Proactive and Reactive Infrastructure Investment*

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Abstract

Maintaining infrastructure requires investment. Faced with uncertain quality degradation, managers choose to invest proactively to prevent failure or reactively to address problems. Using a new dataset on drinking water systems, I estimate a dynamic discrete choice model of infrastructure investment. Simulations indicate that tightening regulations without financial support increases failures and raises costs. Reactive projects enable timely intervention as systems approach noncompliance, reducing disparities stemming from income and size. Efficiently restoring compliance for all systems requires expanded proactive investment to maintain quality and an even greater increase in reactive funds to address unexpected failures.

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1 Introduction

The condition of durable assets degrades over time. Preserving functionality requires an optimal timing decision: should maintenance occur proactively, before signs of decline, or reactively to address breakdowns? Proactive interventions prevent predictable problems, but at the expense of prematurely replacing components. Reactive interventions allow for targeted improvements but incur an increased risk of failure. Balancing these strategies is a fundamental problem in the economics of maintaining capital, requiring decisions over when to commit scarce resources to sustain functional assets. I analyze this dynamic through the lens of American infrastructure, where the consequences of deterioration and the scale of required investment are substantial.[1]

Infrastructure underpins the American economy, enabling commerce through transportation and communication networks, and supporting public health by delivering clean water, electricity, and waste management services. Investment maintains existing infrastructure by financing improvements and enabling compliance with changing regulatory standards. However, infrastructure is expensive, and untargeted expenditure can lead to overspending or inefficiently deferred maintenance (Duranton and Turner, 2011; Glaeser and Poterba, 2021; Winston and Langer, 2006). Recent research shows that strategically allocated infrastructure investment can deliver substantial welfare gains, yet achieving efficiency in spending remains a central policy challenge (Allen and Arkolakis, 2022; Barwick et al., 2024; Donaldson, 2018; Gramlich, 1994; Keiser and Shapiro, 2019).

Prior work shows that infrastructure contributes to aggregate productivity, influences the location of economic activity, and yields returns to public capital (Allen and Arkolakis, 2022; Balboni, 2025; Donaldson and Hornbeck, 2016; Faber, 2014; Fernald, 1999). Less is known about how managers make dynamic maintenance decisions under uncertain rates of deterioration, especially when direct measures of functionality, or asset quality, are unavailable to the researcher. I address this gap by developing a dynamic model of investment that treats infrastructure quality as a serially correlated latent state, subject to uncertain decline. To estimate the model, I adapt likelihood-based methods from the operations research literature that enable integration over the unobserved state. The model connects observed investment and compliance behavior to the evolution of infrastructure quality, offering a framework for evaluating how uncertainty and resource constraints shape investment timing and for determining the effectiveness of policy interventions.

I study the trade-off between proactive and reactive investment in the context of community water systems, which provide drinking water to over 310 million Americans—approximately 94% of the population. The Environmental Protection Agency (EPA) estimates that $625 billion will be needed over the next 20 years to replace and repair aging drinking water infrastructure, even as new public health threats emerge that require regulatory revisions. The EPA tightened national drinking water standards in 2006, and in 2020, 7% of systems experienced at least one health-based violation. Each year, roughly 19.5 million cases of waterborne illness are attributed to contaminants in drinking water provided by systems (Reynolds et al., 2008). According to the American Society

[1] In 2017 alone, the United States public spent $441 billion on transportation and water infrastructure (Congressional Budget Office, 2018).

of Civil Engineers (ASCE), the industry is shifting toward proactive investment, but no empirical comparison of proactive and reactive strategies exists. Understanding how managers allocate investment as systems age and standards evolve is critical for designing policies that ensure systems can continue to provide safe drinking water.

In this paper, I empirically examine the role of proactive and reactive projects in maintaining infrastructure quality, the effects of regulatory changes on compliance and investment, and the efficiency of policies that promote compliance through targeted increases in each project type. To understand decision making in this setting, I develop a dynamic discrete choice model of system manager investment in the spirit of Rust (1987). Results show that proactive projects occur when quality is high and only mitigate deterioration, while reactive projects occur closer to failure and are crucial for maintaining compliance. Tighter standards increase violations, highlighting that local resources are insufficient to sustain compliance without external support. Larger systems can spread costs more effectively, while smaller and lower-income systems rely more on reactive projects. Efficient compliance-restoring policies combine proactive investment expansions, which allow managers to maintain high levels of infrastructure quality at minimal violation risk, with larger increases in reactive investment that enable recovery from unexpected failures.

The paper proceeds as follows. Section 2 introduces the conceptual framework of the paper, detailing the infrastructure of a drinking water system and compliance standards set by the EPA. To analyze investment, I collect a novel dataset on drinking water systems and infrastructure projects in the Commonwealth of Kentucky. Kentucky provides an advantageous setting due to the existence of the Water Resource Information System (WRIS), which serves as a comprehensive registry for systems and their infrastructure projects.[2] I use scraping methods to collect over 350 water system reports and more than 3,000 project reports corresponding to the investments pursued by these systems. The reports contain detailed information about the timing, costs, and areas affected by each infrastructure project. I supplement these data with details on violations issued when systems fail to meet federal health-based standards and use natural language processing to classify projects as proactive or reactive.

In Section 3, I present stylized facts that inform the structure of the dynamic discrete choice problem. First, data confirm that small, lower-income systems invest less frequently and undertake lower-cost projects, likely due to resource limitations for these populations. Second, following the EPA's standards change, infrastructure exhibits signs of decline: systems increasingly invest reactively and spend a growing fraction of the year in violation. Third, the probability of a health-based violation decreases with more proactive spending, signaling that proactive investments successfully prevent future violations. Lastly, reduced-form evidence indicates that reactive spending reduces the probability of a health-based violation only for those systems that spent more time out of compliance in the prior period. I interpret this final result as an indication that both reactive projects and violations are driven by unobserved infrastructure deterioration and are likely to occur when

[2]Kentucky is not entirely unique in terms of publicly available investment data. Other states, e.g., Wisconsin and California, host similar information online.

infrastructure quality is low. Motivated by these facts, I develop a structural model that links latent infrastructure quality to investment decisions and compliance outcomes to uncover the mechanisms driving observed investment behavior.

Section 4 formalizes the dynamic discrete choice model developed from these findings. Infrastructure quality is the primary state variable, which is a composite measure that captures a system's ability to deliver safe drinking water to consumers. I assume managers are responsible for maintaining their system's infrastructure quality but face uncertainty over the extent of deterioration each period, consistent with how systems operate in practice. Every period, managers decide to undertake a quality-improving project or to delay investment, anticipating the uncertain path of future quality. Managers balance a desire to avoid providing consumers with water that violates health-based standards against the cost of infrastructure projects. Without investment, quality declines, increasing the probability that the system will violate standards and that a project will be reactive, as opposed to proactive.

Section 5 estimates the two cost functions that govern infrastructure investment decisions: the avoidance costs consumers bear when exposed to unsafe drinking water, and the investment costs associated with improving quality. I first recover avoidance costs by linking changes in bottled water purchases to health-based violations using a random coefficients demand model. Estimates indicate that consumers are willing to pay to avoid violations, and that there is heterogeneity in violation sensitivity across income levels. In the dynamic model, I parameterize violation costs by assuming managers' aversion to providing unsafe drinking water is proportional to consumers' avoidance costs. I recover investment costs from observed project expenditures, correcting for sample selection and misclassification. I find significant heterogeneity in community support for proactive investment, with larger systems investing in greater quantities. Consumers are also sensitive to deteriorating quality, as they are willing to invest in larger amounts when projects are reactive and following health-based violations.

In Section 6, I present the estimation procedure and identification strategy, and then discuss the results. The key empirical challenge is that no systematic data exist on the evolution of the underlying infrastructure quality of Kentucky's drinking water systems. Moreover, quality is highly persistent, complicating computation of the likelihood function. To make estimation tractable, I extend the recursive likelihood integration technique to obtain the full model solution, inferring the evolution of unobserved quality from the joint dynamics of observed outcomes. Identification relies on variation in the history and co-evolution of investment frequency, project type, and time spent in violation across systems with different income levels and population sizes. Estimation combines simulation techniques to approximate the initial quality distribution, fixed-point methods to solve for conditional choice probabilities, and recursive likelihood integration over possible quality histories to recover the structural parameters. The model fits the data well. Simulated outcomes closely match observed trends in the fraction of systems investing, the share of reactive projects, and the average time systems spend in violation each year.

Estimates from the structural model reveal that before the EPA altered standards, systems maintained high quality levels and minimal violations through frequent, minor investments by small and medium systems and infrequent, substantial investments by large systems. After the revisions, standards tighten and the definition of infrastructure quality expands to include new components. As a result, systems' ability to provide safe drinking water deteriorates more rapidly, captured by a faster measured rate of quality decline. Together, these shifts lead to higher rates of reactive projects and violations. Parameter estimates indicate that reactive projects typically occur before systems enter a state of violation, implying that managers can detect impending failures. Investment effectiveness differs by type: proactive projects are smaller and slow the decline of quality, whereas reactive projects are larger and provide temporary quality gains.

Section 7 examines the long-run effect of the regulatory change on compliance and simulates counterfactual investment policies. I first explore the evolution of infrastructure quality under the tighter standards and show that due to insufficient investment, steady-state quality declines, leading to higher violation rates and a greater reliance on reactive projects. Under stricter standards, smaller systems face greater violation exposure because investment levels are insufficient to offset ongoing quality deterioration. Larger systems can raise more capital and invest more frequently, limiting the rise in violations, but compliance declines across all system types. Simulations reveal that without reactive investment, systems would experience more failures, indicating that reactive projects play a crucial role in limiting violations, especially for disadvantaged communities. Counterfactuals demonstrate that restoring compliance to pre-regulatory change levels requires sustained increases in both types of investment. Larger proactive projects allow managers to invest regularly when infrastructure is high to maintain compliance, while reactive increases prevent excessive investment and allow managers to recover from unexpected declines in quality.

I conclude in Section 8 by discussing limitations, outlining directions for future research, and connecting the results to recent policy changes. In 2021, Congress passed the Infrastructure Investment and Jobs Act (IIJA), a $550 billion package that included significant funding for drinking water systems. Understanding when managers invest and how proactive and reactive projects differ is critical for ensuring these resources are used efficiently. More broadly, the framework describes a general class of maintenance problems in which only the consequences of deterioration are observed. In my setting, reactive projects, which typically occur before a state of failure, play an important role in maintaining functional infrastructure.

1.1 Literature Review

I contribute to a growing literature on safe drinking water in the United States (Allaire et al., 2018; Christensen et al., 2023; Hadachek, 2025; Marcus, 2022; Graff Zivin et al., 2011). Specifically focusing on drinking water system management, Timmins (2002) uses a dynamic structural model to study pricing in aquifer-based systems, where managers often set prices below marginal cost. My focus is on infrastructure investment decisions and how investment facilitates the long-term provision of safe drinking water. Agrawal and Kim (2022) and Posenau (2022) show that investment is sensitive to financial constraints; in my approach, I model the investment decision process directly, enabling evaluation of counterfactual investment policies. While Keiser et al. (2023) demonstrates that drinking water investments yield net benefits, I take that premise as given and focus on how managers make investment decisions over time. A key feature of my model is that managers seek to avoid EPA violations, consistent with evidence that public disclosure reduces violations (Baker et al., 2023; Bennear and Olmstead, 2008; Grooms, 2016) and that some managers act strategically to avoid them (Bennear et al., 2009).

Several articles examine firm responses to environmental regulation, including investment and operational choices (Fowlie et al., 2016; Ryan, 2012), while others model strategic interactions between regulators and regulated firms (Abito, 2019; Blundell et al., 2020; Kang and Silveira, 2021; Leisten and Vreugdenhil, 2025; Lim and Yurukoglu, 2018), or focus explicitly on the uncertain application of environmental standards (Chen, 2025; Gowrisankaran et al., 2025). These models often involve profit-maximizing firms and complex incentive distortions. My analysis examines publicly owned systems that aim to provide safe drinking water at minimal cost, which allows for a simpler state space. This structure enables estimation using full-solution methods with a continuous, serially correlated unobserved state variable—a specification that would be less tractable in a strategic games setting. By embedding infrastructure quality as a continuous latent state, I recover smooth relationships between system decline, regulatory standards, and investment.

Methodologically, the estimation approach extends likelihood integration techniques developed by Reich (2018) to a setting in which the entire state space is unobserved. Combining this approach with the model's transition structure, I simulate a steady-state distribution for initial infrastructure quality and evaluate the likelihood of observed investment, project classification, and violation outcomes to recover the structural parameters. This procedure integrates over all latent states implied by the model rather than conditioning on observed state variables. The initialization step follows Blundell et al. (2020) in assuming that behavior reflects the steady-state distribution of regulatory conditions. Alternative approaches to unobserved heterogeneity in dynamic models typically assume a discrete latent state or rely on relationships between latent and observed states, using simulation, instrumental variables, or Bayesian updating in estimation (Pakes, 1986; Ericson and Pakes, 1995; Keane and Wolpin, 1997; Norets, 2009; Arcidiacono and Miller, 2011; Blevins, 2016; Connault, 2016; Berry and Compiani, 2022; Kalouptsidi et al., 2021). The recursive likelihood approach accommodates a continuous latent state and integrates directly over the model's state transitions, allowing likelihood evaluation without requiring the same adjustments.

2 Background and Data

2.1 Background

Drinking Water Systems Systems source water from one of three options: the surface (e.g., lakes or reservoirs), underground (e.g., aquifers), or through a recycling process (e.g., highly treated wastewater). Water from these sources is pumped into the system, filtered until it is considered safe for human consumption, and then either stored in tanks or delivered directly to consumers.

The infrastructure enabling the distribution of safe drinking water includes pumps for water movement, pipes for distribution, filtration systems for treatment, meters and sensors for monitoring contaminants, and tanks for long-term storage. This infrastructure serves as the first line of defense against harmful contaminants.

Infrastructure Quality I define *infrastructure quality*, or system quality, as the state of a drinking water system's physical components. Infrastructure quality determines a system's ability to provide safe drinking water and refers to the persistent, underlying features of the system—such as pipe integrity or filtration capacity—rather than short-term fluctuations in contaminant concentrations. I model quality as a latent state expressed in monetary terms: a $100,000 investment increases quality by one unit. Quality serves as the channel linking the timing of investments to the consequences of system failure. Expressing quality on a monetary scale allows the parameters governing deterioration, failure risk, and investment behavior to be recovered from observed outcomes. This formulation captures how managers weigh the cost of investment against the risk of service failures and provides a structural connection between spending and the underlying condition of the system.

A useful analogy is that of a physician monitoring a patient's health. Just as a physician evaluates multiple physical indicators beyond blood tests to assess overall well-being and decide when costly treatments are needed, a system manager must consider factors beyond contaminant levels to maintain system quality and determine when to invest. Nonetheless, both seek to avoid negative test results, an aspect I incorporate into managers' utility functions.

Drinking Water Standards Water is considered "safe" based on federal standards set by the EPA on 94 different contaminants, which include both chemical and microbial pollutants. When a system fails to meet these standards, the EPA mandates that consumers are informed. Customer notifications are classified into three levels depending on the severity of the infraction: Tier 1 and 2 violations pertain to contaminants that threaten consumer health and Tier 3 violations encompass monitoring and reporting violations (Environmental Protection Agency, 2009). Tier 1 violations pose the most severe health risks and require notification within 24 hours of discovery. Consumers frequently experience Tier 1 notifications in the form of "boil water advisories." Tier 2 violations are for contaminants that pose a less imminent risk, and notification is required within 30 days of detection. For the duration of the paper, I focus my analysis on Tier 1 and 2 violations and refer to them as health-based violations collectively.

