Proactive and Reactive Infrastructure Investment*

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Abstract

Properly functioning infrastructure is maintained through investment. A proactive investment strategy prevents failures but requires expenditures before quality deteriorates. A reactive investment strategy accepts some risk of failure to avoid unnecessary expenditures. I explore proactive and reactive investments in a newly collected dataset on Kentucky water systems to assess the ability of system managers to maintain infrastructure quality. I establish that proactive and reactive investments differentially reduce the probability of a future system failure, and that both managers and consumers are sensitive to system quality. I construct and estimate a dynamic discrete choice model of system manager infrastructure investment decisions incorporating the empirical relationships and investment strategy intuition. Through simulations, I determine that investment is currently too low to successfully prevent the decline of water infrastructure quality. Counterfactual policies that promote only proactive projects lead some systems to make unnecessary investments even as others become vulnerable to extreme quality decline. By contrast, policies that facilitate more effective reactive policies incorporate more equitable levels of risk, reduce overspending, and enable all systems to maintain system quality.

JEL Codes: C61, H54, Q25

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1 Introduction

Infrastructure investments fund projects that maintain the quality of existing systems or, when necessary, construct new ones.[1] However, quality can be difficult to observe and measure, and the pace at which systems deteriorate can be uncertain. When managing the allocation of an infrastructure budget, decision makers choose between proactive and reactive investment. Proactive investment, sometimes referred to as preventative maintenance, is made in advance of infrastructure issues whereas reactive investment is made in response to signs of quality deterioration and often becomes necessary when systems are no longer functioning properly. Although proactive investment can be effective, it is more challenging to anticipate infrastructure issues than to address existing problems and this uncertainty can lead to overinvestment. A substantial literature studies the costs and benefits of infrastructure investment in transportation, but little research has explored the trade-off between proactive and reactive expenditures and the relationship between investment and the ability of a system to function properly.[2]

In this paper, I examine the proactive and reactive infrastructure investment decisions of community water system managers. Community water systems provide drinking water to over 310 million Americans, or about 94% of the population. In 2020, the Environmental Protection Agency (EPA) found that 7% of community water systems reported at least one health-based violation. Each year roughly 19.5 million cases of waterborne illnesses can be attributed to contaminants in drinking water provided by water systems (Reynolds et al., 2008). The American Society of Civil Engineers (ASCE) has scored America's drinking water infrastructure well below average since 1998 and describes it as "aging and underfunded." The ASCE's Infrastructure Report Card highlights increased costs to maintain and operate systems as well as insufficient funding as significant challenges that water systems face:

> "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."

Motivated by these facts, I construct a dynamic optimal stopping problem for water system managers in the spirit of Rust (1987) to study managers' proactive and reactive investment decisions, and whether infrastructure investments are sufficient for systems to provide safe drinking water now and in the future. The model is consistent with a number of empirical relationships that emerge from an analysis of data on infrastructure projects and water quality violations in Kentucky over 2007-2019. I then integrate these empirical relationships into the model and quantify the effectiveness of proactive and reactive projects. I find that proactive projects increase quality more than reactive projects for the same level of expenditure. I also determine that current levels of

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

[2] See Allen and Arkolakis (2022), Aschauer (1989), Brooks and Liscow (2022), Glaeser and Poterba (2021), Gramlich (1994), Jaworski and Kitchens (2019), Kline and Moretti (2013), Mehrotra et al. (2021) for examples of research on infrastructure investment.

investment are insufficient to maintain water quality above health-based standards. Among a set of policy prescriptions that I consider, I find that subsidies for larger proactive projects lead to most systems overinvesting to maintain quality well above required levels, and leaves some systems vulnerable to extreme, unrecoverable emergencies. Subsidies for larger reactive projects result in more widespread occasional violations but eliminate unnecessary expenditures and provide all systems with the ability to recover from an unexpected quality disaster.

The paper proceeds as follows. Section 2 provides background information on United States water quality standards and introduces the data sources. I collect a novel dataset on community water systems and infrastructure projects in the Commonwealth of Kentucky and use these data for my analyses. Kentucky provides an advantageous setting due to the existence of the Water Resource Information System (WRIS), which serves as a comprehensive registry for water systems and infrastructure projects. 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. To track the ability of Kentucky's systems to provide safe drinking water over time, I supplement these data with details on violations issued to systems when their water does not meet federal health-based standards. With the ASCE's assessment in mind, I employ natural language processing techniques to categorize projects as either reactive or not, with non-reactive projects referred to as proactive projects. I consider a project to be reactive if it contains text indicating that the project is necessary for the system to provide safe drinking water e.g., references to public health emergencies, extensive breaks, overstressing, or unsafe conditions. If a project does not meet these criteria, it is classified as proactive.

In Section 3, I develop the four main empirical relationships that motivate the dynamic optimal stopping problem. First, the probability of a health-based violation decreases with more proactive project spending. I interpret this as indicating that proactive investments successfully prevent future violations. Second, the probability of a health-based violation decreases with more reactive project spending, but only for those systems that spent more time in violation during the prior period. I interpret this as an indication that reactive project expenditures are more effective at reducing the probability of a future violation because prior period failures indicate which infrastructure components are most in need of repair. Third, system managers are more likely to pursue reactive projects if the system experienced a health-based water quality violation in the prior period. This implies that managers take action to correct low quality infrastructure issues when they occur. Lastly, consumers are sensitive to receiving water that violates health-based standards. Using Nielsen scanner data on bottled water sales, I confirm that consumers seek alternative clean water sources when faced with contaminated water at home.

Section 4 presents the model developed from these findings. In the model, managers face a cost-minimizing decision: make an investment to improve the underlying quality of their system, or delay infrastructure investment and risk incurring negative consequences. Infrastructure quality decays over time, and the consequences of delaying investment take two forms. First, as infrastructure quality declines, systems are more likely to provide consumers with water that violates health-based standards, and second, system managers are more likely to have to undertake a reactive, as opposed to proactive, project. The only tool system managers have to combat quality decay is to invest in an infrastructure project. To determine the magnitude of manager disutility from providing violating water, I construct a baseline estimate for consumer willingness to pay for clean water based on changes in consumer bottled water consumption during a water quality violation. System managers further weight consumer disutility as consumers' private value of safe drinking water is likely a lower bound on the costs to system managers from prolonged infrastructure neglect.[3]

I discuss the estimation, identification, and results in Section 5. I find the full solution to the model using maximum likelihood to maximize the probability of the observed length of time each system spends in violation every year, the timing of infrastructure investments, and realizations of reactive projects. The main challenge for estimation is that system quality is known to system managers, but unobserved by the econometrician, and depends on the prior year's quality level. To reduce the computational complexity of dynamic discrete choice models, unobserved state variables are often assumed to be independent over time. The intertemporal dependence of quality means that all the possible histories of quality need to be considered in the estimation. This can become computationally intensive for a continuous state variable over 13 years of observations. To overcome the high dimensionality of the quality histories, I employ methods outlined in Reich (2018) to reduce the problem to lower dimensional integrals. I use a combination of fixed-point methods to solve for conditional choice probabilities and recursion methods over the possible quality histories to estimate the model parameters. Due to the unobserved values of quality, some normalizations are required to identify the remaining model parameters. The recursion over quality histories is solved by iterative interpolations and approximations in order to progressively construct the probability of the observed outcomes as driven by unobserved quality.

I demonstrate that the model fits the data well. In simulations, the model matches trends for the number of systems that spend time in violation as well as the number of systems undertaking proactive and reactive projects each year. The model reveals that investments made at system quality levels just above health-based standards are the most effective at reducing the overall time a system spends in violation. I interpret this result as indicating that a strategy of just-in-time investment is optimal for systems. I find that system managers weight consumer disutility at ten times higher than the estimated consumer willingness to pay for safe drinking water, corroborating that willingness to pay estimates serve as a lower bound on true valuations for safe drinking water and that system managers internalize the proper valuation.[4] Despite system managers placing a high weight on consumer disutility, I find that systems are on a path to increasingly violating

[3] This weight can also be thought of as a proxy for the "citizen's voice" phenomenon discussed in Brooks and Liscow (2022), who attribute growing infrastructure costs to increased public influence in government decision making.

[4] Wu and Huang (2001) provide empirical evidence for the prior theoretical results of Bartik (1988) and Courant and Porter (1981) that averting expenditures serve as a lower bound on the mean willingness to pay for a desired environmental improvement.

health-based standards because projects are minimally effective at counteracting system decay. I determine the maximum effect of an average investment reduces the expected amount of time spent in violation by just over one quarter. This effect is too low to warrant constant investment and is insufficient to offset systems' quality decline.

Section 6 explores counterfactual policies. First, I assess the efficacy of possible policy interventions to increase the number of projects at the current levels of infrastructure investment. I start by implementing a multiplicative penalty to water systems for any time spent in violation. I find that even the highest penalties only decrease the average expected amount of time each system spends in violation over 2007-2057 by roughly 17 quarters. I also simulate a government subsidy that eliminates infrastructure investment costs incurred by the system. Even for fully subsidized proactive and reactive projects, the average expected amount of time each system spends in violation over 2007-2057 is reduced by just over five and nine quarters respectively. These simulations reveal that additional penalties and subsidies can entice systems to invest more frequently in infrastructure projects, but the effects are limited. The relatively small average project size places an upper bound on the benefit of additional project investment, which is too low to prevent infrastructure decay.

To address the low effectiveness of infrastructure projects at preventing system decline, I run simulations in which I increase the size of investments, which is the same as relaxing the system manager's budget constraint. On its own, increased investment size leads to fewer projects. Although the effect on quality is higher, the increase in project effectiveness is not offset by the increased project cost in the system manager's cost-minimization calculation. In order to obtain different long run outcomes, I simulate scenarios that combine increased project size with project subsides. Policies targeting proactive investment and policies targeting reactive investment are both effective at reducing the average expected time in violation. When comparing the effects for individual systems, it becomes clear that these two policies result in different distributional outcomes. Proactive policies incentivize many system managers to invest at rates that lead to sustained infrastructure quality substantially above required levels – most system managers overinvest. In addition, due to the continued low effectiveness of reactive projects, systems are unable to recover from large negative shocks to quality. This results in some systems entering into inescapable long run states of violation. Counterfactual policies that fully subsidize larger reactive projects enable managers to undertake projects at their maximum effectiveness and eliminate overspending but result in systems incurring a higher risk of occasional health-based violations. Under a policy of large reactive projects, if any system's quality falls below required levels, managers are able to restore their infrastructure through effective investment. This prevents the unequal long run outcomes that can occur under a proactive only subsidy program.

