	Adjacent	Non-Adjacent	Adjacent	Non-Adjacent
Waterbody Impairment	0.074*	0.050***	-0.099*	0.018	-0.059	-0.049**
	(0.042)	(0.017)	(0.059)	(0.016)	(0.061)	(0.021)
R^2	0.54459	0.48833	0.64704	0.60723	0.61026	0.58026
Observations	2,617	12,468	1,313	10,305	1,521	7,817

Notes: This table presents robustness checks estimating separate models for adjacent properties ($\leq$ 150 m from a waterbody) and non-adjacent properties (150–750 m from a waterbody). All specifications include the same property characteristics, year fixed effects, and census tract fixed effects as the baseline model. Standard errors are clustered at the census tract level and are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

In addition to our preferred fixed effects specification, we estimate alternative models that vary the fixed-effects structure as robustness checks. These specifications include school-district-by-year, census-tract-by-year, county-by-year, and separate year and geographic fixed effects. These results are reported in Table 6.4 and demonstrate that our primary findings are robust across alternative fixed-effects specifications. Across the different models, the direction and magnitude of the estimated effects remain largely consistent, providing confidence that the results are not driven by a particular choice of fixed effects. While a small number of coefficients vary in statistical significance across specifications, these differences are minor and do not alter the overall conclusions of the analysis.

Table 6.4: Effects of Water Quality Impairment on Property Values Across Regions and Fixed-Effect Specifications

Panel A: East Tennessee

	(1)	(2)	(3)	(4)	(5)
Adjacent	0.091*	0.116***	0.094*	0.087*	0.092*
	(0.047)	(0.035)	(0.048)	(0.048)	(0.050)
Adjacent × Impaired	0.080	0.050	0.074	0.080	0.069
	(0.058)	(0.053)	(0.058)	(0.058)	(0.059)
Non-Adjacent × Impaired	0.058***	0.054	0.056**	0.053**	0.051**
	(0.020)	(0.035)	(0.021)	(0.019)	(0.021)
R^2	0.46608	0.57536	0.44700	0.46030	0.44362
Observations	15,236	15,085	15,236	15,236	15,236

Panel B: Middle Tennessee

	(1)	(2)	(3)	(4)	(5)
Adjacent	0.106**	0.094***	0.106**	0.104*	0.104*
	(0.051)	(0.032)	(0.050)	(0.052)	(0.051)
Adjacent × Impaired	-0.081	-0.101*	-0.067	-0.081	-0.065
	(0.071)	(0.056)	(0.063)	(0.075)	(0.068)
Non-Adjacent × Impaired	0.018	-0.014	0.031	0.018	0.032
	(0.023)	(0.035)	(0.020)	(0.024)	(0.021)
R^2	0.59011	0.67853	0.57165	0.58876	0.57106
Observations	11,689	11,618	11,689	11,689	11,689

Panel C: West Tennessee

	(1)	(2)	(3)	(4)	(5)
Adjacent	0.273***	0.269***	0.259***	0.272***	0.259***
	(0.059)	(0.045)	(0.063)	(0.060)	(0.063)
Adjacent × Impaired	-0.188**	-0.206***	-0.179**	-0.188**	-0.178**
	(0.083)	(0.070)	(0.085)	(0.086)	(0.087)
Non-Adjacent × Impaired	-0.009	-0.029	-0.009	-0.008	-0.008
	(0.028)	(0.044)	(0.024)	(0.028)	(0.024)
Year-School District FE	Yes				
Year-Census Tract FE		Yes			
Year FE			Yes		Yes
Census Tract FE					
School District FE			Yes		
Year-FIPS FE				Yes	
FIPS FE					Yes
R^2	0.56653	0.67292	0.53136	0.56261	0.53108
Observations	9,395	9,338	9,395	9,395	9,395

Notes: The dependent variable is the log of real property price. Models include structural housing characteristics and fixed effects as indicated. Standard errors are clustered at the geographic level corresponding to the fixed effects and are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Chapter 7

Conclusion

Across Tennessee, proximity to a non-impaired waterbody is consistently associated with higher property values, although the extent to which impairment affects this amenity varies across regions. In East Tennessee, adjacent properties experience an estimated 10.7 percent premium, equivalent to approximately $25,500 relative to the regional mean sale price, and there is no statistical evidence that impairment reduces this premium. Similarly, in Middle Tennessee, adjacency to a non-impaired waterbody is associated with an approximate 10.3 percent increase in property values, but while the estimated effect of impairment is negative, it is not statistically significant. The largest and clearest effects are observed in West Tennessee, where adjacency to a non-impaired waterbody is associated with a 27.6 percent premium, or approximately $55,200 relative to the regional mean sale price. However, impairment significantly reduces this premium, indicating that although properties adjacent to impaired waterbodies continue to retain a positive amenity value, the value

associated with water proximity is substantially diminished. Across all regions, we find limited evidence that impairment affects property values among non-adjacent properties, suggesting that the economic impacts of impairment are concentrated among properties with the greatest exposure to affected waterbodies. These findings suggest that water quality impairment does not eliminate the economic value of proximity to water but can substantially reduce the amenity premium associated with living immediately adjacent to impaired waterbodies. However, this relationship is not uniform across Tennessee.

Our findings provide important implications for policymakers by demonstrating that water quality degradation has measurable economic consequences through its potential effect on properties located immediately adjacent to impaired waterbodies. Quantifying these impacts can help inform cost-benefit analyses of water quality improvement programs, restoration efforts, and regulatory actions associated with Total Maximum Daily Loads (TMDLs). Additionally, the results highlight the importance of accessible water quality information. Because impairment designations may not always be visible to residents or prospective homebuyers, improved public access to water quality information, including recreational advisories and localized impairment status databases, could help increase awareness of environmental conditions and support more informed housing decisions.