In 2006, the EPA finalized three pivotal changes to national drinking water standards, prompting a wave of health-based violations among many systems. These rules increased compliance burdens both by tightening existing contaminant standards and by requiring physical upgrades, such as new filtration systems, lab improvements, and expanded monitoring. When the changes came into effect in 2007, funding for compliance relied mainly on existing mechanisms, most notably the loan-based Drinking Water State Revolving Fund (DWSRF).[3]

[3] The Stage 2 Disinfectants and Disinfection Byproducts Rule, Long Term 2 Enhanced Surface Water Treatment Rule,

2.2 Data Sources

I collect and aggregate data from multiple sources. Below, I outline the methods used to clean, assemble, and prepare the data for analysis. All prices and costs are adjusted to real 2012 dollars using the GDP deflator.

2.2.1 Kentucky Water Systems and Infrastructure Projects

I compile data on Kentucky's water systems and infrastructure projects using information published by the Kentucky Infrastructure Authority (KIA) on the WRIS online portal. The primary purpose of WRIS is to consolidate information on Kentucky's public water systems for use in water planning, emergency decision making, and to track and allocate funding to support infrastructure projects. Two WRIS reports provide the richest data: system and project reports. I source additional information regarding projects and the project approval process from historical Intended Use Plans (IUPs) and the KIA's Annual Reports, which I obtained through Freedom of Information Act requests to Kentucky's Department of Local Government.

Community Water System Reports For this analysis, I consider publicly owned community water systems that are active as of 2021.[4] Kentucky's WRIS system reports provide detailed information on each system, including the total population served, establishment date, number of employees, water source type (purchased, groundwater, or surface water), and geographic location. More than 95% of Kentuckians receive water from public water systems.[5] The reports also contain median household income data for each county population subset served by a system, typically derived from the American Community Survey (ACS) and integrated into WRIS. Kentucky uses median household income to allocate financial assistance through programs such as the DWSRF. Systems and projects are classified into three Non-Standard Rate Levels (NSRLs) based on their relation to the statewide median household income:

- NSRL = 0 (High-Income): Greater than or equal to Kentucky Median Household Income
- NSRL = 1 (Middle-Income): Between 80% Kentucky Median Household Income and Kentucky Median Household Income (exclusive)
- NSRL = 2 (Low-Income): Less than or equal to 80% Kentucky Median Household Income

and Ground Water Rule were all finalized in 2006. The most significant changes prior to 2006 occurred in 1998 with the first stage of the Disinfectants and Disinfection Byproducts Rules. Grant programs such as the Water Infrastructure Finance and Innovation Act (2014), the Water Infrastructure Improvements for the Nation Act (2016), and America's Water Infrastructure Act (2018) were passed near the end of the observation period and generally provided assistance to small, low-income systems only.

[4] A community drinking water system serves an average of at least 25 customers year-round. Of the 377 systems with available data, 361 systems are publicly owned community water systems. After removing systems with missing demographic data (e.g., serviceable population), the final sample includes 353 systems.

[5] Figure D.1 in Appendix D provides an example of a public water system's geographic overlay with county borders.

In line with EPA definitions, systems are also grouped by size based on population served: small systems serve fewer than 3,300 consumers, medium systems serve 3,301-10,000 consumers, and large systems serve more than 10,000.

Infrastructure Project Reports Investment in infrastructure can take many forms, including pipe repairs, new water meter installations, and water tank replacements. To initiate an infrastructure project, system managers must submit a project profile within WRIS detailing the project's purpose and the anticipated: costs, beneficiaries, responsible parties, timeline, and funding sources. Project plans undergo review and approval processes from multiple agencies within Kentucky (e.g., the Energy and Environmental Cabinet, Department of Water, Infrastructure Authority, Area Development District Water Management Planning Councils) before they are allowed to proceed. WRIS is used as a "registry" for Kentucky's water infrastructure projects. As a result, most project profiles are complete. Information on projects dates to the beginning of WRIS in 2001. Project profiles are also required by Kentucky for a project to be eligible to receive financial support from the state. Many other financial support programs have also adopted this requirement.[6]

I determine whether an infrastructure project is reactive using natural language processing (NLP) on the descriptions contained within each report. The classification draws on ASCE assessments of U.S. drinking water infrastructure. According to the 2021 Infrastructure Report Card, "maintenance costs reached an all-time high of $50.2 billion above capital in 2017, in part due to deferred capital projects. A recent survey found that 47% of the maintenance work undertaken by utilities is reactive and done as systems fail." In light of this assessment, I classify a project as reactive if the text indicates that investment is necessary for the system to provide safe drinking water e.g., references to public health emergencies, extensive breaks, overstressing, or unsafe conditions. Projects that do not meet these criteria are classified as proactive. Details on the classification process and the NLP model can be found in Appendix A.

Project reports reveal the investment intentions of system managers. Reports provide a historical record of planned investments as of July 2021, when the data were collected. I leverage the unique detail in project reports to distinguish between proactive and reactive projects, enabling a comprehensive analysis of the investment behavior of public water system managers in Kentucky.[7]

2.2.2 Water System Violations

I collect violation data covering 2006-2019 using the EPA's nationwide database, the Safe Drinking Water Information System (SDWIS).[8] This database provides details on each violation, including its detection date, remediation status, triggering event, and public notification tier. Systems are required to report contaminant standards failures. I merge this dataset with the detailed system information from WRIS. Over 2007-2019, approximately 60% of systems reported at least one

[6] Information on WRIS is obtained from multiple Kentucky sources, including the "2015 Water Management Plan."

[7] Other sources, such as the Census of State and Local Governments and Kentucky's Public Service Commission records, contain partial financial information, but no dataset links WRIS projects to bond issuances or rate changes.

[8] SDWIS data were obtained from the EPA's Envirofacts API (accessed July 2021).

health-based violation. In the model, I assume that contaminant standards remained constant following the 2006 regulation changes. Although the EPA revised the National Drinking Water Contaminant List twice after 2007, these revisions were minor, and only 16 of 1,191 violations—less than 2%—stemmed from these changes.

2.2.3 Additional Data Sources

The NielsenIQ Retail Scanner and Consumer Panel Datasets (2006-2019), made available through the Kilts Center at the University of Chicago, allow estimation of consumer responses to violations. The scanner data contains weekly UPC-level sales, including prices and volumes, across multiple product categories in stores throughout the United States. I reduce this dataset to products with a product module code "Bottled Water" and stores that fall within Kentucky. All observations of powdered additives and filters are removed from the dataset. The final dataset includes 937 stores across 112 of Kentucky's 120 counties, covering at least part of the 730 NielsenIQ weeks from 2006-2019. The consumer panel dataset provides demographic information on a panel of 3,369 Kentucky households that track their purchases over time, totaling 2.4 million trips. I use the bottled water purchases of these panelists to incorporate income heterogeneity into the demand model. Lastly, I employ five-year ACS data covering 2005-2019 to obtain county-level demographics on total population, median household income, and housing units (Manson et al., 2021). I disaggregate this data to the yearly level by averaging values from the surveys covering a given year.

3 Motivating Results

I begin by exploring patterns in system activity and violations across income levels and population sizes. Descriptive statistics and time trends reveal systematic differences in project frequency, scale, and violation exposure. I then assess the effect of infrastructure investment on health-based violations, using probit models to explore whether spending reduces the likelihood of violation. The findings provide descriptive evidence that proactive and reactive projects reflect distinct underlying quality conditions, and that reactive projects are closely tied to existing system failures.

3.1 System Activity

Table 1 presents aggregate statistics on system characteristics and activity from 2007-2019, by income level and the size category of the population served.[9] I focus on these factors because financial resources influence both consumers' capacity and willingness to avoid health-based violations and fund capital expenditures. On average, systems spend 5% of the year in violation, undertake a proactive project every six to seven years, and a reactive project every ten years.

[9] Figure 1 and Table 1 reflect the data used in estimating the dynamic model. Systems are limited to one project per year, and violation time represents the fraction of the year spent in violation of health-based standards. When multiple projects are approved in a year, I pool them by project type into a single investment. In 3% of cases, both project types are approved in the same year; in these instances, I retain the type with the greater total expenditure.

Table 1: Kentucky Community Water System Average Annual Activity 2007-2019

	Systems		Proactive			Reactive			Violation
	Count	Avg Pop	Count	($M)	($PP)	Count	($M)	($PP)	Pct. of Year
High-Income									
Small	22	1,514	0.115	3.62	183.6	0.063	2.30	159.2	0.89%
Medium	32	5,975	0.154	4.19	169.6	0.113	3.06	156.2	4.95%
Large	33	53,538	0.170	6.83	79.31	0.107	5.89	80.16	1.88%
Middle-Income									
Small	32	1,817	0.120	0.49	179.2	0.079	0.64	204.5	8.11%
Medium	40	6,487	0.163	1.38	113.1	0.092	2.79	212.6	6.71%
Large	30	25,062	0.215	2.30	83.85	0.128	5.88	149.8	7.10%
Low-Income									
Small	75	1,627	0.098	0.88	331.6	0.079	1.80	411.1	5.32%
Medium	59	6,373	0.173	1.46	191.2	0.121	2.38	177.8	6.56%
Large	30	19,052	0.195	2.61	114.3	0.136	3.68	134.3	6.51%
All Systems	353	11,701	0.151	2.57	163.7	0.101	2.96	196.6	5.56%

Notes: System and project statistics are calculated using WRIS data collected in July 2021, and corresponding violation information is constructed based on SDWIS data from the same period. The percentage of the year spent in violation of health-based standards is calculated based on the start and end date of the reported violation in SDWIS.

Investment patterns differ systematically. High-income systems invest the most in proactive projects and experience the least amount of violation time. Middle-income systems invest more than low-income systems but spend longer periods in violation. Across income levels, larger systems invest more in aggregate and spend the least per person. These differences likely reflect both economies of scale and variation in access to financial assistance and administrative resources across systems. Higher-income populations may have a greater capacity to finance infrastructure investment than lower-income populations. Further, larger systems can spread infrastructure costs across more consumers, reducing per-person expenditures. In contrast, smaller systems face higher per-person costs, which may limit their ability to invest in infrastructure improvements.

Figure 1 shows investment and violation trends over time, by income level. Four key patterns emerge. First, the share of systems investing proactively has declined slightly. This decline partly reflects a temporary increase in investment during 2009, when the American Recovery and Reinvestment Act (ARRA) provided funding for projects that could be completed quickly. However, proactive project size remained stable over time and does not appear to have been affected by ARRA incentives.[10]

Second, violation time is increasing. As systems spend more time in violation, reactive expenditures also rise. Third, middle-income systems spend the most time in violation and show the strongest response to ARRA incentives, increasing proactive investment in 2009. The ARRA offered a rare opportunity for middle-income systems to receive assistance, as low-income systems are typ-

[10]The 2011 spike in proactive spending among high-income systems stems from a single large relocation project.

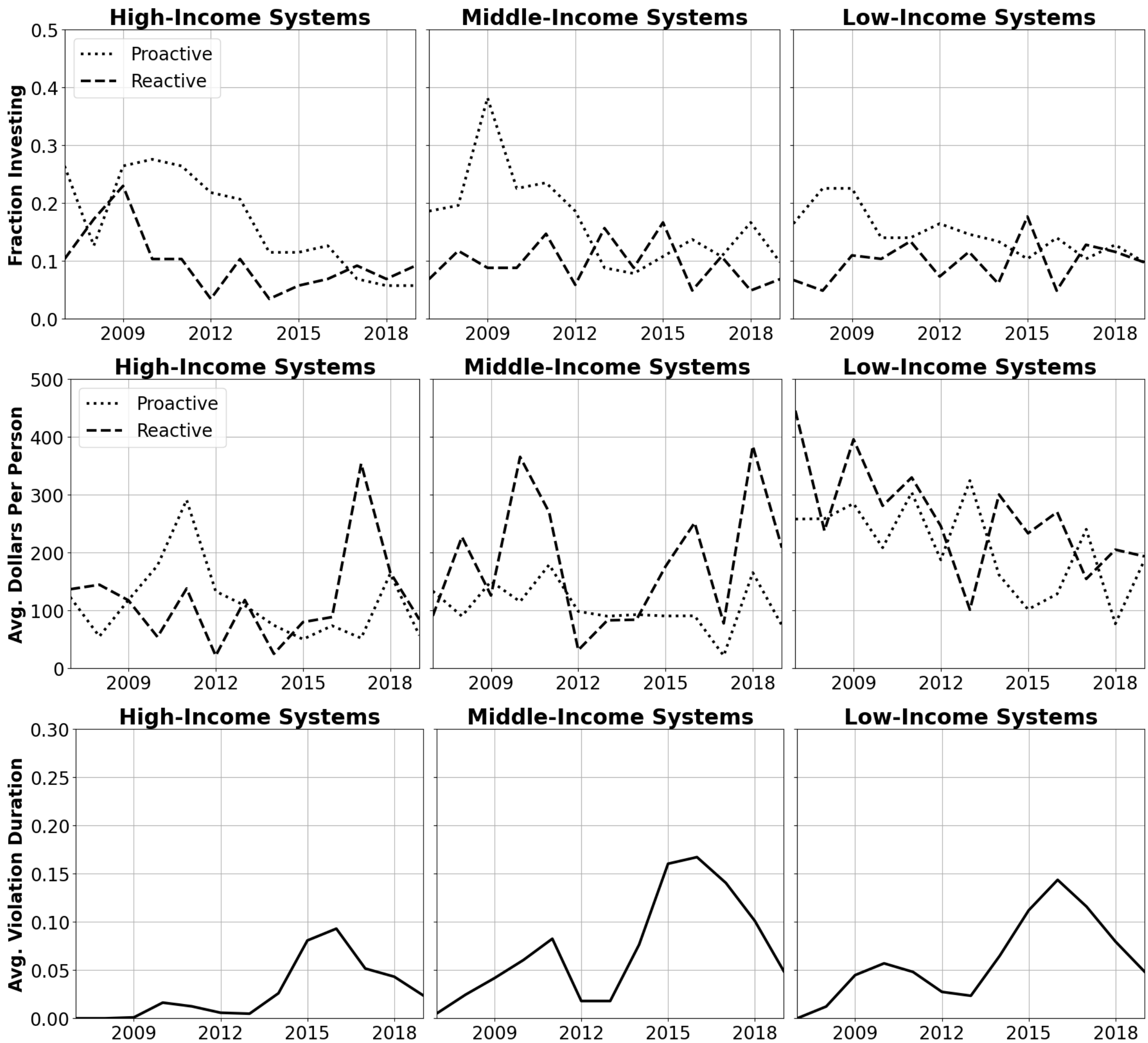

Figure 1: System Activity by Income Level

Notes: Panels display activity of high-, middle-, and low-income systems. The top panels plot the fraction of systems investing in proactive (dotted) and reactive (dashed) infrastructure projects (2007-2019); middle panels plot the average expenditure per person for each type of project; bottom panels plot the average fraction of the year in violation of health-based standards.

ically targeted by government programs.[11] Finally, in the years following the ARRA, systems invest in proactive and reactive projects at similar rates and expenditure levels. These patterns support the ASCE's claim that nearly half—and in Kentucky, more than half—of expenditures are reactive, raising concerns about investment practices and increasing time spent in violation.

[11]Kentucky's Intended Use Plans, which outline how DWSRF support is allocated, prioritize principal forgiveness for low-income systems.

Table 2: Health-Based Violation Probability

	(1)	(2)
Expenditure ($M in last 5 years)	−0.002	—
	(0.003)	—
Expend. × Lag Violation Fraction	−0.031	—
	(0.016)	—
Proactive Expend. ($M in last 5 years)	—	−0.015
	—	(0.005)
Proactive Expend. × Lag Violation Fraction	—	0.029
	—	(0.029)
Reactive Expend. ($M in last 5 years)	—	0.008
	—	(0.004)
Reactive Expend. × Lag Violation Fraction	—	−0.064
	—	(0.025)
Lag Violation Fraction	2.417	2.400
	(0.149)	(0.151)
Pseudo R^2	0.261	0.264
Observations	4,589	4,589

Notes: The dependent variable is an indicator for a health-based violation. Controls include system size, log median household income, housing density, indicators for water source, non-white population fraction, and the number of employees. The model also includes year and ADD fixed effects.