I conclude in Section 7 by tying the results of my analysis to current policy discussions and providing suggestions for future research. In 2021, Congress passed the Infrastructure Investment and Jobs Act, which includes $550 billion for infrastructure. My analysis indicates that policies targeting investment types can be effective but distribute risks differently. This risk distribution leads to different outcomes for systems and should be considered when constructing programs to incentivize investment. My results are specific to water infrastructure in Kentucky, but I present a model that is both applicable to other infrastructure investment settings and provides the tools to assess alternative policy applications. The Appendix contains additional analysis and details on the data.

1.1 Literature Review

I contribute to a literature examining the decisions of system managers. In water specifically, Timmins (2002) and Sears et al. (2022) examine the decisions of managers of water systems with underground aquifers to price water below marginal cost. Both use dynamic structural models of decision making but focus on the pricing decisions rather than system managers' long term infrastructure investments. In my model system managers are motivated to undertake infrastructure projects to prevent, or reduce the likelihood, of a water quality violation. Other papers study water systems' aversion to receiving an EPA Safe Drinking Water Act violation. Bennear and Olmstead (2008) find that the number of violations decreases in systems that are required by a change in federal law to mail violation notifications to consumers. Grooms (2016) shows that receiving a violation leads to a reduction in levels of the violating contaminant and concludes that public disclosure may deter systems from violating. Bennear et al. (2009) demonstrate that some system managers even strategically alter their testing behavior to prevent triggering a water quality violation. I capture violation aversion in my structural model through a weighted consumer disutility term that varies as the expected time in violation changes.

Additionally, my paper relates to a literature studying the connection between infrastructure investment and public health outcomes. Safe drinking water has not always been readily available in the United States. Considerable investment has occurred in order to construct preliminary versions of the systems which are still in place today. Beach (2022) examines the drop in instances of waterborne disease outbreaks from 1900-1930 and provides evidence that the benefits of infrastructure investment outweighed the costs. Cutler and Miller (2005) and Alsan and Goldin (2019) investigate the drop in mortality rates during the same time period, which they attribute to the construction of water and sewer systems and the implementation of clean drinking water technologies. I build on this literature by connecting modern infrastructure investments to compliance with federal water quality standards.

I also add to an operations research literature that studies the optimal timing for repair or replacement of deteriorating systems. Jardine et al. (2006) provides an extensive review of the "condition-based" maintenance literature, which advocates for replacement of system components based on assessments of their condition, as opposed to a regular maintenance schedule. Many operations papers assess methods for determining the appropriate timing of infrastructure repairs and discuss best practices for monitoring systems in order to detect signs of decline (Keizer et al., 2017; Kim and Makis, 2013; Si et al., 2011; Kurt and Kharoufeh, 2010). In my analysis, I assume that system managers are already optimally monitoring their system's infrastructure and use the language of system managers to infer investment behavior. I demonstrate that there are two distinct types of investments, which I call proactive and reactive, and that pointed policy interventions incorporating these distinctions can lead to unexpected outcomes for consumers.

Finally, the policy analysis in this paper is connected to a growing structural environmental economics literature investigating environmental regulation. Blundell et al. (2020) study the dynamic effect of violator status used by the EPA to enforce air pollution standards. They find that the increased fines associated with high priority violator status, and the dynamic nature of this status, are effective at reducing air pollution. Kang and Silveira (2021) employ a structural model to quantify the advantages of regulator discretion in applying penalties to wastewater treatment plants that violate water pollution standards. I add to this literature by exploring the relative benefits of penalties and incentives to systems providing drinking water, and the ability of these incentives to induce infrastructure investment in order to obtain compliant water quality levels.

2 Data and Background

2.1 Community Drinking Water Systems

A community drinking water system serves an average of at least 25 customers for the duration of the calendar year. Systems source their water from one of three options: surface water (e.g., lakes or reservoirs), ground water (e.g., aquifers), or recycled water (e.g., highly treated wastewater). After pumping in water from these sources, systems further filter this water until it is considered safe for human consumption. A water system's infrastructure consists of all the components involved in the movement and treatment of water from the time water enters the system until the point where it reaches the final service connection, e.g., a house or apartment building. The types of structures that typically make up a water system include: pumps to actively move water, pipes for distribution, filtration systems to process water, meters and sensors for measuring contaminants, and tanks for long term storage. Infrastructure maintenance is the responsibility of the system manager and generally entails the replacement or repair of the above structures. For the duration of the paper, I focus on the unobserved quality of the infrastructure comprising a water system. I examine the decisions of system managers to invest in infrastructure projects to improve infrastructure quality, and how these investments relate to the system's ability to provide safe drinking water to consumers.

2.2 United States Water Quality

In 1974, Congress passed the Safe Drinking Water Act to prevent threats to public health by setting standards for acceptable drinking water. The EPA currently sets maximum acceptable levels for 94 different contaminants, which include both chemical and microbial pollutants. EPA regulations dictate that if a system provides water exceeding the maximum allowable concentration of a contaminant, fails a testing requirement, or provides water posing a health risk, then the public water system must notify its customers. Customer notifications fall into three levels based on the severity of the infraction (Environmental Protection Agency, 2009). Tier 1 notifications involve violations that pose the most severe health risks and require notification within 24 hours of discovery. Tier 2 public notification violations are for contaminants that pose a less imminent public health risk and notification is required within 30 days of detection. Tier 3 public notification violations mostly encompass monitoring and reporting violations and customers are often informed about these through an annual report.[5] Because of the lower severity of these violations, I exclude them from my analysis.

2.3 Data Sources

I collect and aggregate data from multiple sources. Below I provide details on these data sources and the methods I employ for cleaning and compiling the data for use. All prices and costs are adjusted to real 2012 dollars using the GDP deflator.

2.3.1 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 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. There are two primary WRIS reports that provide the richest data: the system and project reports. I source additional information regarding projects and the project approval process from historical Intended Use Plans (IUPs) and Kentucky Infrastructure Authority's Annual Reports, which I obtained through Freedom of Information Act requests to Kentucky's Department of Local Government.

Community Water System Reports

For my analysis, I consider publicly owned community water systems that are active as of 2021.[6] I source information on Kentucky's community water systems from WRIS system reports. These reports contain a county-level breakdown of the population served by the public water system, the date the system was established, the number of employees, the type of water source used, e.g., source water or purchased water, ground water, or surface water etc., and the exact geographical location of the public water system. More than 95% of all Kentuckians receive water from public water systems. Figure 1 provides the layout of all pipes comprising Kentucky's public water systems, and Figure 2 shows examples of the geographic layout of public water systems.

System reports also contain the median household income for each county population subset

[5] Findings in the Environmental Protection Agency (2008) report "2006 Data reliability analysis of the EPA safe drinking water information system/federal version", indicate that only 30% of these types of violations are reported to the federal Safe Drinking Water Information System.

[6] I extracted data from WRIS in July 2021. Of the 377 systems with some data at the time of extraction, 361 systems are publicly owned community water systems. This number shrinks to 353 systems when removing those with missing demographic data, e.g., serviceable population, etc.

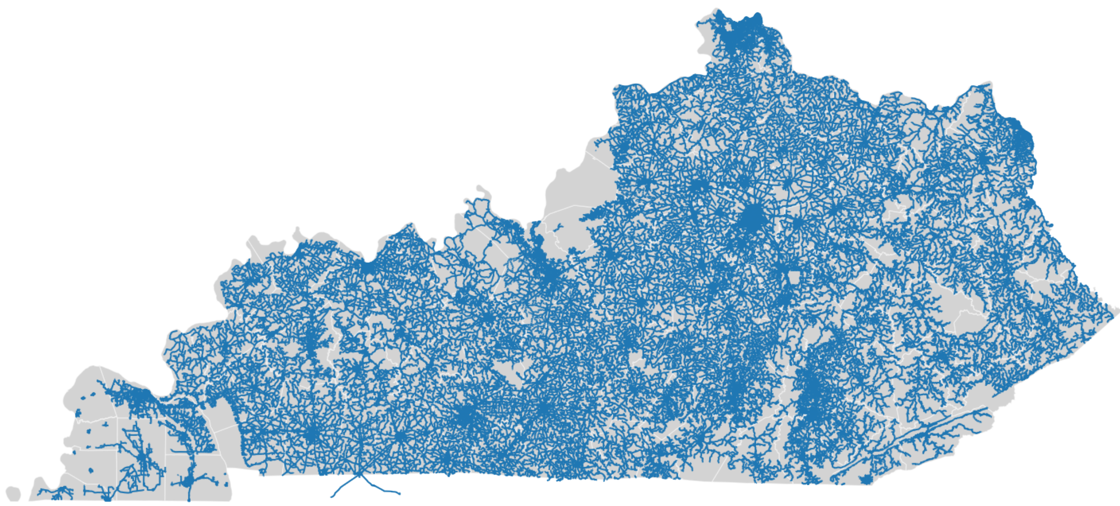
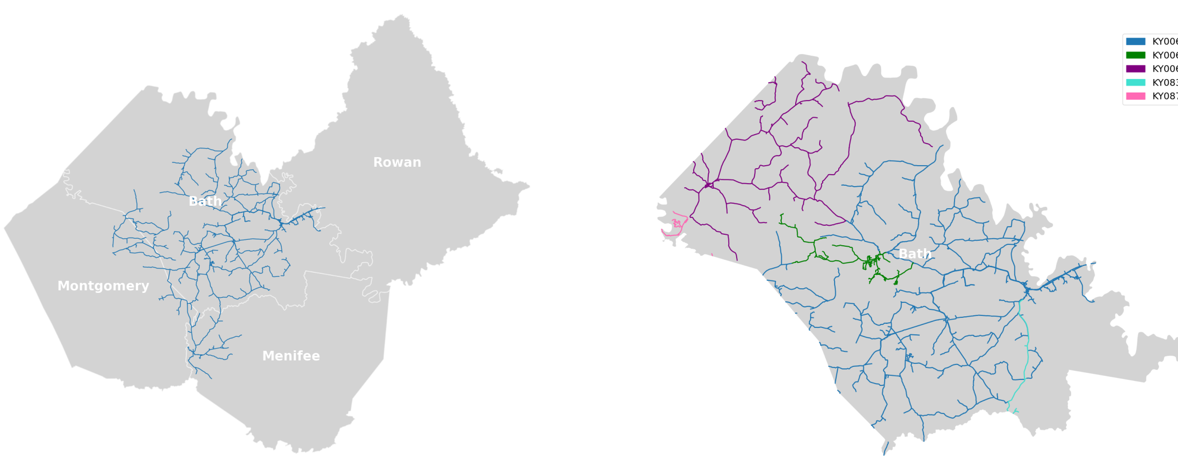


Figure 1: Map of Water Lines Comprising Kentucky's Public Water Systems

Notes: Data compiled from geojson files obtained from the geographic information system (GIS) portion of WRIS, collected in July 2021. Water lines for Louisville Water Company, covering approximately 800,000 people in Louisville, are unavailable.