Despite these findings, additional research is needed to strengthen identification and further understand the mechanisms through which water quality affects property markets. Future work could implement repeated sales models with parcel-level fixed

effects to better address potential omitted variable bias from time-invariant property characteristics. Expanding the analysis to include the urban counties excluded from this study would provide additional insight into differences between urban and rural housing markets. Such extensions should incorporate parcel boundaries over time to account for changes in parcel configurations and improve the accuracy of spatial comparisons. Additionally, defining more precise housing market boundaries would further address concerns regarding the single-market assumption in hedonic models (Leggett and Bockstael, 2000).

Future research could also examine heterogeneity across different pollutants, impairment causes, and waterbody characteristics to determine which environmental conditions generate the largest economic impacts. Incorporating additional neighborhood characteristics and household-level information, like number of bedrooms or bathrooms, could provide further insight into the mechanisms driving capitalization. Survey-based approaches examining whether and how homebuyers perceive water quality impairment would also complement hedonic estimates by identifying the role of information and awareness in environmental valuation.

Extending this analysis to additional geographic contexts remains important for understanding how water quality affects property markets under different institutional and environmental conditions (Russ et al., 2022). Although water quality impairment status is a U.S.-specific regulatory designation, many regions face challenges associated with limited water quality monitoring and inconsistent reporting systems (Olmstead, 2010). Even within the United States, differences in monitoring

practices across states suggest that applying similar methods in other locations would provide valuable evidence regarding the generalizability of these findings. Continued research integrating improved environmental data, property-level information, and measures of household preferences will strengthen our understanding of how water quality improvements generate economic benefits for communities.

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Appendix

Appendix A

Supplementary Appendix

A.1 Supplementary Data

Table A.1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Property Price (USD 2023)	36,320	230,894.90	153,247.60	13,014.54	858,959.80
Log Property Price (USD 2023)	36,320	12.11	0.76	9.47	13.66
Adjacent	36,320	0.15	0.36	0	1
Adjacent × Impaired	36,320	0.09	0.28	0	1
Non-Adjacent × Impaired	36,320	0.50	0.50	0	1
Stories	36,320	1.26	0.45	1	4
Age of Building	36,320	34.17	28.30	0	217
Number of Buildings	36,320	1.02	0.16	0	6
Dist Urban (km)	36,320	10.87	20.50	0.00	131.63
Dist Highway (km)	36,320	3.56	4.65	0.02	41.62
Log Base Area	36,320	7.19	0.34	3.26	8.98

Notes: Summary statistics are for 36,320 residential parcels within 750 meters of a waterbody in Tennessee. Sale prices are adjusted to 2023 USD using CPI. Observations below the 1st percentile and above the 99th percentile of sale price are excluded. Distances to urban clusters and highways are measured in kilometers.

A.2 Supplementary Results

Waterbodies may differ in their economic value due to differences in recreational opportunities, accessibility, visibility, and how households interact with them. For example, lakes often support activities such as boating, fishing, and swimming, and while rivers provide similar opportunities, they vary more widely in accessibility, flow characteristics, and recreational use. These differences may influence how households perceive water quality and the extent to which impairment is capitalized into nearby property values. To examine whether the effect of water quality impairment varies across waterbody types, we estimate the model separately for subsamples of properties located near rivers and lakes.

Table A.2 presents regression results using a $\leq$ 750m comparison group for subsamples of river- and lake-adjacent properties across Tennessee. We find that adjacency to impaired waterbodies is associated with a negative and statistically significant effect on property values for both rivers and lakes, with the magnitude of the reduction being substantially larger for lakes. At the same time, properties adjacent to waterbodies receive a positive and statistically significant premium, regardless of impairment status, indicating that proximity to water remains a valued amenity even when water quality is impaired. Among properties located nearby but not directly adjacent to waterbodies, impairment is associated with a negative and statistically significant effect for lakes, but no statistically significant effect for rivers. These results suggest that the capitalization of water quality impairment differs across

waterbody types, potentially reflecting differences in recreational use, visibility, and perceived amenity value.

Table A.2: Regression Results of Water Quality Impairment on Property Values by Waterbody Type

Panel A: Rivers	
	Preferred Specification
Adjacent	0.073***
	(0.017)
Adjacent × Impaired	-0.049**
	(0.021)
Non-Adjacent × Impaired	0.017
	(0.012)
R^2	0.57551
Observations	21,814
Panel B: Lakes	
	Preferred Specification
Adjacent	0.237***
	(0.019)
Adjacent × Impaired	-0.077**
	(0.032)
Non-Adjacent × Impaired	-0.051**
	(0.025)
R^2	0.51073
Observations	11,760

Notes: This table reports the preferred specification estimated separately for rivers and lakes. The sample includes residential parcels within $\leq$ 750 m of the nearest waterbody. All models include the same control variables and year and census tract fixed effects as the preferred specification reported in Table 6.1. Standard errors are clustered at the census tract level and are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Vita

Lindsey Hickok-Perry was born in Knoxville, Tennessee but grew up primarily in Lawrenceburg, Tennessee. She attended the University of Tennessee to receive a Bachelor of Science in Business Administration with a major in Economics and a concentration in International Business in 2024. After conducting undergraduate research in environmental economics, she chose to pursue graduate studies at the University of Tennessee, where she is working toward a Master of Science degree in Agricultural and Natural Resource Economics with a concentration in Natural Resource Economics. Her research focuses on valuing environmental goods, with particular emphasis on water quality. After graduation, she hopes to continue her work in environmental valuation and understanding consumer behavior related to environmental goods to encourage policy change, specifically in rural areas.