3.2 Relationship Between Projects and Violations

Kentucky's Infrastructure Authority states that "[v]iolations of drinking water standards occur primarily as a result of inadequate infrastructure." To explore this claim, I next examine whether there is empirical evidence that planned expenditures improve a system's ability to provide safe drinking water, using health-based violations as an indicator of system performance. To that end, I estimate two probit models using data on 353 community water systems in Kentucky from 2007-2019. The first model examines total project expenditures over the previous five years, while the second separates proactive and reactive investments. In both cases, the dependent variable is an indicator for whether a system experiences a health-based violation in a given year.

The novel variable included in the model is adjusted infrastructure investment, calculated from project expenditures approved in the preceding five years. I use this metric because there is often a delay between the timing of a project's approval and the project's completion. In keeping with the literature, I also control for a set of system attributes known to influence the probability of a violation, including the fraction of the previous year spent in violation.[12]

Column (2) splits investments into proactive and reactive projects. Wald tests confirm a signif-

[12] Allaire et al. (2018) find evidence that water source, population size, population income, and housing density are strong predictors for violations across the United States.

icant difference between proactive and reactive projects, both directly and when interacted with prior violation time.[13] Larger cumulative proactive investments are correlated with a lower probability of a health-based violation regardless of the amount of time spent in violation in the previous year. Reactive projects, however, reduce the probability of a health-based violation only if the system was in violation in the previous year. The relationship between reactive projects and past violations suggests that both reflect deteriorating infrastructure quality. Managers may invest reactively as infrastructure quality declines, linking reactive projects to violations. These patterns imply that proactive projects play a preventative role, while reactive projects serve as a response to existing failures.

4 Model

In the model, system quality, q_{wt}, reflects the cumulative effect of past infrastructure investments on a system's ability to provide safe drinking water. Quality is normalized so that each $100,000 investment increases quality by one unit. This scale allows for granular modeling of investment decisions, particularly among smaller, lower-income systems. Over time, quality deteriorates as infrastructure ages. This state is unobserved by the econometrician but known to managers, who must decide each year whether to invest in a project or to defer the decision.

Managers face two types of quality uncertainty: temporary shocks (e.g., good weather or chemical spills) that affect the system's ability to provide safe drinking water in the current period, and persistent shocks (e.g., flood damage or unexpected pipe breaks) that occur at the end of the period and capture lasting changes in quality. As quality declines, systems are increasingly likely to spend more time in violation and require reactive investments. To capture the pressures managers face, I assume they balance the weighted cost of exposing consumers to contaminated water against consumers' willingness to financially support quality-improving expenditures. The following sections detail the mechanisms of the model.

System Quality I model quality decline as an $\mathrm{AR}(1)$ process that managers can counteract by initiating infrastructure projects. In the following law of motion, $i_t \in \{0, 1\}$ indicates whether a project is undertaken in the current period, and $k_{nz}(\cdot)$ represents the magnitude of the project. The magnitude depends on the system's income level, $n \in \{0, 1, 2\}$, size category, $z \in \{s, m, \ell\}$, and quality level. The error term, ϵ_q, is realized at the end of the period and captures lasting changes to quality.

$$q_{wt+1} = \begin{cases} \alpha^q q_{wt} + i_t k_{nz}(q_{wt}; \boldsymbol{\kappa}, \sigma^\kappa) + \epsilon_q & \text{if } q_{wt} > 0 \\ k_{nz}(0; \boldsymbol{\kappa}, \sigma^\kappa) + \epsilon_q & \text{if } q_{wt} = 0 \end{cases} \tag{1}$$

$$\alpha^q \in (0, 1), \quad \epsilon_q \sim -|\mathcal{N}(0, 1)|$$

[13]The results of these two tests are $W(1) = 11.73, p < .001$ and $W(1) = 4.62, p < .05$ respectively.

If infrastructure quality reaches zero, managers must undertake a reactive project to address the failure. This assumption is consistent with observed responses to major infrastructure failures, such as those following natural disasters. The parameter α^q characterizes quality persistence, where values near one indicate that quality degrades slowly and that investments in infrastructure are long-lasting. The shock ϵ_q is drawn from a negative half-normal distribution, defined as the negative of the absolute value of a normally distributed random variable, which ensures that quality always deteriorates while allowing uncertainty in the extent of the deterioration.

Time Spent In Violation Health-based violations are triggered by the presence of contaminants in drinking water. Systems with higher infrastructure quality (e.g., better pipes, meters, etc.) are less likely to experience violations but may still experience failures due to fluctuations in weather patterns, water flow, and treatment adjustments. To capture this variability, I model the probability that a system experiences a violation in a given month, denoted $p_{vt}(\cdot)$, and assume the number of months in violation (y_{vt}) follows a binomial process. This probability is characterized by the system's infrastructure quality and a parameter δ^v, which controls how sensitive the violation probability is to quality changes. The violation probability is defined as:

$$p_{vt}(q_{wt}; \delta^v) = \exp(-q_{wt}/\delta^v) \tag{2}$$

therefore, if quality reaches zero, the system will spend the entire year in violation with probability one. For very high levels of infrastructure quality, the probability of a violation becomes negligible. The expected number of months in violation is $E[y_{vt}] = 12 \cdot p_{vt}(\cdot)$, and the expected fraction of the year a system spends in violation is $p_{vt}(\cdot)$.[14]

Violation Costs I model violation costs based on the expenditures consumers incur when the system provides water below health-based standards. In Section 5.1, I estimate consumer willingness to pay to avoid unsafe drinking water, allowing preferences to vary by income level. To obtain an annualized value, I assume consumers shop once per week (52 times per year) and choose whether to purchase bottled water for the week (1.75 gallons per person) or consume tap water. The violation costs for each system are given by:

$$\mathcal{VC}_{nz}(q_{wt}; \delta^v) = 52 \cdot 1.75 \cdot WTP_n \cdot pop_{nz} \cdot p_{vt}(q_{wt}; \delta^v) \tag{3}$$

where pop_{nz} indicates the average population served (in millions) by a system of income level n and size category z. Lower infrastructure quality results in a higher fraction of the year spent in violation, increasing consumer costs. Managers are motivated to invest in infrastructure-improving projects to mitigate the consumer aversion costs associated with declining water quality.

[14] In estimation, I assume a constant violation threshold throughout the observation period. For details on EPA standards and their applicability to the data, see Section 2.2.2.

Project Type At the start of the year, the system manager knows the current level of infrastructure quality and, when considering whether to invest in an infrastructure project, forms expectations about whether the project will be proactive or reactive. When quality is high, projects are likely proactive; when quality is low, they are more likely to be reactive. To capture this relationship, I model the probability of a reactive project ($y_{rt} = 1$) as:

$$Pr(y_{rt} = 1) = p_{rt}(q_{wt}; \delta^r) = \exp(-q_{wt}/\delta^r). \tag{4}$$

The parameter δ^r governs how sensitive the probability of a reactive project is to changes in quality. Larger values of δ^r imply a gradual increase in probability across a wide range of qualities, while smaller values imply a steep increase over a narrow range. The probability of a reactive project approaches one as quality approaches zero and declines as quality increases.

Project Costs Infrastructure project size, measured in millions, depends on system heterogeneity and measures of quality decline:

$$\begin{aligned} k_{nz}(q_{wt}; \boldsymbol{\kappa}, \sigma^{\kappa}) &= \exp\left(\kappa_{nz} + \kappa^r y_{rt}(q_{wt}) + \kappa^v y_{vt}(q_{wt}) + \sigma^{\kappa}\epsilon_{\kappa}\right) \\ \epsilon_{\kappa} &\sim \mathcal{N}(0, 1) \end{aligned} \tag{5}$$

where κ_{nz} defines the baseline magnitude of a proactive investment for a system, by income level and size category. The κ^r and κ^v terms reflect the increase in project size due to reactive projects (y_{rt}) and months spent in violation (y_{vt}), collectively capturing the effect of low quality. The true costs of investment are often difficult to predict and adjustments to initial estimates can be required to bring projects to completion. Uncertainty in project size is determined by a mean-zero shock, ϵ_{κ}, with variability governed by σ^{κ}. Estimation details are described in Section 5.2.[15]

System Manager's Decision Problem I model the system manager's decision problem as an infinite-horizon, stationary dynamic program. The timing of the model is as follows: first, idiosyncratic choice-specific shocks are realized. The manager then decides whether to undertake an infrastructure project, anticipating the amount of time the system will spend in violation and the project's type. If investing, the manager then learns whether the project is proactive or reactive. Next, monthly shocks are realized and, conditional on these shocks and the quality level inherited from the prior year, the system spends y_{vt} months in violation. Investment size uncertainty is then revealed, and the project application is submitted. Finally, quality updates based on the investment decision and a draw of the persistent quality shock.

Manager's flow utility consists of the weighted costs to consumers from violation time and infrastructure projects. The weights vary with the population's income level, indexed by n, and denoted as $\lambda_n^{\mathcal{VC}}$ and λ_n^x, and reflect manager preferences for the frequency of projects. These weights

[15] Bajari et al. (2014) study the renegotiation of procurement contracts in a similar infrastructure setting, supporting that precise costs are often unknown ex-ante.

capture additional heterogeneity in how managers across income levels value consumer expenditures, beyond what is accounted for in the cost function formulations—reflecting differences in budget constraints, political pressure, or service priorities.[16]

Beyond the federal standards for safe drinking water, the model incorporates two additional channels through which federal regulation shapes system management. First, under the SDWA, the EPA may impose civil penalties of up to $25,000 per day for persistent violations. I annualize this fee to $9.125 million and include it as a noncompliance cost incurred whenever system quality falls to zero.

Second, I account for the effect of the ARRA as a one-time project cost reduction in 2009 for middle- and high-income systems. The ARRA provided 50% principal forgiveness for eligible projects across all systems, comparable cost reductions were already available to low-income systems prior to the program. Among middle- and high-income systems, however, the ARRA incentives were temporary and did not fundamentally shift investment preferences. The subsidy relaxed borrowing constraints but left the engineering scope of projects unchanged. Thus, ARRA increases the probability of investment but is excluded from the investment size equation. Figure 1 provides visual support for this claim, showing increased uptake in 2009 without corresponding changes in project size, especially among middle-income systems.

Let $\boldsymbol{\theta} = (\delta^v, \delta^r, \mathbf{WTP}, \boldsymbol{\kappa}, \sigma^\kappa, \boldsymbol{\lambda}^{\boldsymbol{\mathcal{VC}}}, \boldsymbol{\lambda}^{\boldsymbol{x}}, \alpha^q)$ denote the model parameters, ARRA$_n$ be an indicator equal to one if the year is 2009 and the system is middle- or high-income, and F^{NC} be the noncompliance penalty. I hold fixed the rate at which system managers discount the future at $\beta = 0.95$. Per-period utility is therefore:

$$\begin{aligned} u_{nz}(q_{wt}, i_t; \boldsymbol{\theta}) = \quad & - \quad \lambda_n^{\mathcal{VC}} E[\mathcal{VC}_{nz}(q_{wt}; \boldsymbol{\theta})] - F^{NC}\mathbb{1}\{q_{wt} = 0\} \\ & - \quad i_t \lambda_n^x (1 - 0.5 \cdot ARRA_n) E[k_{nz}(q_{wt}; \boldsymbol{\theta})] \end{aligned} \tag{6}$$

which depends on the manager's decision to invest and the level of infrastructure quality. Managers undertake projects when the expected reduction in violation costs from improving quality exceeds the expected cost of an investment.

Combining the components of the model, the value function for a water system manager has the following form:

$$V_{nz}\big(q, \boldsymbol{\epsilon}; \boldsymbol{\theta}\big) = \max_{i \in \{0,1\}} \left\{ u_{nz}(q, i; \boldsymbol{\theta}) + \epsilon(i) + \beta E V_{nz}\big(q', \boldsymbol{\epsilon'} | i, q; \boldsymbol{\theta}\big) \right\} \tag{7}$$

where $\big(\epsilon(0), \epsilon(1)\big)$ capture choice-specific states observable only to the system manager. For notational simplicity, I omit time and water system subscripts.

If quality falls to zero, the manager is required to invest and cannot defer the decision. Last

[16]Prior studies (e.g., Bennear and Olmstead (2008); Bennear et al. (2009); Grooms (2016)) find that managers are sensitive to consumer exposure to unsafe drinking water, sometimes altering testing behavior to avoid triggering violations. The weights also incorporate the "citizen's voice" phenomenon discussed in Brooks and Liscow (2023), who attribute growing infrastructure costs to increased public influence in government decision making.

period's quality determines the amount of time a system spends in violation during the current period. Therefore, each period the manager decides whether to invest in a project to improve the following period's quality.

5 Costs to Consumers

In this section, I estimate the two main costs driving project decisions: the cost of avoiding unsafe tap water as infrastructure deteriorates, and the cost of improving quality through investment. Both costs are borne by consumers, either through purchases of drinking water from alternative sources or by funding projects via higher water rates or tax increases. I begin by examining changes in consumers' bottled water purchases following exposure to unsafe drinking water to recover consumers' willingness to pay to avoid health-based violations. I then estimate the size of investments, allowing the magnitude to vary by project type, violation time, and community characteristics.

5.1 Cost to Avoid Unsafe Drinking Water

To recover consumer willingness to pay for safe drinking water, I estimate a random coefficients logit demand model, assuming that each week consumers choose between buying bottled water and drinking tap water. I construct a county-level panel of weekly bottled water sales and prices from the NielsenIQ dataset, which covers 937 stores across 112 of Kentucky's 120 counties from 2006 to 2019. I link these data to records of health-based violations and treat each county-week as a distinct market. I then augment the dataset with measures of consumer heterogeneity such as income and exposure to violations. County-level annual income is obtained from the Census, while weekly violation probabilities are computed based on the share of each week that systems serving a county were in violation, weighted by the fraction of the population served by each system.[17]

The indirect utility consumer i derives from purchasing bottled water in market t is given by:

$$u_{i1t} = \gamma^c + \gamma^v v_{it} + (\gamma^p + \gamma^p_0 inc_{0i} + \gamma^p_1 inc_{1i} + \gamma^p_2 inc_{2i})\, p_{1t} + \xi_\tau + \Delta\xi_{1t} + \epsilon_{i1t} \tag{8}$$

where v_{it} is an indicator for consumer exposure to a health-based violation, p_{1t} is the average price per gallon of bottled water, and $(inc_{0i}, inc_{1i}, inc_{2i})$ represent normalized income levels for high-, middle-, and low-income consumers. I assume that each person consumes 32 oz of water per day, which equates to 1.75 gallons per person per week.[18] Using this as a baseline, I construct market shares for bottled water (s_{1t}) and tap water (s_{0t}) in each county-week.[19]

[17]Bottled water facilities are regulated by the FDA and are subject to different standards. However, during periods of noncompliance, system managers often recommend or provide bottled water as a substitute. For example, during the public health crisis in Flint, the government distributed free bottled water from January 2016 to April 2018.

[18]There is no definitive rule for daily water intake, but Harvard Health Publishing recommends 32-48 oz for healthy individuals. To allow for variation in beverage consumption, I use the lower bound in my estimation. Deviations from this assumption are absorbed by the estimated weight system managers place on consumer costs (Section 4). Sourced from: `https://www.health.harvard.edu/staying-healthy/how-much-water-should-you-drink`

[19]I assume tap water is free. The cost of 1.75 gallons per week is negligible relative to total consumption; for instance,

In the model, γ^c represents the average preference for bottled water over tap water, γ^v measures the shift in bottled water demand following violation exposure, and γ^p reflects average disutility from price. The $\boldsymbol{\gamma_i^p}$ terms allow for heterogeneous price sensitivity across income groups. I include year fixed effects, ξ_τ, to account for broader trends in bottled water demand, and a structural error term, $\Delta\xi_{1t}$, which reflects county-week deviations from this mean.[20]

I estimate the model parameters using a two-step generalized method of moments (GMM) procedure implemented in PyBLP (Conlon and Gortmaker, 2020). To aid identification, I incorporate micro-moments derived from the Consumer Panel Dataset (Conlon and Gortmaker, 2023), matching the annual probabilities of bottled water purchases for low- and middle-income consumers, as well as the average price paid by these groups, conditional on purchase. When constructing the empirical moments, I weight observations using ACS data and the share of households in the Consumer Panel Dataset that belong to each demographic bin.