(a) Counties Served by KY0060022

(b) Bath County Water Systems

Figure 2: 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.

Table 1: Kentucky Community Water System Statistics

Characteristic	System Count	Mean	St. Deviation	Min	Max
Operational					
Employees	353	12.805	29.215	0	437
Purchaser	185	0.524	0.499	0	1
Surface Water Source	290	0.822	0.383	0	1
Very Small (<500)	12	0.034	0.181	0	1
Small (501 - 3,300)	117	0.331	0.471	0	1
Medium (3,301-10,000)	131	0.371	0.483	0	1
Large (>10,000)	93	0.263	0.441	0	1
NSRL = 0	87	0.247	0.431	0	1
NSRL = 1	102	0.289	0.453	0	1
NSRL = 2	164	0.465	0.499	0	1
Demographic					
Non-white Population	353	0.068	0.048	0.002	0.288
ln(Housing Density)	353	3.509	0.632	2.275	6.728
ln(Med. HH Income)	353	10.575	0.243	10.013	11.395

Notes: Operational statistics are constructed using data drawn from WRIS as of May 2021. Population categories are based on data from the Safe Drinking Water Information System, and the demographic statistics are compiled using the county breakdown percentages from WRIS in conjunction with 2019 county-level data from the ACS.

served by the system. Relative median household income data is typically calculated using American Community Survey (ACS) data integrated into WRIS. Median household income dictates how Kentucky assigns financial assistance to specific areas through programs such as the Drinking Water State Revolving Fund (DWSRF). Kentucky groups systems and projects into three levels, called Non-Standard Rate Levels (NSRL), which are tied to the Kentucky-wide median household income. These classifications are defined as follows:

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

Table 1 summarizes the WRIS system data. Roughly 82% of systems source their water from surface water sources, which generally require more treatment than ground water sources due to sediment and pollutant exposure. Most systems provide drinking water to households that fall below Kentucky's median household income (75% of systems have an NSRL categorization of 1 or 2), and approximately 35% of all systems serve populations of less than 3,300.

Infrastructure Project Reports

Investment in water system infrastructure can take many forms, including leaking pipe repairs, installation of newer water meters, and water tank replacements. To initiate an infrastructure project, community water systems must complete a project profile within WRIS outlining the purpose of the project, the expected cost of the project, who is responsible for oversight, the expected timing of the project, and the anticipated funding sources. These project plans are then reviewed and approved by 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. Most project profiles contain complete information and WRIS is used as a "registry" for Kentucky's water infrastructure projects. Information on projects date to the beginning of WRIS in 2001. Project profiles are also required by Kentucky in order for a project to be eligible to receive financial support from the Drinking Water State Revolving Fund, and many other financial support programs have also adopted this requirement.[7]

2.3.2 Project Classification

Prior to the analysis of the relationship between infrastructure projects and violations, I classify projects as *reactive* or not reactive. 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 such as pipe deterioration, extensive breaks, or over-stressing, are all considered to be reactive. See Table 2 for examples of project excerpts and their classifications.

I employ natural language processing (NLP) tools in order 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 not reactive. At this time, I also exclude extension projects, projects that add new customers to the water system, from inclusion in further analysis.[8] I identify extension projects by nonzero values in the "Total

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

[8] In 1999, Governor Patton issued an executive order to provide the "best available water and sewer service to every Kentuckian by 2020." As part of this initiative, Kentucky increased the percent of the population serviceable by public water systems to 95% through projects which extend public water systems to replace, for example, rural wells across the

Table 2: 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."	Not Reactive
WX21173050 ($49,357)	"The project will increase water pressure, improve customer service, water quality, and water delivery."	Not Reactive

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

New Households" field included in the project reports. Figure 3 depicts the histogram of assigned reactive probabilities for project descriptions and project needs. There is a clear divergence in the probabilities assigned to the non-training set, indicating that there are few cases where text classification is ambiguous, and lending further credibility to the model.

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. I hand label the remaining projects that have unclear reactive assignments based on the model classification. Table 3 contains a breakdown of the final project classifications across the entire sample of project reports. Approximately 30% of all projects are extensions and are not included in further analysis. The population of remaining projects is about 30% reactive, which is slightly larger than the fraction in the original hand labeled set.

2.3.3 Water Quality Violations

Water systems are required to test regularly in order to monitor for EPA regulated contaminants and to report the results of these tests to the EPA's nationwide database, the Safe Drinking Water Information System (SDWIS). This database includes details on each violation, including the date the violation was first detected, the current status, the triggering event, and the public notification

Commonwealth. I exclude these projects from my analysis.

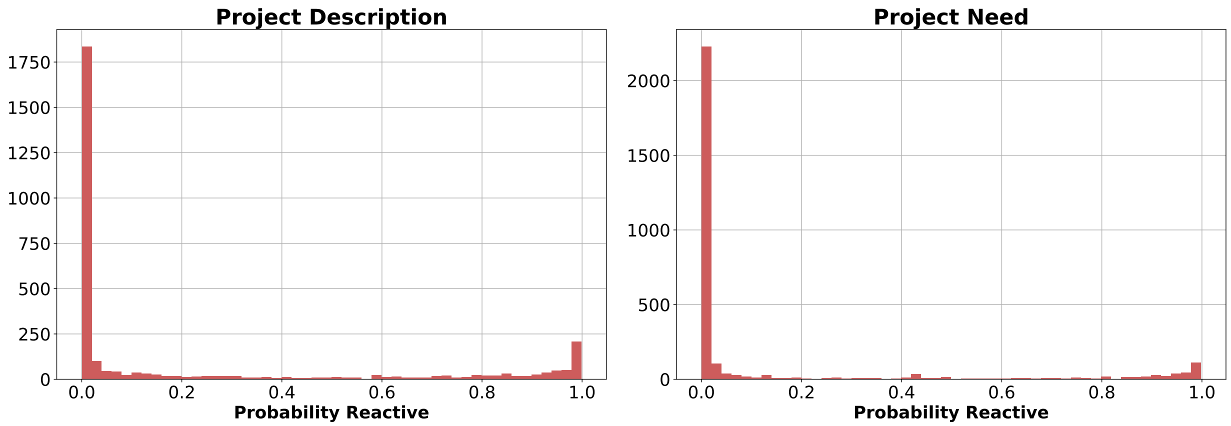


Figure 3: Histogram of Reactive Probabilities Predicted by NLP Model
Notes: Data are from WRIS and collected via web scraping. The high concentration of probabilities around 0 and 1 indicate there were few cases in which the NLP model had difficulty classifying the text.

Table 3: Project Classification Breakdown

	Project Count
Reactive Projects	683
Not Reactive Projects	1,486
Extension Projects	859
Total Projects	3,028

Notes: Data omits 34 withdrawn projects, 97 projects with a missing approval date, and 10 projects with missing costs.

tier. I collect SDWIS violation data over 2006-2019 using the EPA's API.[9]

I restrict my observation period based on the timing of EPA changes to the National Drinking Water Contaminant List and observed water system responses. In 2000, the EPA introduced one new contaminant to the list, and two public water systems experienced compliance issues between 2000-2003. From 2004-2006, there were no water systems in Kentucky with health-based violations but following the introduction of three new contaminants in 2006, many systems began to experience health-based violations. Approximately 70% of water systems in my data have at least one health-based violation from 2007-2019. I exploit the change in monitored contaminants to estimate the relationship between infrastructure investment behavior and violations that would otherwise be unidentifiable in a period of complete compliance.

2.3.4 Additional Data Sources

I use the Nielsen Corporation's Retail Scanner Data (2006-2019), made available to me through the Kilts Center at the University of Chicago, to estimate consumer responses to water quality

[9]The SDWIS data can be accessed using the EPA's Enforcement and Compliance History Online. The analysis in this paper uses data last accessed in July 2021.

violations. The scanner dataset contains weekly sales data including pricing and volume for UPCs covering an extensive list of product categories and information from 30,000-50,000 stores across 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. This leaves observations at 937 stores within Kentucky, covering 112 of the 120 Kentucky counties for at least some part of 2006-2019. There are 352 consolidated brands of bottled water providers in the remaining dataset, including the "control brand," which is a label Nielsen uses to protect an identifiable private label at a specific store (e.g., store-brand bottled water labels). Most frequently, the largest share of bottled water sales in a given week are of the control brand and the average yearly revenue shares for the control brand are 38.9%.

I also 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. Temperature and precipitation data come from the National Oceanic and Atmospheric Administration. I use daily weather station readings from 2006-2019 for stations in and around Kentucky. I construct data for the average maximum temperature, average minimum temperature, and average total precipitation for each county on a weekly basis using the coordinates of the stations to map each county to the closest weather reading.

3 Motivating Results

I present here the findings from my initial descriptive regressions. The results demonstrate that proactive and reactive infrastructure expenditures successfully reduce the probability of a health-based water quality violation, but act in different ways. I confirm that both system managers and consumers are sensitive to health-based violations: system managers undertake reactive projects and consumers act by increasing bottled water consumption. The behavior of system managers further cements that reactive projects are generally undertaken when infrastructure quality is low. I incorporate these findings into the dynamic discrete choice model presented in Section 4.