A potential endogeneity concern arises if bottled water prices respond to local demand shocks, such as those triggered by health-based violations. In the baseline specification, I do not instrument for price, drawing on evidence from DellaVigna and Gentzkow (2019). Using the same NielsenIQ dataset, they show that major retail chains set uniform prices across geographic markets, suggesting price variation is largely independent of local demand conditions and unlikely to respond to sudden water system failures. For robustness, I also estimate the model using Hausman-type instruments based on the average price of bottled water in neighboring markets. The first-stage yields a Cragg-Donald F-statistic of 120.78, but the Kleibergen-Paap F-statistic is 3.24, suggesting that the instruments are weak when accounting for heteroscedasticity at the county level. Given this result, I treat the IV specification as a robustness exercise. I consider the OLS estimates as the baseline, under the assumption that retail pricing is largely exogenous to local systems' compliance status.

The estimation results are presented in Table 3, with columns (1) and (2) reporting results from the baseline and IV specifications, respectively. Both models indicate that consumers are sensitive to price and exposure to health-based violations, as reflected in the negative estimates for these parameters. The parameter γ^c is also negative, suggesting a baseline preference for tap water. Instrumenting for prices increases the magnitude of the violation and price coefficients and slightly reduces precision, as expected. The IV estimates imply higher willingness to pay to avoid violations—approximately 30% higher for middle- and low-income consumers and 13% higher for high-income consumers. These differences are consistent with upward bias in price sensitivity under the baseline model, though the qualitative conclusions remain unchanged. Because willingness to pay enters the system manager's problem multiplicatively, any misspecification would be absorbed into the inferred weight managers place on time spent in violation. In Section 6.3, I present results under the baseline specification and explore how the model's implications change when using the IV estimates.

the Muldraugh Water Department charged \$20.50 for 4,000 gallons—less than \$0.01 per gallon.

[20] The dataset includes 352 consolidated bottled water brands, including a "control brand" used by NielsenIQ to protect private labels (e.g., store-brand bottled water). As this control brand accounts for 38.9% of annual revenue on average, I do not model brand-level preferences.

Table 3: Demand Estimates and Derived Statistics

		(1)	(2)
Linear Parameters			
Constant	γ^c	-1.918	-2.456
		(0.081)	(0.461)
Price	γ^p	-1.042	-0.799
		(0.055)	(0.187)
Nonlinear Parameters			
Violation Exposure	γ^v	-1.942	-1.833
		(0.109)	(0.133)
Price, High-Income	γ_0^p	-0.548	-0.546
		(0.144)	(0.144)
Price, Middle-Income	γ_1^p	-0.319	-0.318
		(0.101)	(0.118)
Price, Low-Income	γ_2^p	-0.144	-0.144
		(0.058)	(0.064)
Derived Statistics			
Willingness to Pay			
High-Income	$\gamma^v/(\gamma^p + \gamma_0^p * inc_0)$	$1.35	$1.53
Middle-Income	$\gamma^v/(\gamma^p + \gamma_1^p * inc_1)$	$2.20	$2.86
Low-Income	$\gamma^v/(\gamma^p + \gamma_2^p * inc_2)$	$2.21	$2.88
Demand Elasticity			
High-Income	$(\gamma^p+\gamma_0^p*inc_0)p_1(1-s_1)$	-2.35	-1.95
Middle-Income	$(\gamma^p+\gamma_1^p*inc_1)p_1(1-s_1)$	-1.45	-1.05
Low-Income	$(\gamma^p+\gamma_2^p*inc_2)p_1(1-s_1)$	-1.44	-1.04
Year Fixed Effects		Yes	Yes
Observations		77,466	77,466

Notes: Column (1) reports two-step GMM estimates without a price instrument. Column (2) uses the mean bottled water prices from other stores in the same week as a price instrument. Models include micro-moments for purchases and average prices conditional on purchase among low- and middle-income consumers to identify heterogeneity. Both estimations were run with multiple starting values; reported results correspond to the smallest objective.

5.1.1 Consumer Avoidance Costs Discussion

Baseline estimates imply that high-income consumers are willing to pay $1.35 per gallon to avoid a violation, which translates to $2.36 per person per week under the assumed 1.75 gallons of weekly consumption. Willingness to pay estimates for middle- and low-income consumers are $2.20 and $2.21 per gallon, respectively, implying a per-week cost of about $3.85 and $3.87, which is 63% more than high-income consumers. Demand elasticity estimates suggest that high-income consumers are the most price sensitive. A possible explanation is that affluent consumers may have greater access to filtered tap water or other substitutes, which are captured in the utility of the outside good.[21] Based on these weekly values, a system that spends the entire year in violation imposes a per-person avoidance cost of $122.72 for high-income consumers, $200.20 for middle-income consumers, and $201.24 for low-income consumers. For the average-sized system in each income category, this translates to total annual violation costs of $2.81 million, $2.1 million, and $1.3 million, respectively.

5.2 Cost to Improve Infrastructure Quality

I estimate infrastructure project size using data on health-based violations and approved expenditures for 353 community water systems in Kentucky from 2007-2019. Following empirical patterns in the data (see Appendix Figure D.2), I model total annual expenditures with a lognormal distribution. Investment levels vary with system income and population size, reflecting that larger and wealthier service areas spend more on infrastructure. Expenditures also depend on violation exposure and whether a project is reactive, capturing the potential effects of declining quality. Reactive projects may be more urgent and costly than preventative measures, and systems in violation may require larger investments to return to compliance.

Selection bias arises because unobserved infrastructure quality influences both the decision to invest and the magnitude of the investment. As infrastructure quality deteriorates over time, investment is more likely when quality is low. However, at lower quality levels, projects are likely larger, as greater deterioration can necessitate more extensive repairs or replacements. This interdependence creates a challenge in estimation because project amounts are observed only when investment occurs. To correct for selection bias, I use the control function approach of Heckman (1979). I first estimate a probit model for the decision to invest, with the decision depending on the system's population, income level, and time spent in violation in the prior year, since the investment decision precedes the determination of investment amount.[22]

In the probit estimation, I include two instruments that shift the probability of investment but not investment magnitude. The first instrument is an indicator for the ARRA, which temporarily

[21] Allaire et al. (2019); Hadachek (2025); Graff Zivin et al. (2011), using different datasets and empirical approaches, document significant changes in bottled water consumption in response to health-based violations. These studies examine heterogeneity in responses based on store locations, whereas my study employs an indirect utility model that leverages panelist purchases to identify heterogeneous responses based on consumer demographics.

[22] The structural model collapses the drafting, approval, and implementation into a single period for tractability; in estimation, I use realizations of the prior year's violations.

Table 4: Log Infrastructure Project Expenditure ($M)

	(1)	(2)
	OLS	Heckit
Reactive Project	0.762	0.796
	(0.096)	(0.095)
Violation Months	0.037	0.043
	(0.019)	(0.020)
Medium System	0.557	0.783
	(0.117)	(0.130)
Large System	1.249	1.552
	(0.126)	(0.141)
High-Income System	0.466	0.453
	(0.129)	(0.134)
Middle-Income System	−0.223	−0.163
	(0.108)	(0.115)
Constant	−1.189	−2.829
	(0.105)	(0.361)
Inverse Mills Ratio	—	1.181
	—	(0.244)
Std. Error of Residual	1.628	1.898
	(0.757)	(0.118)
Project Observations	1,175	1,175
Total Observations	1,175	4,589

Notes: The dependent variable is the log total amount approved for infrastructure projects in the year. Column (2) controls for sample selection bias, using ADD fixed effects and an indicator for the 2009 ARRA as instruments.

increased available funding for all systems. Identification relies on the assumption that the ARRA expanded investment incentives without directly affecting infrastructure quality; thus, the program affected only the probability of investment. The second instrument is a set of fixed effects for the Area Development District (ADD) where each system is located. Because ADDs coordinate regional water planning and approve projects, variation across ADDs likely affects the decision to invest but not project size, since funding falls primarily to a system's consumers. After correcting for sample selection, I then estimate a model that more accurately captures the determinants of project expenditures.

Table 4 presents regression results with and without the selection correction in columns (1) and (2), respectively. Projects are larger in years with more violation time, consistent with consumer willingness to support additional spending in response to system failures. High-income systems invest the most, followed by low-income systems, while middle-income systems invest the least. Results are consistent with existing government assistance targeting low-income facilities and greater community support for investment among high-income populations. Systems with larger populations also undertake more expensive projects, reflecting a broader revenue base. Interactions between reactive projects and system income or population size are not statistically significant and omitted. This finding suggests that the additional expenditure associated with reactive projects is uniform across systems, consistent with the idea that urgency drives larger investment regardless of community characteristics.

The inverse Mills ratio in column (2) confirms the presence of sample selection bias. After applying the Heckman correction, estimated effects of reactive projects, violation time, and size category are slightly larger, suggesting that OLS understates the influence of infrastructure decline and system scale on investment size.

In the data, project type is potentially misclassified. Following the literature on mismeasured binary regressors (Aigner, 1973; Hausman, 2001), I correct for attenuation bias by estimating misclassification rates using external data. Some WRIS project profiles include a contemporaneously completed checklist, *DW Specific Impacts*, indicating whether a project was required for regulatory compliance. I treat this checklist as indicative of the true project type and estimate the implied false positive and false negative rates of the NLP model. I assume checklist completion is conditionally independent of classification error; projects with and without checklists are equally likely to be misclassified. Based on 731 completed checklists, the estimated misclassification rates imply an attenuation factor of 0.388, with a false positive rate of 38.9% and a false negative rate of 22.4%. I apply this correction to the coefficient on project type in the investment size regression. The adjusted estimate for reactive projects is $\hat{\kappa}^r_{adj} = 2.05\ (0.245)$, confirming that misclassification biases the original estimate toward zero.

5.2.1 Consumer Investment Costs Discussion

Project size estimates provide the empirical foundation for the structural model. The expenditure function approximates the budget constraint faced by managers and links investment to a system's underlying infrastructure quality. I assume that observing a project reveals managers' preferences over investment timing and frequency, while project size reflects the scale managers believe their communities are willing and able to finance. Evidence from Keiser and Shapiro (2019) shows that federal clean water grants translate directly into higher spending on wastewater infrastructure, rather than being diverted to other areas. Jerch (2022) finds that localities facing filtration mandates primarily increase water rates instead of reallocating existing funds. Accordingly, I assume investment costs are passed through to consumers via rate increases or tax adjustments, rather than drawn from other parts of the operating budget, and that managers only request the funds they expect to raise.[23] I therefore interpret expenditure requests as indirect evidence of community support for investment, driven by demonstrated infrastructure needs.

[23] Consumers do not bear the entire burden, as municipalities can issue bonds to cover costs. For more on financing drinking water investments through municipal bonds, see Posenau (2022), Agrawal and Kim (2022), and Brancaccio and Kang (2022).

In the model, I assume that consumer expenditure responses to quality deterioration are invariant to regulatory standards. As a result, I treat project type and violation time as sufficient statistics for the effect of declining quality on expenditures, and assume these preferences hold regardless of federal standards for safe drinking water. Under this assumption, the estimated expenditure function applies to alternative definitions of compliance and extends to the predominantly unobserved prior regulatory period (pre-2007). While the assumption simplifies estimation and supports counterfactual analysis, it rules out the possibility that declining quality influences investment intensity through other, unobserved channels or that consumer expenditure preferences change over time.

Based on the misclassification-adjusted estimates, the coefficient on the reactive-project indicator implies an average increase of about $7 million in project size relative to proactive projects, implying a substantially greater increase in infrastructure quality per project. Additionally, systems that spend an entire year in violation invest about $1.68 million more per project than those without violations. These findings suggest greater community support for financing projects when they address imminent issues, such as visible deterioration or compliance failures, while support for proactive investment is more limited. This pattern underscores the importance of accurately identifying project types and accounting for selection and misclassification biases when estimating the relationship between infrastructure quality and investment behavior. In the next section, I incorporate these results into the estimation of the full dynamic discrete choice model, where they serve as key inputs for the expected increase in quality from investment.

6 Estimation, Identification, and Results

I find the full solution of the model using maximum likelihood methods. Identification comes from observed project decisions, NLP-classified project types, approved project sizes, and violation durations. Infrastructure quality serves as the primary state variable because it parsimoniously captures the core mechanism underlying system manager decisions. However, this modeling choice presents identification challenges: quality is unobserved by the econometrician and its evolution is path dependent, requiring consideration of all possible quality histories over 13 periods. To make estimation tractable, I adapt recursive likelihood integration (RLI) to integrate over the continuous, serially correlated latent state.

6.1 Estimation

I recover the model parameters through a nested three-stage process. In the outermost estimation loop, I start with a candidate parameter vector and use simulation to recover the initial distribution of infrastructure quality. The second stage estimates the probabilities of observed outcomes, treating infrastructure quality as known. The final stage evaluates the likelihood of the observed sequence of outcomes by integrating over the unobserved evolution of infrastructure quality, conditional on the simulated initial distribution.

6.1.1 First Stage: Recover the Steady-State Distributions

In 2007, regulatory standards changed. After a decade of mostly minor revisions, several significant changes to the National Drinking Water Contaminant List began to be enforced.[24] Changes to safe drinking water regulations influence outcomes through three channels. First, more stringent standards increase the probability of violations across quality levels (a *level effect*), captured by higher values of δ^v. Second, new standards may also alter the probability that projects are reactive at a given quality level (a *composition effect*), captured by a change in δ^r. Third, regulatory shifts may expand the set of physical components required to deliver safe water, effectively redefining what qualifies as adequate infrastructure. Because quality summarizes the performance of all critical components, broadening the definition increases the probability that some part of the system requires replacement at any point in time, as these components often degrade at different rates. As a result, infrastructure may appear to deteriorate more rapidly following a regulation change, reflected in lower values of α^q, (a *decline effect*).

In estimation, I assume that initial quality in 2007, the first period of observation, follows a log normal distribution, $q_{w0} \sim \log \mathcal{N}(\mu_{nz}(\theta_{ss}), \sigma_{nz}(\theta_{ss}))$, which is determined by steady-state parameters, $\theta_{ss} = (\delta^v_{ss}, \delta^r_{ss}, \alpha^q_{ss})$ that reflect the regulatory environment prior to 2007. To ensure consistency between model predictions and observed initial outcomes, I forward simulate investment and violation behavior over an extended horizon for each guess of the parameters. I then recover the corresponding mean and standard deviation of the quality distributions (μ_{nz}, σ_{nz}) implied by the simulated steady state. I allow the steady-state distributions to vary by system income and size categories.

The distribution of infrastructure quality at the start of 2007 matches the distribution in 2006, before the regulatory change. To help identify the parameters governing the steady-state distribution, I incorporate probabilities of the 2006 outcomes into the likelihood function. After recovering the steady-state distributions, I construct the remaining components of the likelihood using RLI. Additional details on the estimation procedure are provided in Appendix B.2.

6.1.2 Second Stage: Estimate Quality-Dependent Parameterized Outcome Probabilities

Manager behavior depends on three unobserved state variables: infrastructure quality and two choice-specific shocks. The estimation of models with unobserved, choice-specific shocks is well established in the literature (see, e.g., Aguirregabiria and Mira (2010)). Following this literature, I assume that the choice-specific error terms $\epsilon(i)$ are independent across periods and follow a Type I extreme value distribution with mean zero and variance $\pi^2/6$. Treating infrastructure quality as known, I apply a fixed-point algorithm to compute the conditional value functions and construct the implied probability of investment. In each iteration of the contraction mapping, I update the violation and reactive investment probabilities using equations (2) and (4) from Section 4, conditional on the expected size of an infrastructure project described by equation (5).

[24] See Section 2.2.2 for additional details.

6.1.3 Third Stage: Implement RLI Method to Integrate Over Unobserved Quality

In the final stage of estimation, I address the identification challenges posed by the unobserved, serially correlated state. To do so, I evaluate the likelihood function via backward induction: combining successive interpolations and approximations to integrate over the history of the unobserved state. Leveraging the panel structure of the data, this method allows me to recover parameter values that best match observed investment behavior and quality decline consequences over time.

Denoting project investment as i_t, NLP-classified reactive projects as $\tilde{y}_{rt}$, observed project costs as k_t, and the number of months in violation as y_{vt}, the recursive likelihood function for a single system is:

$$\begin{aligned} L^{RLI}(\boldsymbol{\theta}) \quad &= \quad \int ... \int \prod_{t=1}^{T} \Big[p_{i|q}(i_t \mid q_t; \boldsymbol{\theta}) p_{\tilde{y}_r|q}(\tilde{y}_{rt} \mid q_t, i_t; \boldsymbol{\theta}) p_{y_v|q}(y_{vt} \mid q_t; \boldsymbol{\theta}) \\ &\times \quad p_{k|q}(k_t | q_t, i_t; \boldsymbol{\theta}) p_q(q_t \mid i_{t-1}, k_{t-1}, q_{t-1}; \boldsymbol{\theta}) \Big] \\ &\times \quad p_{i|q}(i_0 \mid q_0; \boldsymbol{\theta}) p_{\tilde{y}_r|q}(\tilde{y}_{r0} \mid q_0, i_0; \boldsymbol{\theta}) p_{y_v|q}(y_{v0} \mid q_0; \boldsymbol{\theta}) \\ &\times \quad p_{k|q}(k_0 \mid q_0, i_0; \boldsymbol{\theta}) p_q(q_0; \boldsymbol{\theta}) dq_T dq_{T-1} ... dq_0 \end{aligned} \tag{9}$$

where $\tilde{y}_{rt}$ and k_t are only observed when projects are undertaken $(i_t = 1)$ and incorporate classification error, based on the false positive rate and false negative rates obtained from a comparison to the *DW Specific Impacts* Checklist.

To simplify estimation, RLI reduces this T-dimensional integral to a sequence of one-dimensional integrals, solved via backward induction over the history of infrastructure quality inferred from observed outcomes. The recursion performs a form of backcasting, in which future choices and outcomes are used to refine inferences about earlier values of the latent state. I define the following recurrence relation to obtain the likelihood of future outcomes given that current quality is $\tilde{q}$:

$$g_t(\tilde{q}) = \begin{cases} 1 & \text{if } t > T \\ \int p_{i|q}(i_t \mid \tilde{q}'; \boldsymbol{\theta}) p_{\tilde{y}_r|q}(\tilde{y}_{rt} \mid \tilde{q}', i_t; \boldsymbol{\theta}) p_{y_v|q}(y_{vt} \mid \tilde{q}'; \boldsymbol{\theta}) p_{k|q}(k_t \mid \tilde{q}', i_t; \boldsymbol{\theta}) & \text{if } t \leq T \\ \quad \times \, p_q(\tilde{q}' \mid i_{t-1}, k_{t-1}, \tilde{q}; \boldsymbol{\theta}) g_{t+1}(\tilde{q}') d\tilde{q}' & \end{cases} \tag{10}$$

For each candidate parameter vector, $\boldsymbol{\theta}$, I use equation (10) to recursively build the likelihood over the support of infrastructure quality. The recursion uses the sequence of observed actions to evaluate, for each possible value of latent quality, the likelihood that it generated the data. The full likelihood is then obtained by integrating over the initial distribution of quality at the start of the observation window. This recursive procedure offers an alternative to simulation-based methods, such as particle filters (Blevins, 2016) and Markov Chain Monte Carlo (Norets, 2009), by computing the likelihood on a fixed grid, using quadrature methods for known distributions and the model's transition structure.

To implement the estimation procedure, I first discretize the support of quality into a grid. I then

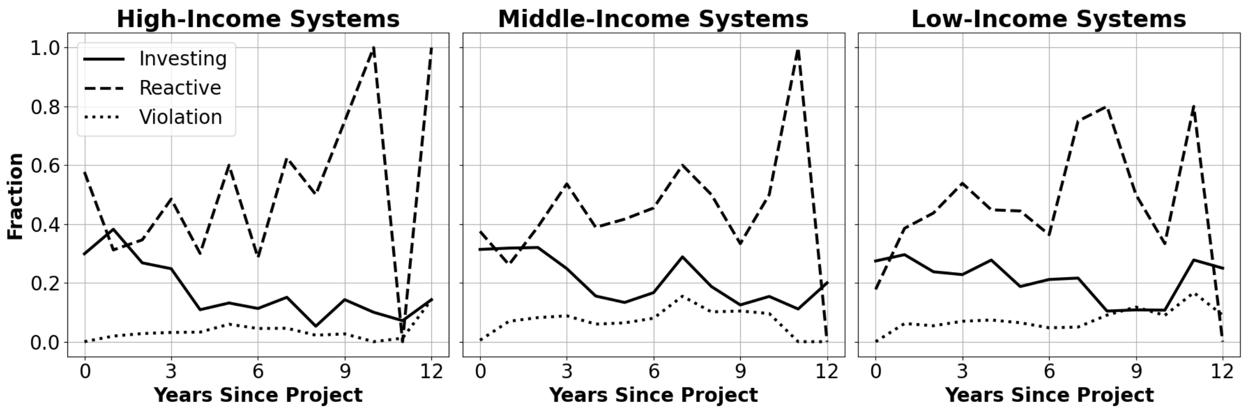

Figure 2: Income-Level Identifying Variation

Notes: Panels show, by income level, the fraction of systems investing, the share of investments classified as reactive, and the average fraction of the year in violation, plotted against the number of periods since the last infrastructure project.

initialize the probability of future outcomes, $g(\cdot)$, to one at each grid point, as there is no further information about the progression of quality contained within the unobserved future periods. Then, for period T, I compute the joint probability of the observed outcomes (investment, project type and size, and violation timing) at each grid point, incorporating the quality progression from period $T-1$ to update $g(\cdot)$. I repeat this process for period $T-1$, using both the observed outcomes and the continuation likelihood propagated from period T.

The backward induction continues until $t = 1$, sequentially updating the likelihood using the observed data and the model's transition structure. Any off-grid values are evaluated via interpolation. This process effectively reweights each grid point to reflect the likelihood that initial-period quality takes on that value, given the entire 13-year sequence of observed outcomes. Finally, at $t = 0$, I complete the likelihood computation by integrating over the initial distribution of infrastructure quality, inherited from periods prior to 2007.

6.2 Identification

In a standard dynamic discrete choice framework, investment decisions, project expenditures, and violation durations together with variation in infrastructure quality would fully identify the model parameters. Without direct quality measures, identification instead relies on the observed sequence and joint evolution of these outcomes, which reflect underlying quality dynamics. Across the observation period, trends in investment frequency, the share of reactive-classified projects, and the amount of time spent in violation reveal information about the latent quality distribution and the parameters that map quality into observed actions and outcomes. As quality shifts over time, distinct patterns in these observables emerge that enable identification.

Figures 2 and 3 plot variation in the data that aid in identification. Figure 2 depicts the fraction of systems investing, the fraction of reactive investments, and the average fraction of the year spent in violation, each as a function of time since the last investment. Among systems delaying investment, the share of reactive projects and violation durations rise over time. High-income sys-

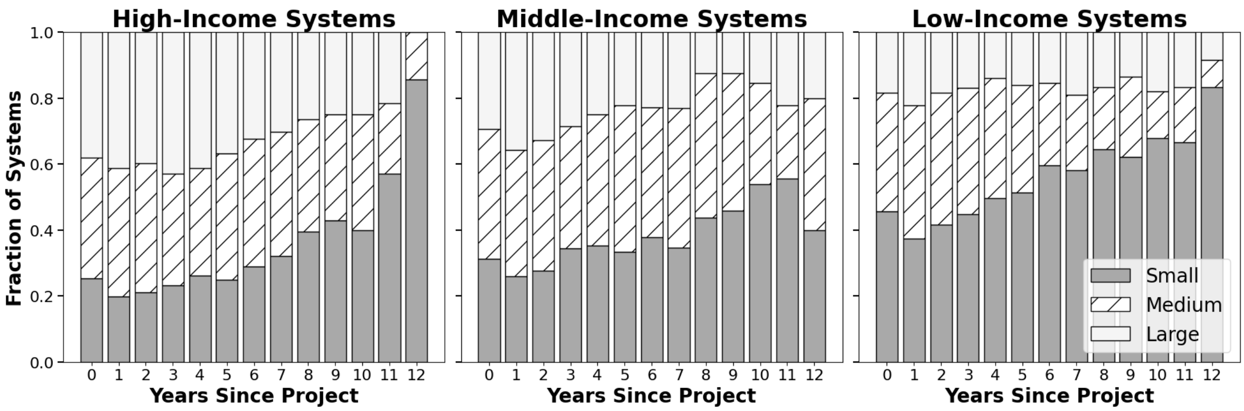

Figure 3: Population Size Identifying Variation

Notes: Panels show, by income level, stacked bars of system size composition by time since last investment.

tems show the steepest declines in investment and steepest increases in reactive projects. Figure 3 shows that long gaps between investments are associated with smaller populations, highlighting population size as another key determinant of investment behavior. Together, the figures indicate that systems serving smaller populations invest less frequently and, when they do invest, are more likely to invest reactively.

Given an initial quality distribution, the fraction of systems in violation in 2007 identifies the violation parameter, δ^v. This parameter determines how latent infrastructure quality translates into health-based violations. Larger values imply that more systems face positive violation probabilities and experience longer violation durations. The evolution of average violation time over subsequent periods identifies the persistence parameter, α^q. Figure 2 plots this relationship. As underlying quality deteriorates without investment, the slope of average violation duration pins down the persistence parameter. Values closer to one indicate slower deterioration and a more gradual increase in violation time.

Investment occurs when the expected reduction in future violation costs exceeds the anticipated expenditure. As infrastructure quality declines, the probability of a reactive project increases, raising both the expected cost and the expected benefit of investment. In the data, investment decisions and project type are simultaneously observed. Therefore, identification of the parameters governing the timing and type of investment relies on the joint distribution of these two outcomes: the conditional choice probability of investment and the probability that a project will be reactive.

When quality is observed, the investment cost weight (λ^x) is identified from the rate of investment when infrastructure quality is high. Smaller values imply managers are less sensitive to passing investment costs on to consumers, resulting in more frequent projects. In particular, low λ^x corresponds to more proactive investment, as managers are willing to invest even when violation risk is minimal. The weight on violation costs ($\lambda^{\mathcal{VC}}$) is identified from the rate of projects at low quality levels, where the threat of violation is more immediate. Higher $\lambda^{\mathcal{VC}}$ indicates a stronger aversion to violation time and is associated with higher investment probabilities in low-quality states, resulting in more reactive investment.

The ratio $\lambda^{\mathcal{VC}}/\lambda^{x}$ determines the quality threshold where investment becomes optimal and is identified by the highest quality at which reactive investment is observed. Given this ratio, the curvature of the conditional choice probability of investment with respect to quality identifies the scale of the managerial preference parameters. Finally, conditional on investment, the reactive project parameter (δ^{r}) is identified by the observed composition of project types: larger values indicate more reactive projects.

When infrastructure quality is unobserved, identification relies on how investment types evolve over time and across systems. In the first period, the ratio of the cost weights ($\lambda^{\mathcal{VC}}/\lambda^{x}$) together with the reactivity parameter (δ^{r}) determines the quality threshold for investment and the expected fraction of reactive projects. Variation in investment rates and project classifications across otherwise similar systems helps recover these parameters. As quality deteriorates, the rate at which the investment probability rises identifies the scale of the managerial preference parameters. A steeper slope indicates a larger scale, or a greater sensitivity to differences in expected costs. Conditional on this scale, δ^{r} is inferred from the rate at which the share of reactive projects increases with declining quality, as shown in Figure 2. Differences in population size among systems with the same income level shift investment costs and benefits, isolating the scale effect. Variation in initial quality distributions and the share of reactive projects isolates the reactivity parameter.

The parameters characterizing the consequences of quality decline under the prior regulatory regime, ($\delta^{v}_{ss}, \delta^{r}_{ss}, \alpha^{q}_{ss}$), are recovered from 2006 investment behavior and from the effect that these parameters have on the steady-state quality distributions. The absence of violations in 2006 requires a sufficiently high steady-state quality distribution. At the same time, 27% of systems invested in that year, and 28% of those projects were reactive. These patterns suggest that the potential for violation was relatively imminent, indicating that investment was productive for many systems.

In keeping with these data patterns, I fix the persistence parameter $\alpha^{q}_{ss} = 0.995$ in the baseline specification. In principle, the persistence parameter is identified from the evolution of average violation time. Because the 2006 cross section contains no such variation, violation data are only observed from 2007 onward, this parameter cannot be estimated from the 2006 data. A value of 0.995 implies a rate of quality decline that is slow enough to generate high steady-state quality but fast enough to induce regular investment in the steady state. Table C.2 in Appendix C presents the results under alternative choices for this parameter.[25]

The steady-state violation parameter, δ^{v}_{ss}, governs the probability of violation. Smaller values indicate more relaxed standards and lower violation probabilities. The effect of stricter standards on steady-state quality depends on the rate of decline. When quality decline is slow, stricter standards raise steady-state quality by increasing investment frequency; when decline is fast, stricter standards can reduce steady-state quality or cause collapse if projects are too small. Cross-sectional

[25] The Environmental Protection Agency (2002) report "The Clean Water and Drinking Water Infrastructure Gap Analysis", states that water treatment plants typically have a useful life of 20-50 years, and that pipe life cycles range from 15-100 or more years. Simulations using the recovered steady-state parameters for this period indicate steady-state investments occur every 1-26 years on average, consistent with these ranges.

Table 5: Dynamic Model Parameter Estimates

Parameter		Estimate	Std. Error
Decline Consequences			
Slope of Violation Probability	δ^v	127.7	8.261
Slope of Reactive Probability	δ^r	445.9	43.98
Rate of Quality Decline	α^q	0.930	0.007
Violation Weights			
High-Income Consumers	$\lambda_0^{\mathcal{VC}}$	3.329	0.578
Middle-Income Consumers	$\lambda_1^{\mathcal{VC}}$	3.162	0.638
Low-Income Consumers	$\lambda_2^{\mathcal{VC}}$	5.650	1.056
Investment Weights			
High-Income Consumers	λ_0^x	0.356	0.018
Middle-Income Consumers	λ_1^x	0.525	0.032
Low-Income Consumers	λ_2^x	0.503	0.025

differences in investment behavior across income and population levels help identify δ_{ss}^v. The lack of violations in 2006 suggests that this parameter is small, but that steady-state infrastructure quality level is high, necessitating a sufficiently high AR(1) parameter.

Variation across systems in the share of reactive projects in 2006 identifies the reactive parameter, δ_{ss}^r. Larger values imply more reactive projects, leading to larger investments and higher steady-state quality. This parameter has heterogeneous effects across systems. Systems with the lowest steady-state quality have a disproportionately greater share of reactive projects than systems with higher steady-state qualities. As a result, δ_{ss}^r is determined by the interaction of the rate of reactive projects with the implied steady-state quality levels, producing distinct patterns of reactive investment across systems in 2006.

6.3 Results

Estimation results are summarized in Table 5 and Table 6. To evaluate the model, I use the recovered parameter estimates and simulate 100 scenarios to approximate manager behavior. Each simulation draws initial quality from the estimated steady-state distributions, after which quality declines and managers make corresponding investment decisions. Figure 4 compares average simulation outcomes to observed behavior over 2007-2019. The solid lines depict data, dashed lines correspond to simulated results, and shaded areas indicate standard deviations. The top panels show, by income level, the fraction of systems investing; the middle panels show the fraction of reactive-classified investments; and the bottom panels show the average fraction of the year spent in violation of a health-based standard. Across all panels, simulated outcomes broadly match patterns in the data, suggesting the model fits the data well.