3.1 Investment reduces the probability of a water quality violation

I use probit regressions to examine the relationship between infrastructure expenditure and the probability of a water quality violation. I construct a health-based violation indicator that equals one for either a Tier 1 or Tier 2 violation and use data on the violation outcomes and infrastructure expenditures of 353 community water systems in Kentucky from 2007-2019.

The novel variable included in the model is the adjusted infrastructure investment calculated from project expenditures approved in the preceding five years.[10] This variable approximates the amount each system has invested in infrastructure improvements. I use this metric because there is

[10] For my analysis, I use the project approval year as the basis for adjustment.

often a delay between the timing of a project's approval and the project's construction and installation. I run two regressions to examine the effect of a project on the probability of a health-based violation. In the first regression, I examine the effect of total project investment, regardless of project classification, and in the second regression I examine the separate effects of proactive and reactive project investments.

I control for a series of system attributes known to influence the probability of a water quality violation. In keeping with the literature, I include the fraction of the previous year spent in violation, indicators for the size of the population served by the system, indicators for water source, and finally the number of employees working at each system.[11] I also use ACS data in combination with the WRIS breakdown of consumers in each county to construct weighted median household income, housing density, and the fraction of the population that is non-white for each year-system observation. Lastly, I include year fixed effects to control for a variety of possible yearly shocks, including a few natural disasters that damaged water systems during this time period.

Table 4 presents the results. The primary variables of interest are the cumulative project expenditures approved by utilities in the previous five years, and the interaction between this term and the fraction of the previous year spent in violation. Column (1) depicts the effect of any project investment. For any investment, systems with more time spent in violation in the prior year and larger project expenditures are less likely to experience a health-based violation in the current period. However, looking at proactive and reactive projects separately, it becomes clear that the two types of projects influence the probability of a health-based violation differently.

Column (2) splits investments into proactive and reactive projects. Wald tests confirm a significant difference between the effects of proactive and reactive projects on their own and when interacted with time spent in violation in the prior period.[12] Systems that approve more money for proactive projects are less likely to experience a health-based violation. This effect is unchanged for systems based on the amount of time spent in violation in the previous year. However, the effect of a reactive project is dependent on the amount of time spent in violation. On their own, reactive projects do not decrease the likelihood of a violation. Only those systems that spent more of the prior year in violation and invested in reactive projects are less likely to have a health-based violation. I conclude that reactive projects are more effective at reducing the probability of a future violation because failures indicate to system managers which areas need the most attention. These regressions also support the initial classification of projects into distinct groupings as the two types of projects reduce the likelihood of a violation in different ways.

[11] Allaire et al. (2018) find evidence that across the United States these variables are strong predictors for a water quality violation.

[12] The result of these two tests are $W(1) = 12.61, p < .001$ and $W(1) = 5.83, p < .05$ respectively.

Table 4: Health-Based Violation Probability

	(1)	(2)
Any Investment ($M in last 5 years)	-0.001 (0.003)	—
Any Invest x Lag Viol Frac	-0.031 (0.014)	—
Proactive Investment ($M in last 5 years)	—	-0.016 (0.005)
Proactive Invest x Lag Viol Frac	—	0.035 (0.027)
Reactive Investment ($M in last 5 years)	—	0.007 (0.004)
Reactive Invest x Lag Viol Frac	—	-0.066 (0.025)
Lag Violation Fraction	2.422 (0.149)	2.403 (0.150)
Purchaser	-0.247 (0.067)	-0.239 (0.068)
Surface Water	0.708 (0.139)	0.720 (0.139)
Employees	-0.005 (0.002)	-0.004 (0.002)
Year Fixed Effects	Yes	Yes
ADD Fixed Effects	Yes	Yes
Pseudo R^2	0.242	0.245
Observations	4,236	4,236

Notes: The dependent variable is an indicator for a health-based water quality violation. Additional controls include indicators for the size of the population served by the system, i.e., small, medium, large, as well as the natural log of the median household income and housing density, and a control for the fraction of the population that is non-white. Area Development Districts (ADD) are geographical groupings within Kentucky used for water system management and planning.

Table 5: Probability of an Infrastructure Project

	(1)	(2)	(3)
Lag violation	0.063	-0.007	0.195
	(0.067)	(0.075)	(0.077)
Non-white fraction	-0.470	0.015	-0.862
	(0.594)	(0.642)	(0.697)
Small	0.567	0.486	0.481
	(0.172)	(0.191)	(0.229)
Medium	0.746	0.705	0.556
	(0.172)	(0.189)	(0.229)
Large	0.833	0.819	0.628
	(0.174)	(0.191)	(0.231)
Surface Water	0.215	0.178	0.182
	(0.084)	(0.091)	(0.104)
Year Fixed Effects	Yes	Yes	Yes
ADD Fixed Effects	Yes	Yes	Yes
Pseudo R^2	0.068	0.067	0.074
Observations	4,236	4,236	4,236

Notes: The dependent variable is an indicator for any project approved in the year, a proactive project approved in the year, and a reactive project approved in the year for columns (1), (2), and (3) respectively. Additional controls include the natural log of the median household income and housing density, an indicator for whether the system purchases their water, and the number of employees working at the system. Area Development Districts (ADD) are geographical groupings within Kentucky used for water system management and planning.

3.2 System Managers and Consumers Respond to Violations

3.2.1 System Manager Response

Next, I explore the timing of projects, and if the probability of a system manager undertaking an infrastructure project is linked to the occurrence of a water quality violation. I construct three indicator variables based on (1) whether any type of project is approved in a given year, (2) whether a proactive project is approved, and (3) whether a reactive project is approved. Then I run a series of probit regressions to predict the probability of each outcome. The data cover the violation outcomes and infrastructure expenditures of 353 community water systems in Kentucky from 2007-2019.

Table 5 contains the results of the regressions. The dependent variable is an indicator for any project approved in the year, a proactive project approved in the year, and a reactive project approved in the year in columns (1), (2), and (3) respectively. As depicted in the table, only reactive projects are more likely to be approved in the year following a health-based violation. This is consistent with the finding that reactive projects improve water quality for systems with a history of violations. I interpret these findings as further evidence that both reactive investments and water quality violations are likely to occur when infrastructure quality is low. System managers are more likely to face increased pressure from their constituencies when providing poor quality water and may invest in a reactive project on the heels of a violation as a response to this pressure.

3.3 Consumer Response

One way to determine if consumers care about the violation status of their tap water is to evaluate whether or not consumers seek out alternative safe water sources when exposed to a water quality violation.[13] In keeping with other papers that study consumer avoidance behavior, I examine changes in county-level bottled water sales when a water system experiences a health-based violation.[14]

I regress the weekly log sales of bottled water at each store (mapped to a county), on the fraction of the week each water system spends in violation. For this analysis, I separately consider the fraction of the year spent in a Tier 1 and Tier 2 violation. The time spent in violation is weighted by the fraction of the county population that is served by the community water system to obtain a more accurate measure of the level of exposure within a county.

The regression equation is given by:

$$y_{ct} = a_0 + a_1 p_{ct} + a_2 \sum_{w \in c} v_{1wt}(n_{wc}/n_c) + a_3 \sum_{w \in c} v_{2wt}(n_{wc}/n_c) + \boldsymbol{b x_{ct}} + d_c + f_t + e_{ct} \tag{1}$$

where variable subscripts c and t refer to the county and the week. The weekly log sales of bottled water is captured by y_{ct}, and the fraction of week water system w spends in a Tier 1 and Tier 2 violation are represented by v_{1wt} and v_{2wt} respectively. The fraction of the county population that is served by water system w is captured by (n_{wc}/n_c). I control for consumer price sensitivity using the county average price per gallon of drinking water, p_{ct}. I use the average maximum and minimum temperature as well as the average total precipitation observed in the county for the week, $\boldsymbol{x_{ct}}$, to control for seasonal changes in demand for bottled water. I further include a county fixed effect d_c, and a week fixed effect, f_t. The county fixed effects are included to account for differences such as household income or average population. Certain age groups are more susceptible to water contaminants, and income levels and age differences might account for variation in averting behavior. The week fixed effects are included to control for time trends that are separate from the climate controls.

Table 6 presents the results. Exposure both a Tier 1 and to a Tier 2 violation results in an increase in bottled water sales, with a 22% and 3% increase respectively. This is consistent with the fact that Tier 1 violations pose the most imminent threat to consumer health and require the quickest turnaround to notify consumers. I also find consumers have a negative response to the

[13] Bottled water facilities are regulated by the FDA and are not subject to the same criteria used to evaluate community water systems. However, when a violation occurs that cannot be fixed by boiling, system managers often either suggest or offer bottled water as a substitute. For example, during the public health crisis in Flint, the government sponsored a free bottled water program through April 2018.

[14] Other papers have previously used changes in bottled water sales in different settings to demonstrate consumer sensitivity to water quality. For examples, see Allaire et al. (2019), Christensen et al. (2021), Graff Zivin et al. (2011), and Wrenn et al. (2016).

Table 6: Bottled Water Sales Increase with Water Quality Violations

	Log Sales
Tier 1 Violation	0.217
	(0.075)
Tier 2 Violation	0.029
	(0.010)
Price per Gallon	-0.490
	(0.007)
County Fixed Effects	Yes
Week of Year Fixed Effects	Yes
Adjusted R^2	0.926
Observations	77,466

Notes: Data cover 730 weeks from 2006-2019. Of the 120 counties in Kentucky, 112 have sales information for at least one week. Regression includes additional controls for average county precipitation, maximum temperature, and minimum temperature.

cost of a gallon of bottled water indicating that although consumers are sensitive to violations, they are also sensitive to the cost of substitution. From the above analysis, I conclude that consumers within Kentucky are sensitive to changes in tap water quality and substitute to bottled water as an alternative.

4 Model

I model the system manager's problem as an annual decision to undertake an infrastructure project to improve system quality or to delay investment until the following period. System managers do not know the exact investment costs prior to making an investment decision. However, managers are aware of the distribution of project sizes and use this information to form expectations over the realizations of project costs.

The consequences of noninvestment are driven by the system's infrastructure quality. Each manager knows the current state of their quality and that they face two types of quality uncertainty. The first is an annual shock capturing temporary quality changes that only affect system outcomes in the current period (i.e., storms and chemical spills). This shock and the level of quality at the beginning of the period determine the expected amount of time the system spends in violation and the type of project that is likely to occur if an investment decision is made. The second type of uncertainty is a shock realized at the end of the period that captures lasting unexpected infrastructure changes (i.e., damage due to flooding or unexpected pipe breaks) and leads to uncertainty in the system manager's expectations for future quality levels.

Over time, system quality progressively declines. To offset this decline, system managers can increase quality through project investment. If a manager chooses not to invest, the system is more likely to experience a water quality violation and projects are more likely to be reactive. To capture the pressure placed on system managers from providing poor quality water to consumers, I assume that system managers seek to minimize the weighted costs to consumers from contaminated water exposure against the anticipated costs of an infrastructure project. Below I provide further details on the mechanisms of the model.

4.1 Project Size

In the model, project costs are drawn from pre-estimated distributions. Holding the distributions of project investment size fixed serves two purposes. First, this normalization acts as a budget constraint on manager investment decisions. Data on approved project costs incorporate the existing limitations and opportunities available to system managers at the time of approval. By using this data to estimate project size distributions, I incorporate these constraints into the model. For example, the probability of receiving a loan or principal forgiveness for a project is already accounted for by system managers in the observed project sizes. Additionally, any budgetary constraints imposed by political pressure from increasing water costs to consumers and the overhead of planning and developing an infrastructure project are also integrated into existing project costs. Second, the true costs of investment are often difficult to predict and changes to initial estimates can be required to bring projects to completion.[15] By holding these distributions fixed in the model, I am able to realistically incorporate the project cost uncertainty faced by system managers.

I construct project size distributions from data in the “anticipated budget” section contained within the WRIS project reports. Using observations for proactive and reactive project costs, I employ maximum likelihood methods to estimate the parameters for two lognormal project size distributions. Figure 4 displays the fits for these distributions. I also confirm that proactive and reactive projects are sourced from statistically different distributions, and that reactive projects are statistically larger than proactive projects.[16]

4.2 System Quality

Water system quality, q_{wt}, represents an amalgam of the components of system quality that can lead to a health-based water quality violation. For example, aging water systems are often more susceptible to contamination due to degrading pipe materials, and systems with pipes covering longer distances are more vulnerable to the build-up of harmful contaminants. I assume each water system has an unobserved level of quality in 2007, the beginning of my observation period, which is drawn from a normal distribution, $q_{w0} \sim \mathcal{N}(\mu_q, \sigma_q)$. System quality degrades over time, which I model using an AR(1) process. Management can combat this quality decay by spending money on infrastructure projects. I estimate different effects for proactive and reactive projects in the model to allow the two types of projects to alter quality in their own way.

[15]Bajari et al. (2014) study the renegotiation of procurement contracts in a similar infrastructure setting, supporting that exact infrastructure costs are often unknown prior to completion of a project.

[16]The results of a one sided Kolmogorov-Smirnov test indicate that the reactive project size distribution first-order stochastically dominates the proactive project size distribution ($D(863, 1454) = 0.097, p < .001$).

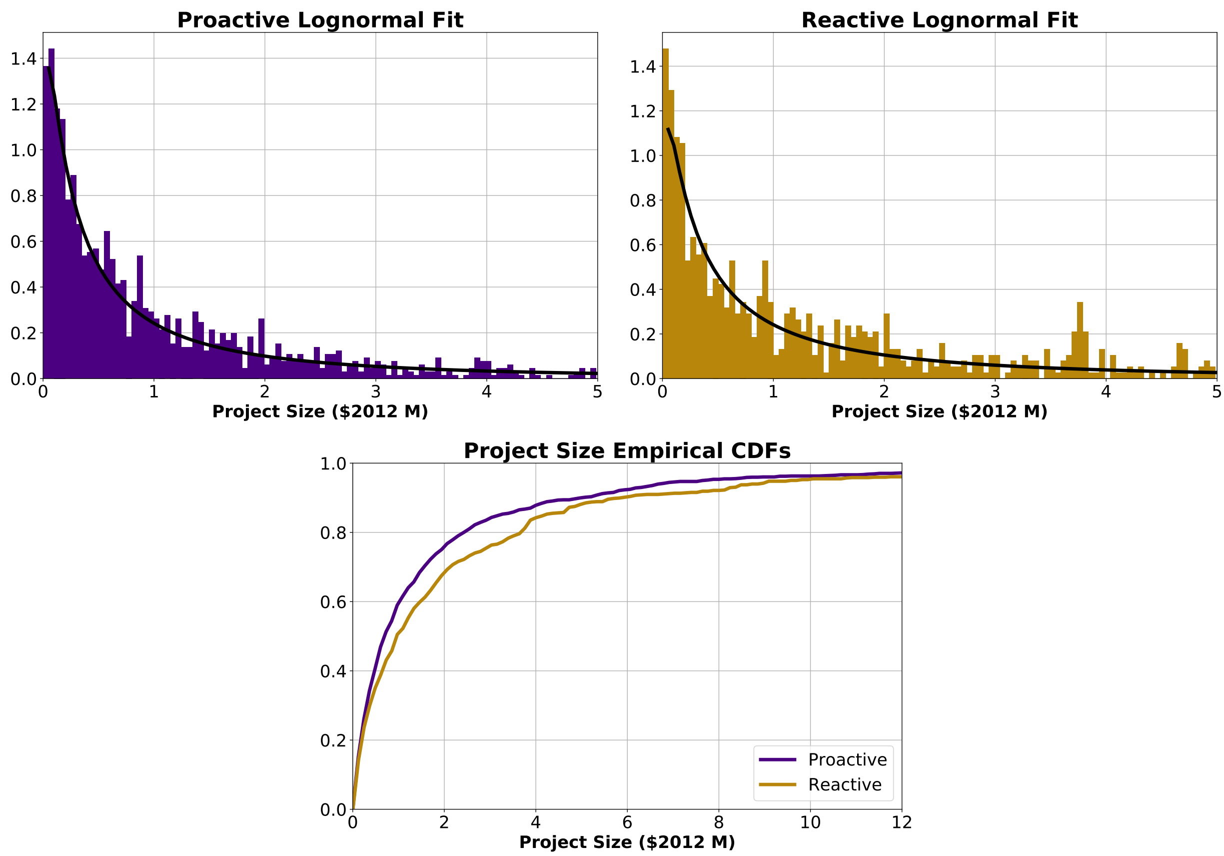


Figure 4: Lognormal Fits for Project Investments

Notes: Data are from WRIS and collected via web scraping. Project costs are adjusted to millions of real 2012 dollars. The top two panels plot the histograms of proactive and reactive projects along with the estimated lognormal fit. The bottom panel plots the empirical cumulative distributions for both project types. The distribution of reactive project size is statistically larger than the distribution of proactive project size.

I use $i_t = \{0, 1\}$ to indicate whether any project is undertaken in the current period, $y_{rt} = \{0, 1\}$ to indicate a reactive project, and (k_{pwt}, k_{rwt}) to represent the amount of money spent on proactive and reactive projects respectively.

The law of motion for quality follows the structure below:

$$\begin{aligned} q_{wt+1} &= \alpha^q q_{wt} + i\big((1 - y_{rt})\alpha^p k_{pwt} + y_{rt}\alpha^r k_{rwt}\big) + \tilde{\epsilon} \\ \alpha^q &\in (0, 1) \\ \tilde{\epsilon} &\sim \mathcal{N}(0, 1) \end{aligned} \tag{2}$$

where α^q captures the persistence of system quality over time, and $\tilde{\epsilon}$ is realized at the end of the period and captures lasting changes to quality such as damage due to flooding, or an unexpected external grant award. A value of α^q close to one implies that quality degrades slowly and that any changes to quality, here made by project investments, are highly persistent. The multipliers on project investment, (α^p, α^r), reflect the effect of a $1 million expenditure on the level of quality for a proactive and reactive project respectively.

Each period the system receives a temporary shock to system quality, $\epsilon_q \sim$ Type I extreme value, to capture year-specific challenges that the system manager might face. This quality shock introduces uncertainty in both the exact amount of time the system spends in violation and whether a project is proactive or reactive if the system manager decides to invest. I employ an ordered logit model to represent the number of quarters the system spends out of compliance, $y_{vt} = m = \{0, 1, 2, 3, 4\}$.[17] As the quality of the system decreases, the expected number of quarters spent in violation increases.

The probability of spending any given amount of time in violation is represented below:

$$Pr(y_{vt} = m) = \begin{cases} 1 - \Lambda\big(q^*_{vm} - q_{wt}\big) & \text{if } m = 0 \\ \Lambda\big(q^*_{vm-1} - q_{wt}\big) - \Lambda\big(q^*_{vm} - q_{wt}\big) & \text{if } m \in \{1, 2, 3\} \\ \Lambda\big(q^*_{vm-1} - q_{wt}\big) & \text{if } m = 4 \end{cases} \tag{3}$$

where $\Lambda(\cdot)$ denotes the logit function.[18] The thresholds, $\boldsymbol{q^*_v} = (q^*_{v0}, q^*_{v1}, q^*_{v2}, q^*_{v3})$, are decreasing in magnitude and represent the relative values of infrastructure quality at which the ability of the system to provide safe drinking water is diminished and the expected number of quarters in violation increases. For any systems with quality above q^*_{v0}, the expected number of quarters in violation is entirely dictated by the annual quality shock. For systems with quality below this threshold, the probability of spending time in violation increases as quality falls.[19]

The probability that a system undertakes a reactive, as opposed to proactive, project is also determined by current system quality. To mirror the results in Section 3, the probability of a reactive project is higher for lower values of system quality. As quality falls below the reactive threshold, q^*_r, the projects undertaken by system managers are increasingly likely to be reactive. Given the yearly shock to quality, the probability that a system draws a reactive project takes the following form:

$$Pr(y_{rt} = 1) = p_r(q_{wt}, q^*_r) = \Lambda\big(q^*_r - q_{wt}\big) \tag{4}$$

The quality threshold, q^*_r, represents the point at which infrastructure begins to display signs of the system's inability to provide safe drinking water, e.g., through breaks and damage, that point to larger problems. As system quality drops, it is increasingly likely that projects are reactive in nature.

Figure 5 plots simulated data to provide further intuition for the progression of quality and the

[17]SDWIS data indicates that violation durations tend to be clustered around month long intervals. I further simplified these observations into quarters of a year spent in violation.