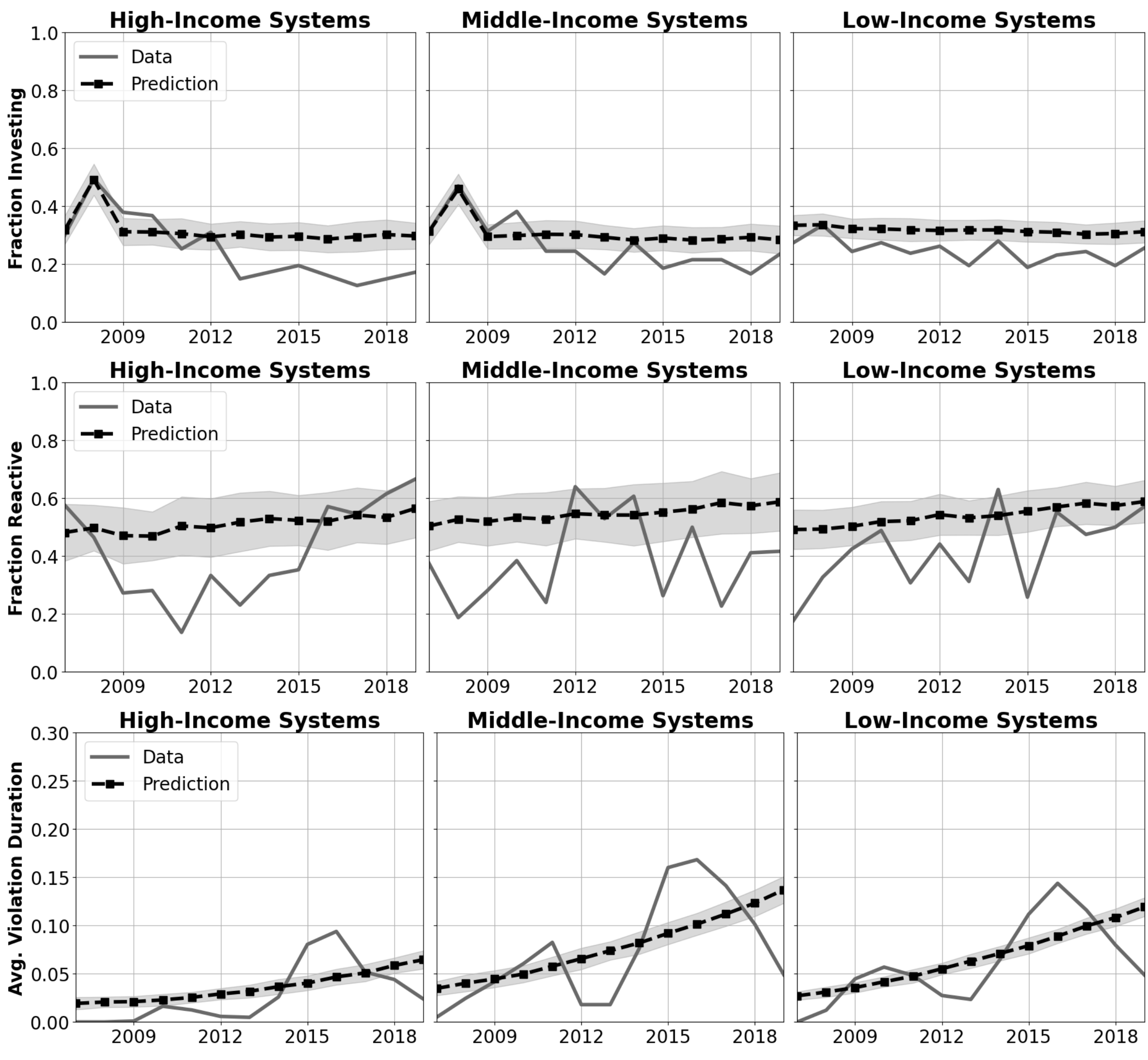

Figure 4: Model Fits by Income Level

Notes: Panels show average system activity for high-, middle-, and low-income systems (solid gray) and predictions (dashed black) with shaded standard deviation bands. Top panels plot the fraction of systems investing in infrastructure projects (2007–2019); middle panels plot the share of projects classified as reactive; bottom panels plot the average fraction of the year in violation of health-based standards.

Observation Period Table 5 reports the estimated parameters governing 2007-2019 outcomes. Standard errors are obtained through a system-level bootstrapping procedure with 100 replications. Three parameters determine the rate and consequences of quality decline: $(\delta^v, \delta^r, \alpha^q)$. The persistence parameter estimate, $\alpha^q = 0.93$, implies relatively rapid deterioration. Combined with the estimated violation slope, $\delta^v = 127.7$, the model predicts that, absent investment, the average system would spend 25% of the year in violation within 18 years and 99% within 42 years, consistent with reported manager expectations during this period (Barfuss and Fugal (2025); 2025 ASCE Drinking Water Infrastructure Report Card). The estimated reactive slope, $\delta^r = 445.9$, is substantially higher, indicating that reactive projects typically occur well before the system enters into a state of violation. Absent investment, the average system's expected probability of a reactive project rises from 21% in 2007 to 54% by 2019.

The interaction between the rate of quality decline and the level of quality at the time of investment determines project effectiveness. In simulations, the average investment is \$2.72 million—an amount that nearly offsets immediate deterioration, returning quality to just below its pre-investment level the following period. Project effectiveness varies by investment type. Proactive projects are smaller, averaging \$0.91 million, and occur when quality is relatively high. As a result, proactive investments slow but do not reverse quality decline in the following period. Reactive projects average \$5.67 million and occur when quality is lower. These investments raise quality for less than three years before returning to pre-investment levels.

Estimated cost weights indicate that managers value avoiding violations more than avoiding investment costs. For high-, middle-, and low-income systems, the cost weight ratio, $\lambda_n^{\mathcal{VC}}/\lambda_n^x = (9.34, 6.02, 11.24)$, implies that managers more than internalize consumers' averting costs from unsafe drinking water. This finding is consistent with the environmental valuation literature, which documents that revealed preference estimates, such as those derived from averting behavior like bottled water purchases, are typically lower than stated preference estimates.[26] Managers' high valuations may reflect political or public pressure, both of which could cause managers to weigh system-wide failures more heavily than consumers' private aversion costs. Using IV rather than OLS willingness to pay estimates scales the violation cost weights proportionally: $(\lambda_{0,IV}^{\mathcal{VC}}, \lambda_{1,IV}^{\mathcal{VC}}, \lambda_{2,IV}^{\mathcal{VC}}) = (2.93, 2.43, 4.33)$, yielding cost ratios $(8.21, 4.63, 8.62)$, all above one. Results confirm that managers' relative cost preferences are robust to the demand specification.

Prior Regulatory Period Table 6 reports estimates for the pre-2007 regulatory parameters, $(\delta_{ss}^v, \delta_{ss}^r, \alpha_{ss}^q)$, and systems' steady-state distributions under the earlier standards. Consistent with the expected effect of the policy shift, estimated violation probabilities are lower under the more relaxed pre-2007 regulations and expected violation durations are negligible (<0.5% of the year). By contrast, for the same level of quality, the probability of a reactive project was higher. Two mechanisms could explain this result. First, consumers may only be willing to pay for reactive projects when they occur infrequently; thus, when regulations tighten, the estimated reactive slope

[26] Among others, see Bartik (1988), Wu and Huang (2001), and Orgill-Meyer et al. (2018).

Table 6: Steady-State Parameter Estimates

Parameter		Estimate	Std. Error
Decline Consequences			
Slope of Violation Probability	δ^v_{ss}	66.16	5.176
Slope of Reactive Probability	δ^r_{ss}	620.8	52.70
Rate of Quality Decline	α^q_{ss}	0.995	
Initial Quality Distributions			
High-Income, Small	(μ_{0s}, σ_{0s})	(6.68, 0.32)	
High-Income, Medium	(μ_{0m}, σ_{0m})	(6.84, 0.43)	
High-Income, Large	(μ_{0l}, σ_{0l})	(6.30, 0.57)	
Middle-Income, Small	(μ_{1s}, σ_{1s})	(6.28, 0.37)	
Middle-Income, Medium	(μ_{1m}, σ_{1m})	(6.50, 0.45)	
Middle-Income, Large	(μ_{1l}, σ_{1l})	(6.10, 0.56)	
Low-Income, Small	(μ_{2s}, σ_{2s})	(6.38, 0.37)	
Low-Income, Medium	(μ_{2m}, σ_{2m})	(6.52, 0.46)	
Low-Income, Large	(μ_{2l}, σ_{2l})	(6.12, 0.53)	

declines as managers internalize these preferences. Second, a regulatory change that redefines infrastructure quality may alter the timing of visible deterioration, causing signs to appear later in the decline and closer to the point of unsafe drinking water. As a result, reactive projects and violations become more closely aligned, shortening the window between detection and failure.

Overall, steady-state quality was high under the earlier standards, although there was substantial variation across systems. Before the regulatory change, systems serving more affluent consumers maintained higher quality levels than their counterparts. Among income groups, medium-sized systems achieved the highest average quality, followed by small and then large systems. Average differences across systems reflect heterogeneity in investment behavior. Small systems invested the most frequently (every three years), but in smaller amounts ($1.16 million). Large systems invested the least often (every 15 years), but in much larger projects ($4.89 million). Medium-sized systems combined moderate investment frequency (every four years) and project sizes ($2 million), yielding the highest steady-state quality under the more relaxed regulatory standards.

Small and large systems had the highest rates of reactive projects (36% and 40%, respectively) compared with medium systems (28%). These patterns were also present within income levels. For small, lower-income systems, higher reactive rates stemmed from proactive projects that were insufficient to maintain quality. Large systems, on the other hand, had the capacity to invest proactively in greater amounts but chose to leave longer intervals between projects. Under more relaxed standards, managers with larger revenue bases undertook a higher percentage of reactive projects than their resource-limited counterparts. These results point to the role of economies of scale and the importance of reactive projects in shaping investment strategies.

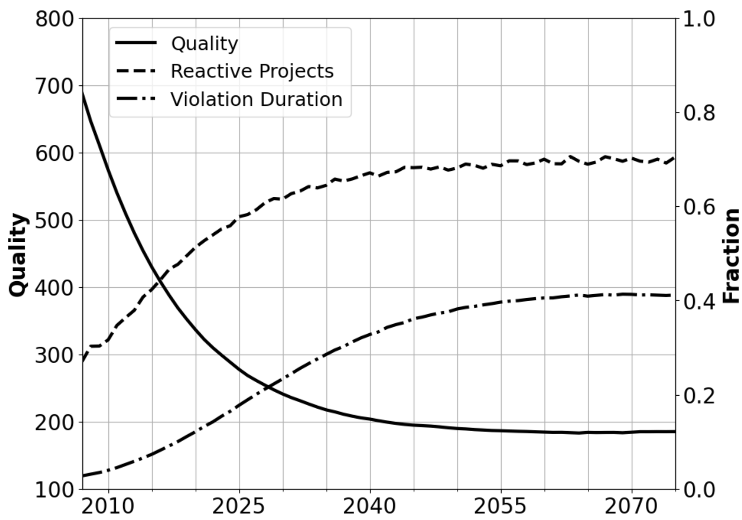

Figure 5: Long-Term Effect of Regulatory Change
Notes: The figure plots average quality from 100 simulations of 353 systems during the transition to a new steady state, with the corresponding average fraction of the year in violation and the share of reactive investments.

7 Policy Evaluation

7.1 Long-Run Implications of the Regulatory Change

First, I examine the long-run effects of the regulatory change on systems' ability to provide safe drinking water. Using the recovered parameter estimates, I simulate the evolution of infrastructure quality along with the resulting share of reactive investments and fraction of the year systems spend in violation. Figure 5 plots these trends as systems transition to a new steady state. Over this period, the quality distribution shifts downward, declining by more than 73% before stabilizing at a substantially reduced level. As a result, the average fraction of the year spent in violation rises from 3% to over 41%, and the rate of reactive projects increases from 27% to 70%. The 2025 ASCE Drinking Water Infrastructure Report Card similarly documents falling life expectancies for systems between 2018 and 2023, consistent with this result. These patterns suggest that investment during this period was insufficient to offset deterioration, highlighting the consequences of tighter standards implemented without additional financial support.

Exploring the effects across income and population levels, the left panel of Figure 6 depicts average violation time in the first period following the regulation change, when very few systems are out of compliance. Large systems have the highest expected violation time, but still spend less than 7% of the year in violation. The projected long-run violation state of systems is represented in the lower portion of the stacked bars in the right panel. Violation increases are most pronounced among small and medium systems, rising from 2% and 1.6% to 60% and 43%, respectively. Large systems, by contrast, experience only a modest increase, from 5.5% to 12.5%.

To assess the importance of project type, I simulate a counterfactual in which managers are unable to invest reactively. The shaded portions of the stacked bars in the right panel of Figure 6

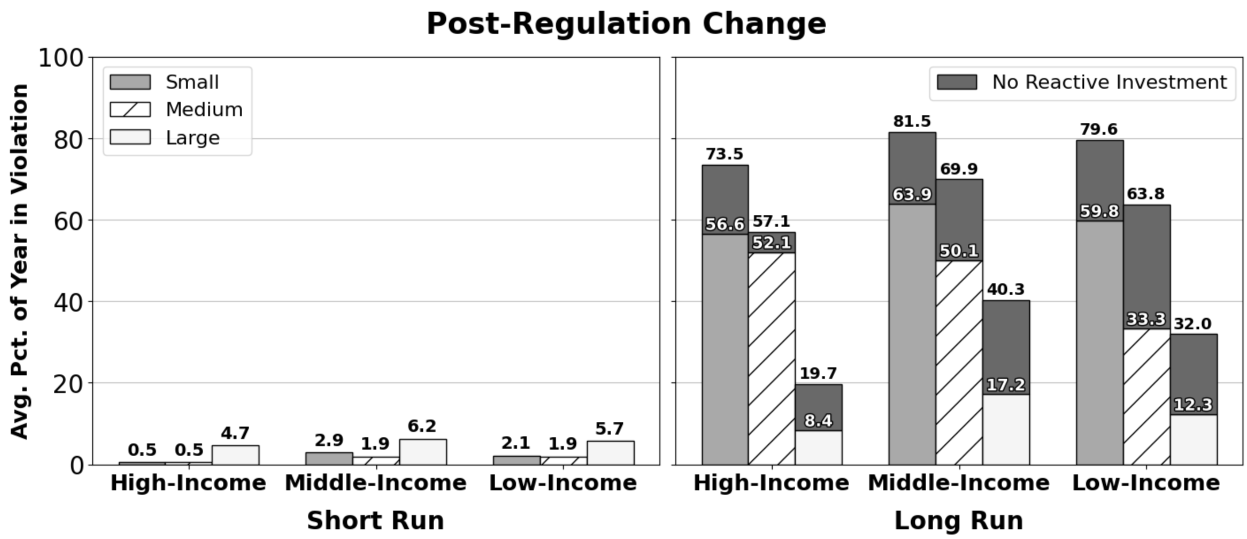

Figure 6: Projected Violation Time Following Regulatory Change

Notes: The left panel and the lower portions of the bars in the right panel show projected average violation durations in the short run (left) and long run (right) following the regulation change. The full stacked bars in the right panel show the corresponding counterfactual violation durations without reactive projects.

reflect the change in the steady-state percentage of the year systems spend in violation under this restriction. Results show that reactive projects enable managers to maintain significantly lower violation rates. Without reactive investment, average violation time rises from 41% to 61%, with the greatest increases occurring in middle- and low-income systems. Large systems across all income levels experience much smaller increases, averaging about ten percentage points. The magnitude of investments and the accelerated rate of quality decline drive these results. As standards tighten, infrastructure quality deteriorates more rapidly, reducing the effectiveness of investments. Because lower-income and smaller systems undertake smaller-scale proactive projects, average quality levels fall, making these systems increasingly dependent on reactive projects to prevent further decline. Eliminating reactive investment would further widen disparities in access to safe drinking water.

Under the new compliance standards, predicted annual steady-state per-person spending on investment and violation costs rises across all system types, but small and medium systems face greater increases than large systems (Table 7). The composition of these expenditures also differs across systems. For all systems, most of the additional per-capita spending is driven by investment, but among smaller systems, violation costs account for a greater share of the total change. Large systems display greater willingness and capacity to invest as quality declines, undertaking projects more frequently and limiting the rise in spending associated with violations. As a result, these populations experience smaller per-capita increases in both investment and violation costs. Smaller systems, by contrast, face a higher per-capita investment burden that yields aggregate project sizes that are too small to mitigate quality decline and are therefore less effective at reducing violation costs following the regulation change. Consequently, smaller and lower-income systems experience greater per-capita increases in both investment and violation costs relative to other systems.

Table 7: Predicted Annual Expenditures Per Person

	Old Steady-State Costs		New Steady-State Costs		Increase
	Investment ($PP)	Violation ($PP)	Investment ($PP)	Violation ($PP)	Total ($PP)
High-Income, Small	275.1	0.742	680.3	71.84	476.3
High-Income, Medium	132.9	0.661	158.8	63.92	89.16
High-Income, Large	34.15	5.117	61.28	9.913	31.93
Middle-Income, Small	164.5	5.657	313.9	127.8	271.5
Middle-Income, Medium	84.60	3.780	157.2	100.4	169.2
Middle-Income, Large	42.27	12.60	95.24	34.55	74.92
Low-Income, Small	235.3	4.205	500.9	120.7	382.1
Low-Income, Medium	74.85	3.687	221.1	65.40	207.9
Low-Income, Large	73.42	12.08	136.1	25.06	75.65

7.2 Compliance-Restoring Investment

As a final exercise, I examine the effects of federal funding programs that subsidize investment. I first simulate a federal grant program that fully covers investment costs, while holding project size constant, which I interpret as fixing community support at observed levels. Under these conditions, average long-run quality declines by 55% rather than by 70% in the baseline. Still, quality remains lower than before the regulation change, and systems spend approximately 20% of the year in violation of health-based standards. Results suggest that insufficient community support for investment, rather than manager aversion, is the primary driver of underinvestment. Therefore, one-time subsidies that shift manager behavior provide only temporary quality gains. To sustain high infrastructure quality under tighter regulations, managers need permanent funding programs that expand community support for investment, increasing the size of infrastructure projects. Without such federal support, investment will remain too low to meet new standards.

I next take sustained external financial support as given and estimate the investment increases required to restore the average simulated fraction of the year spent in violation to pre-regulatory change levels (0.003). The left panel of Figure 7 shows combinations of proactive and reactive increases that achieve this outcome. A key finding from this analysis is that returning to prior compliance levels requires increasing the size of proactive projects; a reactive-only investment increase is incapable of restoring compliance. Because reactive projects occur only after quality has fallen to lower levels, relying solely on larger reactive investments would encourage managers to maintain quality levels that incur a higher risk of violation, preventing a return to prior compliance rates.

Comparing policy combinations, minor proactive increases require substantial expansions in the size of reactive projects. When proactive projects are small, managers must maintain high levels of infrastructure quality through near-constant proactive investment to prevent declines that could

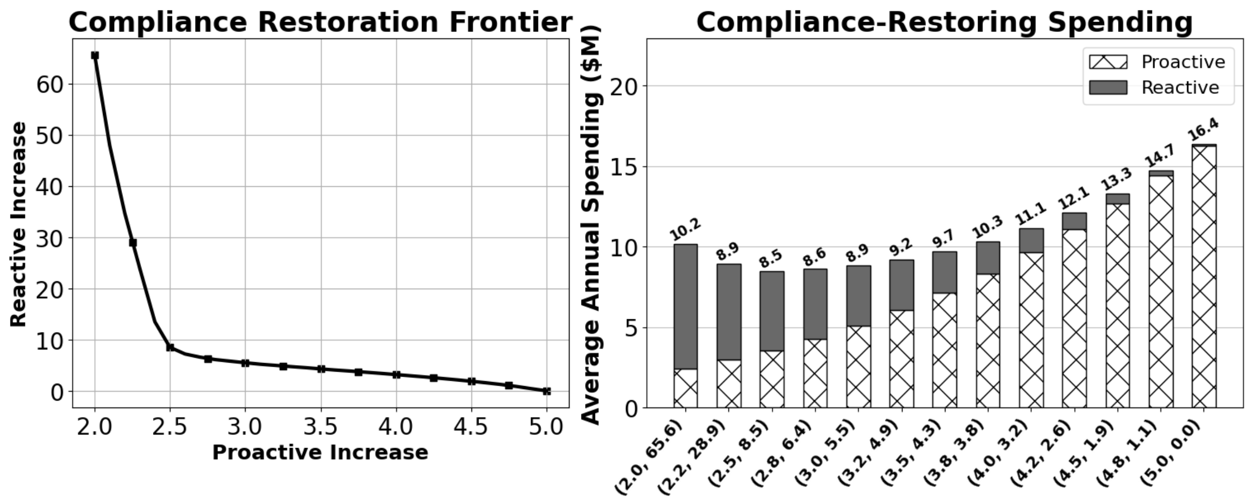

Figure 7: Compliance-Restoring Counterfactual Spending Increases

Notes: The left panel plots combinations of increases in proactive and reactive projects that restore average steady-state expected fraction of the year spent in violation to pre-regulation levels. The right panel reports average annual per-system expenditures under each policy, distinguishing proactive and reactive spending.

trigger compliance failures. If a system experiences a negative shock, such as a natural disaster or an unforeseen physical failure, quality may fall to levels that proactive investment alone cannot reverse. In the event of an unexpected decline, larger reactive investments become necessary to restore infrastructure quality to levels where proactive investment can again maintain quality. As the magnitude of proactive projects increases, the required compensating increase in reactive projects becomes smaller. When proactive projects are larger, managers maintain even higher levels of infrastructure quality, effectively insuring against shocks rather than relying on reactive investment to overcome unexpected declines.

The right panel of Figure 7 plots the average annual increase in expenditures per system implied by these combinations. A proactive increase of $2.5 million paired with an $8.5 million reactive increase restores compliance at the lowest total cost. Under these conditions, managers maintain the minimum quality level that obtains the required compliance condition. Pairing modest proactive increases with large reactive increases enables managers to primarily invest proactively while retaining funds to address severe quality declines when they occur. With these expenditure increases in place, managers do not need to over-invest in proactive projects as insurance against quality disasters, but are instead able to better balance maintaining compliance and avoiding excessive spending. At these investment levels, reactive projects occur only ten percent of the time, indicating that an efficient maintenance strategy relies primarily on proactive investment but still requires a reserve for reactive projects to manage uncertainty and avoid excessive spending.

8 Conclusion

In this paper, I develop a framework for analyzing the timing of infrastructure investment under uncertainty. Using new data on drinking water systems, I estimate a dynamic model of proactive and reactive investment that integrates consumer behavior, managerial incentives, and regulatory constraints. The results show that stricter standards increase the expenditures required to sustain quality and lead to more compliance failures. Larger systems invest more efficiently and can better absorb increased investment requirements, but smaller, lower-income systems struggle to maintain quality and avoid violations, underscoring the need for targeted support. Reactive investment plays a critical role in sustaining infrastructure performance by allowing financially constrained managers to intervene as quality deteriorates and by improving compliance outcomes across systems of all sizes and income levels. Policies that pair moderate increases in proactive spending with larger reactive increases can achieve compliance at a lower cost and ensure access to safe drinking water in all communities.

While my results align with expected effects of regulation and match patterns in the data, several limitations remain. First, infrastructure quality is an unobserved, aggregate measure that is inferred through new methods that capture the influence of a persistent latent state. Consequently, the findings are only meaningful when interpreted through the model's implied outcomes, such as predicted violation times or investment patterns. Second, the model abstracts from interactions between local systems and state agencies that influence resource allocation. State actions are important in balancing resources and needs, and future research could examine how these relationships shape the investment cycle. Third, my analysis focuses on Kentucky, which has relatively high compliance rates, and relies on local terminology to identify reactive investment. A natural extension would be to explore whether similar patterns emerge in states with lower compliance rates or alternative definitions of reactive investment.

The distinction between proactive and reactive investment extends beyond drinking water systems to the management of all durable assets and applies to any setting where long-lived resources face uncertain deterioration. Yet government spending on durable assets, including recent initiatives like the IIJA, rarely allocates funds according to this distinction, potentially reducing the efficiency of federal support. Future research could examine how federal and state programs might incorporate the differing roles of proactive and reactive investment, and how political incentives shape the timing and allocation of spending.

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Appendix

A Project Classification

Before analyzing how infrastructure projects relate to violations, I classify projects as *reactive* or non-reactive. I consider all non-reactive projects to be *proactive*. The primary purpose of this exercise is to isolate the projects that are pursued in response to a system issue relevant to the provisioning of safe drinking water. Project reports include detailed project descriptions and "need for project" justifications that I use to classify projects. I consider a project to be reactive if either the description or the project need contains language alluding to a public health emergency or a system failure. For example, any excerpt that mentions the system facing a public health problem, needing to return to compliance, or a major infrastructure issue that affects whether there are contaminants in the water (e.g., pipe deterioration, extensive breaks, or over-stressing) are all considered to be reactive. See Table A.1 for examples of project excerpts and their classifications.

I employ natural language processing tools to categorize the entire population of projects. To this end, I first manually label 250 project descriptions and needs, assigning each passage as reactive or not. Approximately 26% of the initial 250 assignments are reactive. I then use the manual classifications to train an NLP model. In the training process, the program constructs a statistical model to predict the reactive categorization by adjusting a series of weights placed on a set of unobserved factors. The program determines the values of the model weights by splitting the manually labeled data into different groups and verifying the calculated weights can predict the provided classifications. The NLP model has an AUC value of 0.881, indicating that the classification made correct predictions in approximately 88.1% of the evaluation cases in my training sample.

I then use the NLP model on the unlabeled dataset to assign projects as reactive or proactive. At this time, I also exclude extension projects, projects that add new customers to the water system.[27] Approximately 30% of all projects are extensions and are not included in further analysis. I assign projects as reactive based on the model's classification of the text in both the project description and project need. If both of these passages have a reactive probability classification at 25% or below, the project is classified as proactive. If either the project description or project need has a reactive probability classification at 75% or above, the project is classified as reactive. Figure A.1 depicts the histogram of reactive probabilities for project descriptions and needs. The high concentration of probabilities around 0 and 1 indicate there were few cases in which the NLP model had difficulty classifying the text. I hand-label the remaining projects where the model provides unclear reactive

[27] I identify extension projects by nonzero values in the "Total New Households" field included in the project reports. These extension projects are a direct reflection of a 1999 executive order to provide the "best available water and sewer service to every Kentuckian by 2020." As the motivation for these projects is not to maintain existing infrastructure, I exclude them from my analysis.

Table A.1: Project Classification Examples

Project	Project Text	Classification
WX21103050 ($102,670.20)	"The city needs to replace sections of old cast iron (ci) and asbestos cement (AC) water line; as well as, inoperable gate valves throughout its water system. A majority of the water system is 60-80 years old ci and is corroded and constricts flows. The AC line breaks easily and causes undue concern to the citizens due to the asbestos content in the pipe."	Reactive
WX21135016 ($119,513.26)	"Utilities were damaged due to flooding. Repairs are necessary to maintain service."	Reactive
WX21125552 ($8,673,494.55)	"The project will construct additional filters, controls filter building, drying beds, polymer feed equipment and associated piping and appurtenances to upgrade the plant operation to 3.0 MGD."	Proactive
WX21173050 ($49,357)	"The project will increase water pressure, improve customer service, water quality, and water delivery."	Proactive

Notes: Project costs are adjusted to real 2012 dollars. Classification for project WX21135016 is manually assigned, all others assigned by the NLP model.

assignments. After removing extensions and projects with missing data, 2,169 projects remain. The remaining project population is about 30% reactive, which is slightly larger than the fraction in the original hand-labeled set.

B Estimation Details

B.1 Estimation Procedure

The algorithm below outlines the numerical procedure used to evaluate the recursive likelihood function described in Section 6.1. The algorithm integrates over the unobserved quality state via backward induction, combining successive interpolations and approximations to recover each system's likelihood contribution. Inputs are observed investment, NLP-classified project type, violations, and project size; the output is the estimated likelihood contribution conditional on parameters.

To estimate the model, I discretize q into 2,000 equally spaced bins covering the interval $(0, 2000)$. Conditional choice probabilities at off-grid quality levels are evaluated using linear interpolation. All integrations are performed using Gauss–Legendre quadrature with 15 nodes. The panel of 2007–2019 outcomes is augmented with 2006 outcomes to help identify the pre-regulatory parameters. During the simulation stage, parameter draws that imply a steady-state quality of zero are discarded, since no system in the data experienced a complete failure in 2006.

Algorithm 1 Estimation Procedure

1: Initialize a guess for the parameters $(\boldsymbol{\theta}, \boldsymbol{\theta}_{ss})$

2: Simulate a long horizon (e.g., 1000 years) using $\boldsymbol{\theta}_{ss}$ to recover the steady-state distribution of latent quality:

$$q \sim p_q(\cdot\,; \boldsymbol{\theta}_{ss}) = \mathcal{N}\left(\mu(\boldsymbol{\theta}_{ss}), \sigma(\boldsymbol{\theta}_{ss})\right)$$

3: Construct the recursive likelihood over $t = 1, \ldots, T$:

$$\begin{aligned} L^{RLI}(\boldsymbol{\theta}) = \int \cdots \int \prod_{t=1}^{T} \Big[& p_{i|q}(i_t \mid q_t; \boldsymbol{\theta})\, p_{\tilde{y}_r|q}(\tilde{y}_{rt} \mid q_t, i_t; \boldsymbol{\theta})\, p_{y_v|q}(y_{vt} \mid q_t; \boldsymbol{\theta}) \\ & \times p_{k|q}(k_t \mid q_t, \tilde{y}_{rt}, y_{vt}, i_t; \boldsymbol{\theta})\, p_q(q_t \mid i_{t-1}, k_{t-1}, q_{t-1}; \boldsymbol{\theta}) \Big] \\ & \times p_q(q_0; \boldsymbol{\theta}_{ss})\; dq_T \cdots dq_0 \end{aligned}$$

4: Compute the auxiliary likelihood contribution from 2006:

$$\begin{aligned} L^{2006}(\boldsymbol{\theta}_{ss}) = \int & p_{i|q}(i_{2006} \mid q; \boldsymbol{\theta})\, p_{\tilde{y}_r|q}(\tilde{y}_{r,2006} \mid q, i_{2006}; \boldsymbol{\theta})\, p_{y_v|q}(y_{v,2006} \mid q; \boldsymbol{\theta}) \\ & \times p_q(q; \boldsymbol{\theta}_{ss})\, dq \end{aligned}$$

5: Combine likelihood contributions across all systems $w = 1, \ldots, W$:

$$\max_{(\boldsymbol{\theta}, \boldsymbol{\theta}_{ss})} \sum_{w=1}^{W} \left[\log L_w^{RLI}(\boldsymbol{\theta}) + \log L_w^{2006}(\boldsymbol{\theta}_{ss})\right]$$

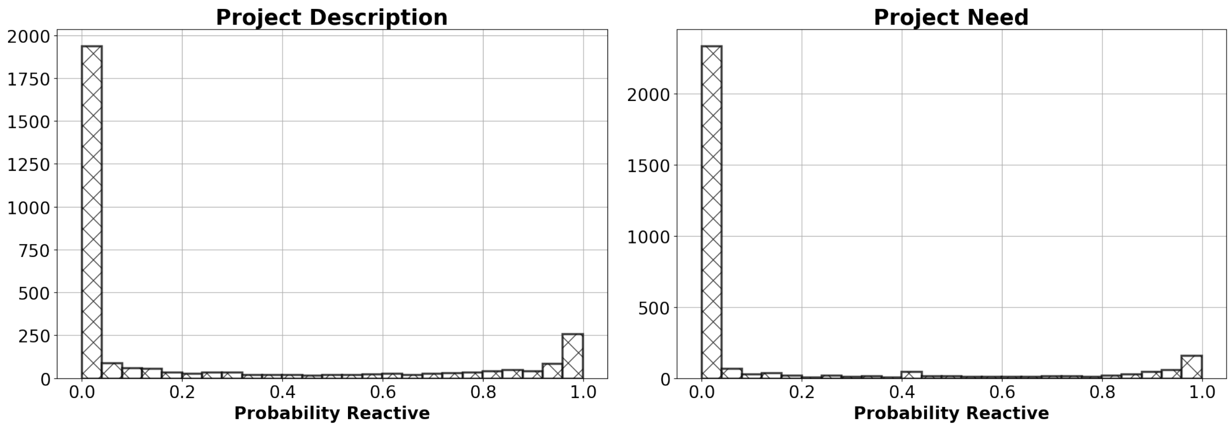


Figure A.1: Histograms of Reactive Probabilities Predicted by NLP Model
Notes: Data are from WRIS and collected via web scraping. Reactive probabilities are assigned using the NLP model.