[18]More explicitly, the logit function has the following form:

$$\Lambda(z) = \frac{\exp(z)}{1 + \exp(z)}$$

[19]I hold the violation thresholds fixed during model estimation. The EPA made two revisions to the National Drinking Water Contaminant List over 2007-2019. Of the 1,329 violations I observe during this period, only 23 violations are due to these revisions.

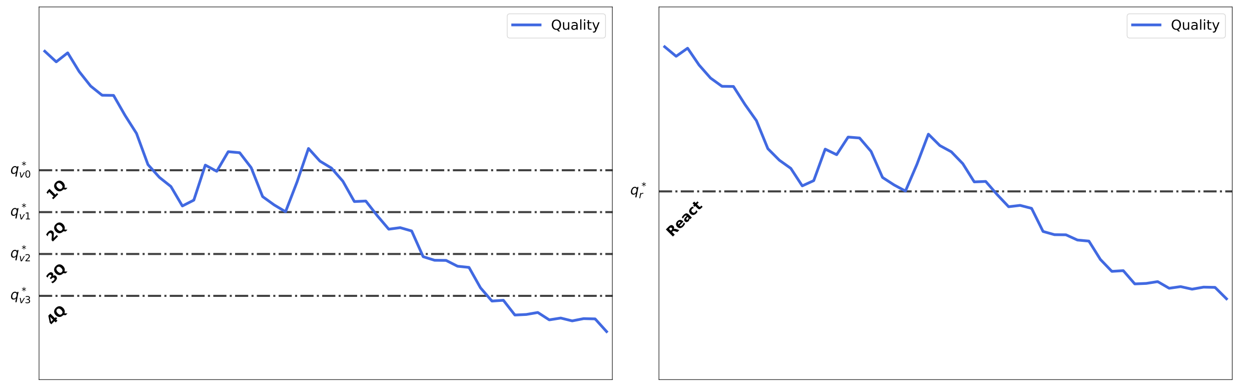


Figure 5: Low Quality Consequences
Notes: The left panel portrays the relationship between quality decline and violation thresholds. The right panel portrays the relationship between quality decline and the reactive threshold. All representations are simulated based on the structure of the model.

consequences from noninvestment. Equation (2) indicates that without project investment, system quality declines over time. As system quality declines to lower levels, the probability of spending time in violation and the likelihood of a reactive project increase. The dynamic program estimates the infrastructure quality thresholds $(q^*_{v0}, q^*_{v1}, q^*_{v2}, q^*_{v3}, q^*_r)$ where these outcomes are increasingly likely.

4.3 Consumer Disutility

System managers incur costs when they are unable to provide safe drinking water to consumers. I assume that these costs are proportional to consumer disutility from receiving tap water that is below health-based standards. In order to determine the value of consumer disutility, I employ a logit-style demand model to estimate consumers' willingness to pay for safe drinking water.

Consumers choose between buying bottled water and drinking tap water. I assume that the indirect utility to consumer i of purchasing bottled water in week t is given by:

$$u_{i1t} = \gamma^c + \gamma^v v_i + \gamma^p p_{1t} + \xi_{1t} + \epsilon_{i1t} \tag{5}$$

where v_i is an indicator for consumer exposure to a health-based water quality violation, and p_{1t} is the average price for a gallon of bottled water in week t.[20] Consumer disutility from exposure to a water quality violation is captured by γ^v, γ^p captures price disutility, and ξ_{1t} is unobserved by the econometrician and captures a demand shock for bottled water in week t. I assume each person consumes 32 oz of water per day, which equates to 1.75 gallons per person per week.[21] Using this

[20] I assume a gallon of tap water is free. As compared to the amount of water used by a consumer for all house-based activities, the relative cost of 1.75 gallons of water per person per week is low. For example, the Muldraugh Water Department currently charges $20.50 for 4,000 gallons of water, which is less than $0.01 per gallon.

[21] There is no definitive rule for how much water consumers need per day. Harvard Health Publishing recommends that healthy people should be drinking four-to-six cups daily (32 - 48 oz). To allow for variation in the types of liquids consumed, I use the lower bound in my estimation. Any deviation from this value is captured in the estimate for the weight system managers place on consumer disutility, λ. Sourced from: `https://www.health.harvard.edu/`

Table 7: Parameter Estimates and Derived Statistics

Parameter		Estimate	St. Error
Demand			
Constant	γ^c	-2.256	(0.014)
Price Parameter	γ^p	-1.007	(0.008)
Violation Parameter	γ^v	-1.313	(0.050)
Derived Statistics			
Willingness to Pay	γ^v/γ^p	1.30	
Demand Elasticity	$\gamma^p p_1(1-s_1)$	-1.651	

as a basis for consumption, I construct shares of bottled water and tap water in each county-week observation, s_{1ct} and s_{0ct} respectively.

The results of my estimation are presented in Table 7. Consumers are sensitive to both the price of a gallon of water and exposure to a health-based violation, which is reflected in negative estimates for (γ^p, γ^v) respectively. According to my estimates, each consumer is willing to pay \$2.28 per week (1.75 gallons $\times$ \$1.30) for bottled water to avoid a health-based water quality violation.

4.4 System Manager's Decision Problem

Last period's quality determines the amount of time the system spends in violation during the current period. Therefore, the system manager decides whether or not to invest in a project in the current period in order to affect the next period's quality level. System managers know the cost distributions for the possible reactive and proactive projects, but not the true realization of these costs until after deciding to undertake a project.

I model the cost to system managers from providing drinking water that is below health-based standards as proportional to consumer disutility, which I construct based on willingness to pay estimates. To obtain an annual value for these costs, I assume every consumer shops once a week during the year (13 times per quarter) and makes a choice to buy the water needed for that week (1.75 gallons per person) or to consume water from the tap. The annual expected disutility to consumers served by community water system w can be represented as:

$$D(q_{wt}, \boldsymbol{q_v^*}) = \big((\hat{\gamma^v}/\hat{\gamma^p}) * 13 * 1.75\big) n_w E\big[y_v(q_w, \boldsymbol{q_v^*})\big] \tag{6}$$

where n_w indicates the average population served by community water system w.[22] The disutility to consumers in equation (6) is increasing in the expected amount of time spent in violation, $E[y_v]$. As quality falls, the amount of expected time in violation increases. This relationship drives system

staying-healthy/how-much-water-should-you-drink

[22]During estimation, I treat all systems identically by holding this value fixed at the average population observed in the data.

managers to make investments in infrastructure to counter quality decay.

There is an extensive literature examining the true value consumers place on a desired environmental improvement. The primary debate concerns contingent valuation (stated preferences) contrasted with often dissimilar averting behavior (switching to bottled water) estimates of consumer willingness to pay.[23] Along the lines of this argument, I anticipate that system managers are better able to internalize the costs to consumers from exposure to contaminated water than the willingness to pay consumers display when they switch to bottled water. As a result, I estimate a scaling parameter on consumer disutility, which I denote λ, in the system manager's optimization problem to capture the anticipated mismatch between consumer valuations and the actual costs considered by system managers. Values of λ less than one indicate that system managers do not fully internalize consumer disutility from unsafe drinking water, and values of λ greater than one indicate that system managers are incorporating additional factors into their valuation such that their costs are larger than estimates for consumer willingness to pay.

Let $\boldsymbol{\theta} = (q^*_{v0}, q^*_{v1}, q^*_{v2}, q^*_{v3}, q^*_r, \lambda, \alpha^q, \alpha^p, \alpha^r, \mu_q, \sigma_q)$ denote the set of parameters to be estimated with the dynamic discrete choice model. The distributions for project costs, $k_p \sim \log\mathcal{N}(\mu_p, \sigma_p^2)$, and $k_r \sim \log\mathcal{N}(\mu_r, \sigma_r^2)$ have been pre-estimated using collected project cost data. I hold fixed the rate at which system managers discount the future at $\beta = 0.95$.

The current period utility takes the following form:

$$u(q_{wt}, i_t; \boldsymbol{\theta}) = \begin{cases} -\lambda D(q_{wt}, \boldsymbol{q_v^*}) & \text{if } i_t = 0 \\ -\lambda D(q_{wt}, \boldsymbol{q_v^*}) - \big(1 - p_r(q_{wt}, q_r^*)\big)E[k_p] - p_r(q_{wt}, q_r^*)E[k_r] & \text{if } i_t = 1 \end{cases} \tag{7}$$

which is dependent on the manager's decision to invest in a project or not. Based on the timing in the model, the cost of pursuing a project in the current period is always greater than choosing to delay investment. System managers only make decisions to undertake in projects based on the future expected increase in quality from those investments.

Combining the components of the model, the value function for a community water system manager has the following form. I introduce an additional set of state variables, $\big(\epsilon(0), \epsilon(1)\big)$ for other choice-specific states that are only observable to the system manager. For notational simplicity, I omit time and water system subscripts.

$$V\big(q, \boldsymbol{\epsilon}; \boldsymbol{\theta}\big) = \max_{i \in \{0,1\}} \Big\{ u(q, i; \boldsymbol{\theta}) + \epsilon(i) + \beta EV\big(q', \boldsymbol{\epsilon'} | i, q; \boldsymbol{\theta}\big) \Big\} \tag{8}$$

5 Estimation

5.1 Methodology

To estimate the model parameters, I use observations of system manager decisions to undertake infrastructure projects, realizations of the type of infrastructure project, and the amount of time

[23]The debate is discussed in Orgill-Meyer et al. (2018), Wu and Huang (2001), and Bartik (1988).

systems spend in violation to construct a maximum likelihood function. The behavior of system managers is driven by three state variables that are unobserved by the econometrician: system quality and two choice-specific shocks. The estimation of models with unobserved choice-specific shocks is covered extensively in the literature, and in keeping with this work I make some preliminary simplifying assumptions about the relationships between the error terms and system quality.[24] I assume that the error terms $\epsilon(i)$ are independent in every period and follow a normalized Gumbel distribution with mean zero and variance $\pi^2/6$. With these assumptions I am able to use fixed-point methods to construct conditional choice probabilities for project investment decisions as a function of system quality. The main challenge for estimation is that system quality is unobserved by the econometrician and depends on the value of quality in the prior period. This history dependence makes estimation of the model computationally intensive as all possible values of quality across 13 periods of observation need to be considered in the evaluation of the maximum likelihood function.