B.2 Recursive Likelihood Algorithm Details

The recursive likelihood function for an individual water system can be expressed as:

$$L^{RLI}(\boldsymbol{\theta}) = \int \cdots \int p_q(q_0; \boldsymbol{\theta}) \, P_{i\tilde{y}_r y_v k q} \left(\{i_t, \tilde{y}_{rt}, y_{vt}, k_t, q_t\}_{t=1}^{T} \mid \{i_0, \tilde{y}_{r0}, y_{v0}, k_0, q_0\}; \boldsymbol{\theta} \right) dq_0 \cdots dq_T \tag{B.1}$$

All transitions from t to $t+1$ are independent, except for the evolution of infrastructure quality, q_t, which follows equation (1) as described in Section 4. For simplicity, I suppress the explicit dependency on parameters $\boldsymbol{\theta}$ in the notation below.

The joint probability can be rewritten as follows:

$$P_{i\tilde{y}_r y_v k q} \left(\{i_t, \tilde{y}_{rt}, y_{vt}, k_t, q_t\}_{t=1}^{T} \right) = \prod_{t=1}^{T} p_{i\tilde{y}_r y_v k q}(i_t, \tilde{y}_{rt}, y_{vt}, k_t, q_t \mid i_{t-1}, k_{t-1}, q_{t-1}) \tag{B.2}$$

Note that $p_k(k_t)$ is pre-estimated (see Section 5.2) and omitted from future expressions of the likelihood.

Incorporating model assumptions and applying Fubini's Theorem, the likelihood becomes:

$$\begin{aligned} L^{RLI} = \int \cdots \int \prod_{t=1}^{T} \Big(& p_{i|q}(i_t \mid q_t) \, p_{\tilde{y}_r|q}(\tilde{y}_{rt} \mid q_t, i_t) \, p_{y_v|q}(y_{vt} \mid q_t) \, p_q(q_t \mid i_{t-1}, k_{t-1}, q_{t-1}) \Big) \\ & \times p_{i|q}(i_0 \mid q_0) \, p_{\tilde{y}_r|q}(\tilde{y}_{r0} \mid q_0, i_0) \, p_{y_v|q}(y_{v0} \mid q_0) \, p_q(q_0) \, dq_T \cdots dq_0 \end{aligned} \tag{B.3}$$

The likelihood function can then be rearranged as:

$$
\begin{aligned}
L^{RLI} = \int \cdots \int \Bigg[\int & p_{i|q}(i_T \mid q_T)\, p_{\tilde{y}_r|q}(\tilde{y}_{rT} \mid q_T, i_T)\, p_{y_v|q}(y_{vT} \mid q_T)\, p_q(q_T \mid i_{T-1}, k_{T-1}, q_{T-1})\, dq_T \Bigg] \\
& \times \prod_{t=1}^{T-1} \Big(p_{i|q}(i_t \mid q_t)\, p_{\tilde{y}_r|q}(\tilde{y}_{rt} \mid q_t, i_t)\, p_{y_v|q}(y_{vt} \mid q_t)\, p_q(q_t \mid i_{t-1}, k_{t-1}, q_{t-1}) \Big) \\
& \times p_{i|q}(i_0 \mid q_0)\, p_{\tilde{y}_r|q}(\tilde{y}_{r0} \mid q_0, i_0)\, p_{y_v|q}(y_{v0} \mid q_0)\, p_q(q_0)\, dq_{T-1} \cdots dq_0
\end{aligned}
\tag{B.4}
$$

Define the following at time $t = T$, where $\tilde{q}_t$ is a latent random variable representing the unobserved quality:

$$
\begin{aligned}
& E\Big[p_{i|q}(i_T \mid \tilde{q}_T)\, p_{\tilde{y}_r|q}(\tilde{y}_{rT} \mid \tilde{q}_T, i_T)\, p_{y_v|q}(y_{vT} \mid \tilde{q}_T) \mid i_{T-1}, k_{T-1}, q_{T-1} \Big] = \\
& \int p_{i|q}(i_T \mid q_T)\, p_{\tilde{y}_r|q}(\tilde{y}_{rT} \mid q_T, i_T)\, p_{y_v|q}(y_{vT} \mid q_T)\, p_q(q_T \mid i_{T-1}, k_{T-1}, q_{T-1})\, dq_T
\end{aligned}
\tag{B.5}
$$

and recursively, at time $t = T-1$:

$$
\begin{aligned}
& E\Big[\prod_{t=T-1}^{T} p_{i|q}(i_t \mid \tilde{q}_t)\, p_{\tilde{y}_r|q}(\tilde{y}_{rt} \mid \tilde{q}_t, i_t)\, p_{y_v|q}(y_{vt} \mid \tilde{q}_t) \mid i_{T-2}, k_{T-2}, q_{T-2} \Big] = \\
& \int E\Big[p_{i|q}(i_T \mid \tilde{q}_T)\, p_{\tilde{y}_r|q}(\tilde{y}_{rT} \mid \tilde{q}_T, i_T)\, p_{y_v|q}(y_{vT} \mid \tilde{q}_T) \mid i_{T-1}, k_{T-1}, q_{T-1} \Big] \\
& \times p_{i|q}(i_{T-1} \mid q_{T-1})\, p_{\tilde{y}_r|q}(\tilde{y}_{r,T-1} \mid q_{T-1}, i_{T-1})\, p_{y_v|q}(y_{v,T-1} \mid q_{T-1})\, p_q(q_{T-1} \mid i_{T-2}, k_{T-2}, q_{T-2})\, dq_{T-1}
\end{aligned}
\tag{B.6}
$$

Proceeding backward from $t = T$, the full likelihood can be expressed as:

$$
\begin{aligned}
L^{RLI} = \int E\left[\prod_{t=1}^{T} p_{i|q}(i_t \mid \tilde{q}_t)\, p_{\tilde{y}_r|q}(\tilde{y}_{rt} \mid \tilde{q}_t, i_t)\, p_{y_v|q}(y_{vt} \mid \tilde{q}_t) \middle| q_0 \right] \\
\times p_{i|q}(i_0 \mid q_0)\, p_{\tilde{y}_r|q}(\tilde{y}_{r0} \mid q_0, i_0)\, p_{y_v|q}(y_{v0} \mid q_0)\, p_q(q_0)\, dq_0
\end{aligned}
\tag{B.7}
$$

C Additional Analysis

Results in Table C.1 report the first-stage probit regression of a project indicator on lagged violation months, system size categories, the ARRA indicator, and ADD indicators. This exercise indicates that the ARRA indicator is a relevant instrument for the investment decision. In addition, the ADD indicators are jointly significant (Wald test, $p < 0.0001$), confirming that they also provide

Table C.1: Infrastructure Project Decisions

	Project Indicator
Medium	0.242
	(0.050)
Large	0.366
	(0.057)
NSRL 1	0.057
	(0.064)
NSRL 2	0.023
	(0.055)
Lag Violation Months	0.003
	(0.011)
ARRA	0.497
	(0.072)
Constant	−0.928
	(0.078)
Pseudo R^2	0.046
Observations	4,589

Notes: Probit regression of a project decision with heteroskedasticity-robust standard errors. Additional controls include ADD indicators.

relevant variation for instrumenting project decisions. These results offer descriptive evidence on instrument relevance for the analysis in Section 5.2.

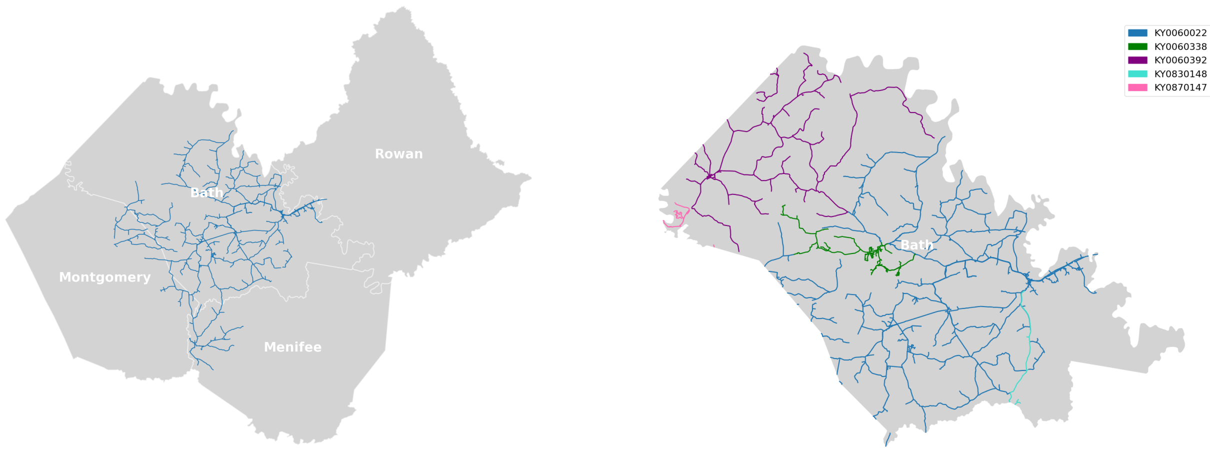
Table C.2 reports parameter estimates from the dynamic model under alternative assumptions about the prior-period AR(1) coefficient governing the evolution of latent quality. The baseline specification sets this parameter at 0.995, while the robustness checks consider lower and higher values. Across these specifications, the main dynamic parameters, violation and investment weights, and initial quality distributions remain stable. The similarity of estimates indicates that the results presented in Tables 5 and 6 are robust to alternative AR(1) processes and that the substantive implications of the analysis do not materially change.

D Additional Figures

This section presents supplementary figures that offer visual context for the main analysis, including maps of water system boundaries and the empirical distributions of project expenditures. These figures illustrate the geographic distribution of systems and provide additional perspective on the magnitude of project expenditures.

Table C.2: Robustness of Dynamic Model Parameter Estimates to Alternative AR(1) Values

Parameter		Baseline	Lower AR(1)	Higher AR(1)
Panel A. Dynamic Parameters				
Decline Consequences				
Slope of Violation Probability	δ^v	127.7	99.83	132.8
Slope of Reactive Probability	δ^r	445.9	501.9	511.5
Rate of Quality Decline	α^q	0.930	0.927	0.931
Violation Weights				
High-Income Consumers	$\lambda_0^{\mathcal{VC}}$	3.329	1.407	3.987
Middle-Income Consumers	$\lambda_1^{\mathcal{VC}}$	3.162	2.183	3.926
Low-Income Consumers	$\lambda_2^{\mathcal{VC}}$	5.650	3.384	5.669
Investment Weights				
High-Income Consumers	λ_0^x	0.356	0.228	0.340
Middle-Income Consumers	λ_1^x	0.525	0.391	0.520
Low-Income Consumers	λ_2^x	0.503	0.363	0.486
Panel B. Steady-State Parameters				
Decline Consequences				
Slope of Violation Probability	δ_{ss}^v	66.16	50.08	54.15
Slope of Reactive Probability	δ_{ss}^r	620.8	707.9	622.7
Rate of Quality Decline	α_{ss}^q	0.995	0.99	0.999
Initial Quality Distributions				
High-Income, Small	(μ_{0s}, σ_{0s})	(6.68, 0.32)	(6.37, 0.39)	(6.69, 0.31)
High-Income, Medium	(μ_{0m}, σ_{0m})	(6.84, 0.43)	(6.60, 0.45)	(6.89, 0.40)
High-Income, Large	(μ_{0l}, σ_{0l})	(6.30, 0.57)	(6.25, 0.62)	(6.31, 0.62)
Middle-Income, Small	(μ_{1s}, σ_{1s})	(6.28, 0.37)	(5.89, 0.45)	(6.29, 0.37)
Middle-Income, Medium	(μ_{1m}, σ_{1m})	(6.50, 0.45)	(6.16, 0.51)	(6.50, 0.46)
Middle-Income, Large	(μ_{1l}, σ_{1l})	(6.10, 0.56)	(5.89, 0.57)	(6.04, 0.59)
Low-Income, Small	(μ_{2s}, σ_{2s})	(6.38, 0.37)	(6.02, 0.44)	(6.39, 0.36)
Low-Income, Medium	(μ_{2m}, σ_{2m})	(6.52, 0.46)	(6.21, 0.50)	(6.54, 0.46)
Low-Income, Large	(μ_{2l}, σ_{2l})	(6.12, 0.53)	(5.97, 0.57)	(6.05, 0.58)
Neg. Loglikelihood	ℓ	10,256.8	10,314.9	10,266.5



(a) Counties Served by KY0060022 (b) Bath County Water Systems

Figure D.1: County Community Water System Overlays

Notes: Data are compiled from WRIS geojson files. Frequently water system geographies do not follow county lines. As a result, multiple systems often serve a single county and a system often serves populations across multiple counties.

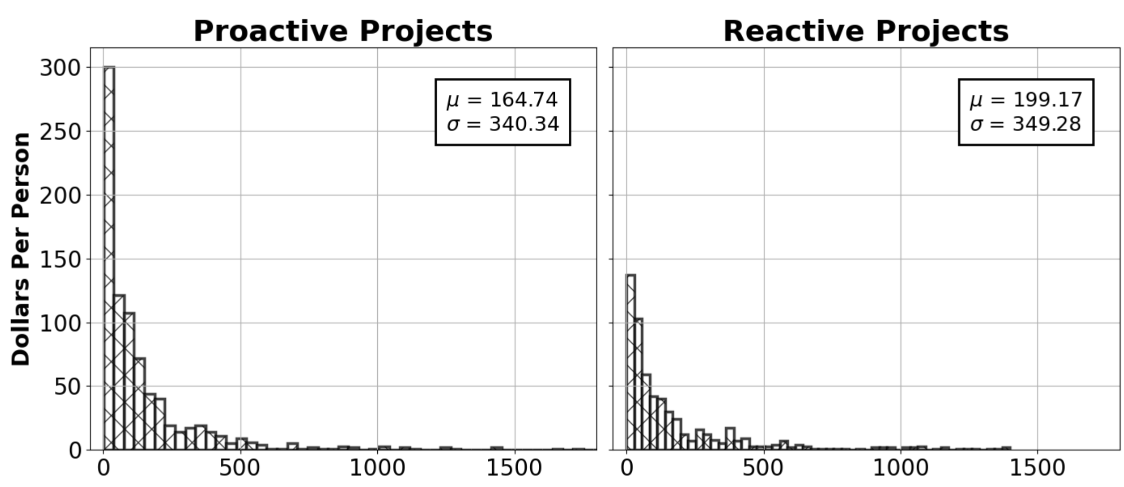


Figure D.2: Histograms of Project Investments

Notes: Data are from WRIS and collected via web scraping. Project costs are adjusted to real 2012 dollars per person. The left panel plots the histogram of proactive projects and the right panel plots reactive projects. The data follow approximately lognormal distributions.