Connault (2016) and Reich (2018) propose applying recursive estimation techniques to reduce computational complexity in models with serially correlated unobserved states. Reich proposes a methodology called recursive likelihood integration that incorporates iterative interpolations and approximations in conjunction with backward induction to solve a likelihood function over possible values of an unobserved state variable. The advantage of this approach over the approach proposed by Connault is that it allows for continuous serially correlated unobserved state variables, so I employ this technique in my estimation.

Data on the timing of project investments, i_t, the number of quarters spent in violation, y_{vt}, realizations of reactive projects, y_{rt}, and project costs, (k_{pt}, k_{rt}) identify the parameters of interest. The likelihood function for a single system can be represented as follows.

$$L_T(\boldsymbol{\theta}) = \int \dots \int \prod_{t=1}^{T} \Big(p_{i|q}(i_t|q_t;\boldsymbol{\theta}) p_{y_r|q}(y_{rt}|q_t, i_t;\boldsymbol{\theta}) p_{y_v|q}(y_{vt}|q_t;\boldsymbol{\theta}) p_q(q_t|i_{t-1}, y_{rt-1}, k_{pt-1}, k_{rt-1}, q_{t-1};\boldsymbol{\theta}) \Big) \times$$
$$p_{i|q}(i_0|q_0;\boldsymbol{\theta}) p_{y_r|q}(y_{r0}|q_0, i_0;\boldsymbol{\theta}) p_{y_v|q}(y_{v0}|q_0;\boldsymbol{\theta}) p_q(q_0;\boldsymbol{\theta}) dq_0 dq_1 \dots dq_T \tag{9}$$

The goal of recursive likelihood integration is to reduce the above equation to T one-dimensional integrals, which are easier to compute, and to apply techniques of backward induction over the history of qualities in the period of observation to solve the maximum likelihood function. To achieve this goal, I follow Reich (2018) and define the following recurrence relation.

$$g_t(\tilde{q}) = \begin{cases} 1 & t > T \\ \int \Big(p_{i|k_p,q}(i_t|\tilde{q}';\boldsymbol{\theta}) p_{y_r|q}(y_{rt}|\tilde{q}', i_t;\boldsymbol{\theta}) p_{y_v|q}(y_{vt}|\tilde{q}';\boldsymbol{\theta}) \times & \text{otherwise} \\ \qquad p_q(\tilde{q}'|i_{t-1}, y_{rt-1}, k_{pt-1}, k_{rt-1}, \tilde{q};\boldsymbol{\theta}) g_{t+1}(\tilde{q}') \Big) & \end{cases} \tag{10}$$

I employ the above recurrence relation to recursively determine the most likely parameters that

[24] A survey of dynamic discrete choice models and methods of estimation is covered in Aguirregabiria and Mira (2010).

generated the observed data, given all the possible paths quality could have taken from the first period to the last period. For each parameter guess, I use equation (10) to build up the likelihood of the observed data over all the possible points of q in each time period. To construct the likelihood, I first discretize quality by establishing a set of grid points for evaluation. I then initialize the recurrence relation to 1 in period T, setting the probability of being at any possible point across the grid of q values in period $T+1$ to be equivalent. Then I calculate, for each grid point of q, the probability that the system quality is that value at period T, given the possible values system quality could have been at $T-1$ and the realizations of quality consequences in period T. Using backward induction, I repeat this process until $t = 1$ to establish the likelihood of a quality path from period $t = 1$ to $t = T$ at each of the grid points of q. At period $t = 0$, I make a final approximation over the possible initial values of quality based on the distribution of q_0, and the observations of project decisions, violations, and reactive projects in the initial period.

5.2 Identification

Identification of the parameters is driven by data on the timing and type of project investments, data on the number of quarters spent in violation, and distributional and functional form assumptions for the progression of quality. Figure 6 depicts the observed data for four different systems. Quality is assumed to be, on average, decreasing over time with increases in quality occurring when managers invest in projects. Although quality is unobserved, Figure 6 can be thought of as a representation of the consequences of an ungraphed quality level that determines when the system chooses to make investments, the type of investment made by the system, and the quarters spent in violation. Data on these consequences help to identify the parameters dictating the progression of system quality, the thresholds for violation, and the threshold for reactive projects.

To understand how the parameters are identified, first consider a model where the quality of each public water system is observed by the econometrician. With values of quality observed and data on the number of quarters spent in violation, the thresholds for violation, $\boldsymbol{q_v^*}$, are quickly pinned down. The threshold for reactive projects, q_r^*, is derived from quality levels at the time of investment and realizations of project types. An OLS regression of current quality on lagged values of quality and observed project costs identify the parameters describing the law of motion for q: the AR(1) parameter, α^q, and the change in quality from a million dollar investment in each type of project, (α^p, α^r). Lastly, the weight that system managers place on the disutility to consumers, λ, is identified by the timing of infrastructure project investment, i.e., when the expected cost of investment, derived from data on the true cost of a project, is less than the cost incurred by inaction.

When considering a model where quality is unobserved, many of the same identifying conditions hold, but quality no longer serves as a grounding foundation for the identification of these parameters. For instance, the identification of the thresholds described above depend on the observed value of quality when systems enter into a state of violation, or undertake a reactive project. Without observations of quality, the parameters in the model are no longer fully identified, only the relative levels of the parameters. To remedy this identification issue, I make two normalizations in

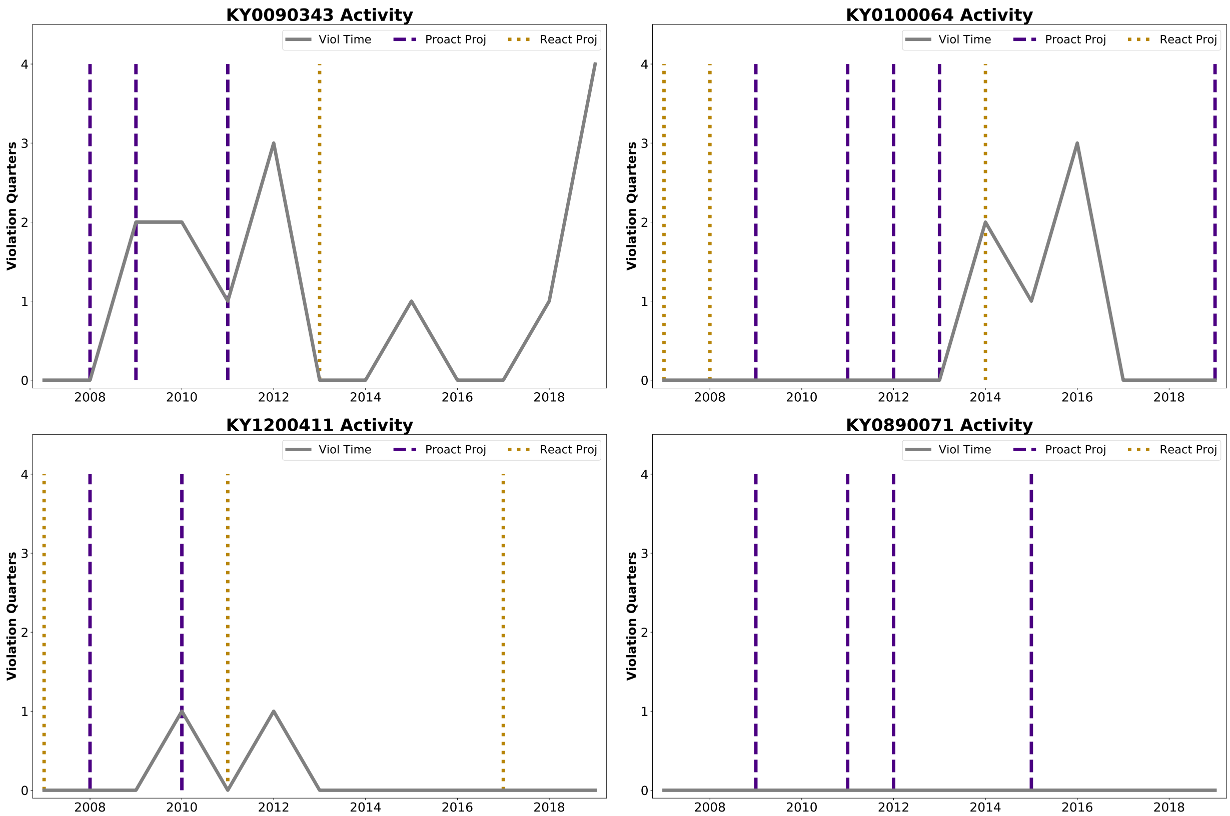


Figure 6: Timing of Projects and Violations

Notes: The panels above portray observed water system activities. Gold tightly dotted vertical lines indicate a reactive project investment, purple dashed lines indicate a proactive project. Solid gray lines indicate the number of quarters spent in violation.

the model. First, I hold the mean of the initial distribution of quality fixed, i.e., $\mu_q = 50$.[25] With this normalization, the model is able to "anchor" the parameters based on the average initial quality level, and all other parameters are interpreted in this context. Second, I hold fixed the rate of quality deterioration, $\alpha^q = 0.99$, which ties the average quality to the penalties from non-investment. I fix the AR(1) parameter close to 1 in order to mimic a setting where quality deteriorates slowly over time.

With the above normalizations, the rest of the parameters in the model are identified from a combination of these values and observed data. The fixed AR(1) parameter in conjunction with the timing between successive violations, violations and projects, and successive project investments identify the magnitude of the effect of a project investment on quality and the gap between violation thresholds. The effectiveness of a project investment is determined by the value of the investment and how many periods pass before the system either makes another investment or enters into violation. The violation thresholds are determined by the timing between changes in the number

[25] I simulate data and run a series of estimations with μ_q fixed at various levels. The value of the objective function at the maximizing parameter estimates remains approximately equal in each of these estimations, with changes in the levels of the threshold parameters commensurate with the difference between the true μ_q and the value used for estimation. See Appendix B for additional details.

of quarters spent in violation given the fixed rate of decay. The effectiveness of projects (α^p, α^r), the decay rate of quality, and the timing of infrastructure investments identify the multiplier on consumer disutility, λ. Projects are only undertaken when the expected penalty from entering into a violation state due to not undertaking a project outweighs the expected expense of a project. The reactive project threshold, q_r^*, is pinned down by the percent of project observations that are reactive. Lastly, the spread of the initial quality distribution, σ_q, follows from the initial distribution of systems in violation and the overlapping distributions of the highest probability q_0 values for each water system.

5.3 Estimation Results and Analysis

5.3.1 Parameter Estimates and Interpretation

I estimate the structural parameters of the model using data on the project decisions and violation outcomes of 353 community water systems from 2007-2019.[26] The point estimates from the dynamic program are presented in Table 8. Based on the estimates, the average proactive project, which costs \$2.35 million, increases the level of quality by 0.131 in the next period, and the average reactive investment, which costs \$3.24 million, increases quality by 0.127. The relative investment benefit depends on the level of quality at the time of investment, and how close quality is to the violation thresholds. For instance, at a quality of two, investing in a project on average increases quality by almost 7%. However, for a quality level that low, there is no benefit from investing in a project because the investment does not alter the number of quarters the system spends in violation.

Any investment has both an immediate effect on quality level and also an effect on quality in future periods. By undertaking a project, the future expected starting level of quality is now higher than it would have been without investment. For example, if a system invests \$10 million in a proactive project when system quality is 47, the expected value of quality next period is 47.09 as opposed to 46.53, and the following period is 46.62 as opposed to 46.06. Figure 7 plots the cumulative benefit of different levels of project investment depending on the value of quality at the time of investment. For both types of projects, the most advantageous time to invest is when quality is close to the violation thresholds, i.e., when the water system is likely to enter into violation in the following period. At this point, an investment decreases the amount of time the system spends in violation in the following period by the maximal amount. If system managers invest in infrastructure prematurely, the investment is less effective at reducing the time spent in violation due to the progressive degradation of system quality. For example, an average project investment made at a quality level of 50 is reduces the amount of time spent in violation by approximately 95% of the same investment made just before entering into a state of violation, at a quality level of 47.

[26]In the event that a system approves multiple projects in a year, I pool observations by project type into a single investment. In approximately 3% of observations both reactive and proactive projects are approved in the same year. In these cases, I keep the project type with greater total expenditure.

Table 8: Dynamic Model Parameter Estimates

Parameter		Estimate	St. Error
Delay Consequences			
Consumer Disutility Weight	λ	10.029	(1.029)
Reactive Project Threshold	q_r^*	47.264	(0.314)
1Q Violation Threshold	q_{v0}^*	44.594	(0.385)
2Q Violation Threshold	q_{v1}^*	43.445	(0.437)
3Q Violation Threshold	q_{v2}^*	42.386	(0.490)
4Q Violation Threshold	q_{v3}^*	41.570	(0.505)
Project Effect on Quality			
Proactive Investment	α^p	0.056	(0.009)
Reactive Investment	α^r	0.039	(0.005)
Initial Quality Distribution			
Initial Quality Variance	σ_q^2	1.480	(0.420)
Fixed Parameters			
Initial Quality Average	μ_q	50	
Deterioration Rate	α^q	0.99	

Proactive projects are more efficient than reactive projects in the sense that proactive projects require smaller investments than reactive projects to have the same quality improvement. The left panel of Figure 7 plots the cumulative expected reduction in quarters spent in violation from a proactive investment of \$0.5 million, the average proactive investment (\$2.35 million), and \$5 million. The right panel displays the same information for a reactive investment of \$0.5 million, the average reactive investment (\$3.24 million), and \$5 million. At maximal effectiveness, the average proactive project reduces the amount of time spent in violation by 1.09 quarters, and the average reactive project reduces the expected amount of time spent in violation by 1.05 quarters. However, the average reactive project costs almost \$1 million more than the average proactive project. At \$5 million investment levels, a proactive project prevents 0.69 more violation quarters than a reactive project.

Estimates of the violation thresholds indicate that a system starting at average initial quality with a system manager that makes no infrastructure investments can expect to reach violating quality levels within 12 years. All of the violation thresholds are estimated to be fairly close to one another, and without any additional investment, the average system crosses the threshold for spending the entire year in violation within 19 years. The estimate for the reactive project threshold is slightly higher than the first violation threshold. The gap between these two values is less than three, indicating that it is possible for a system manager to undertake reactive projects without ever experiencing a health-based water quality violation, but the window is small. I interpret this

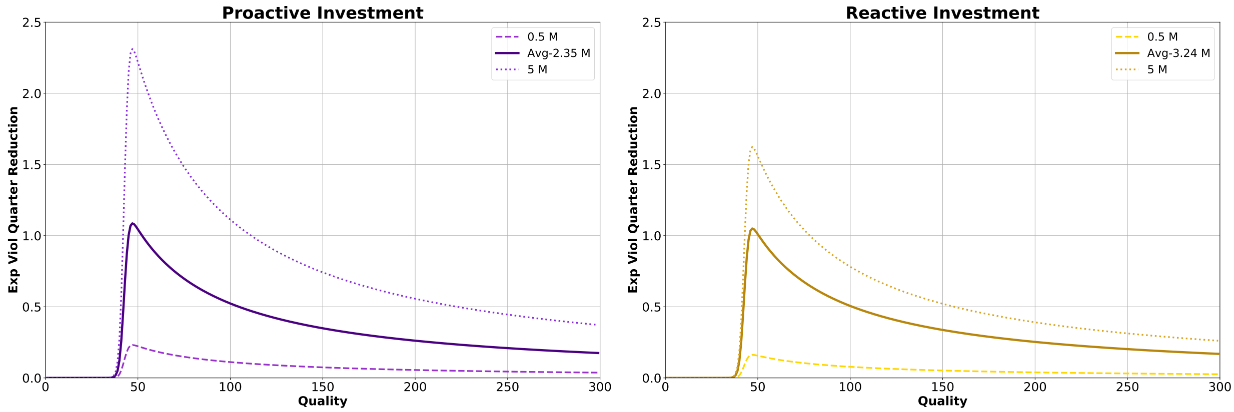


Figure 7: Value of Project Investment

Notes: The left panel displays the cumulative expected reduction in violation quarters for different quality levels at the time of investment. The purple lines graph the reduction in violation time for different amounts of proactive investment, with the solid purple line portraying the average proactive investment. The right panel displays the same information for reactive investments, with the solid gold line indicating the reduction in violation time for the average reactive investment.

result as an indication that there are likely signs of infrastructure degradation prior to a system receiving a health-based violation, but that managers need to respond to these signs quickly in order to prevent a violation.

The multiplier on the disutility to consumers, λ, is determined by the investment behavior observed in the data and the estimated effectiveness of projects. To justify the observed system manager investments, λ is estimated to be 10.03, which is well above one. At a value of one, system managers weight the estimated disutility to their consumers from receiving contaminated water at the cost to consumers displayed by their aversion behavior. Here λ is estimated to be greater than consumers' displayed willingness to pay, in line with expectations that system managers are more averse to water quality violations. There are many possible explanations for this estimate of λ. One possibility is that consumers make poor evaluations of the health risks associated with contaminated water.[27] Another explanation is that water systems imperfectly inform consumers of violations, and therefore the estimated aversion responses are actually lower bounds on consumer willingness to pay for safe water. I construct willingness to pay estimates from Nielsen data, and primarily use WRIS data to estimate the parameters of the dynamic model. The estimate for the weight placed on consumer disutility is consistent with predictions for system manager aversion to providing contaminated water, reflecting that the Nielsen data lends validity my estimation results.

To assess how well the model fits the data, I simulate 100 scenarios to approximate the behavior of system managers. In each simulation, I draw initial quality from the estimated distribution and then allow systems to make investment decisions. I hold fixed the progression of quality implied by the data. Overall, the model is able to match the trends in the data. Figure 8 summarizes the average violation behavior of systems in the simulations. In the top four panels, gray lines indicate the annual number of systems that spend 1-4 quarters in violation of a health-based standard.

[27] Collier et al. (2021) estimate direct healthcare costs for waterborne diseases at $3.33 billion annually.

The blue dashed lines indicate the average predicted number of systems in violation as a result of the simulations. Most systems spend no time in violation, indicating that during my period of observation, systems typically have a water quality level above the standards set by the EPA. Over time, more systems spend time in violation as infrastructure quality decreases. The bottom panel of Figure 8 plots the average amount of time a system spends in violation as observed in the data (gray line) and as predicted (green dashed line). As system quality decreases, the average amount of time a system can expect to spend in violation is increasing.

Figure 9 compares the true and predicted project investment behaviors of system managers. The top panel plots the number of systems with proactive projects in every year, the middle panel plots the number of reactive projects, and the bottom panel plots the ratio of proactive to reactive projects. The observed data are summarized by the gray lines and the dashed colored lines portray the predictions. Over time, the ratio of proactive to reactive projects decreases, which is primarily driven by a drop in the number of proactive projects. As the average quality of all systems declines, the number of systems engaging in any project is decreasing, and a larger proportion of projects are reactive. Reactive projects are estimated to be less effective than proactive projects, so as quality declines, the average project becomes both more expensive and less effective. Therefore, the incentive to undertake any project is slowly declining, even as the probability of experiencing a health-based violation is increasing.

5.4 Long Run Model Implications

The parameter estimates also provide sufficient information to simulate the long run state of water systems. Figure 10 plots the histogram of system qualities, the future predicted project trends, and expected quarters each system will spend in violation. The top panel plots simulated quality distributions in 2010, 2030, and 2050. Over time, the quality distribution becomes increasingly dispersed and steadily shifts downward to increasingly lower levels. To ease interpretation, recall that the average proactive and reactive investments, at their maximal effectiveness, decrease the time spent in violation by roughly one quarter (Figure 7). At the current rate and magnitude of investment, projects are unable to prevent systems from slowly declining to lower and lower levels of quality. The bottom left panel portrays the resulting number and types of projects undertaken by system managers as quality declines. As the average quality level across all systems falls, systems shift to only undertaking reactive projects, and the number of projects progressively declines.

The bottom right panel portrays the predicted average quarters systems will spend in violation over the next 50 years at the current model estimates. The increasing trend in average expected quarters in violation is driven by the progressive change in the quality distribution. As more of the quality distribution falls below the violation thresholds (indicated by the dashed vertical lines in the top histogram), more systems spend longer fractions of the year in violation of a health-based standard. Without policy intervention, more systems will violate these standards and spend increasing amounts of time in violation.

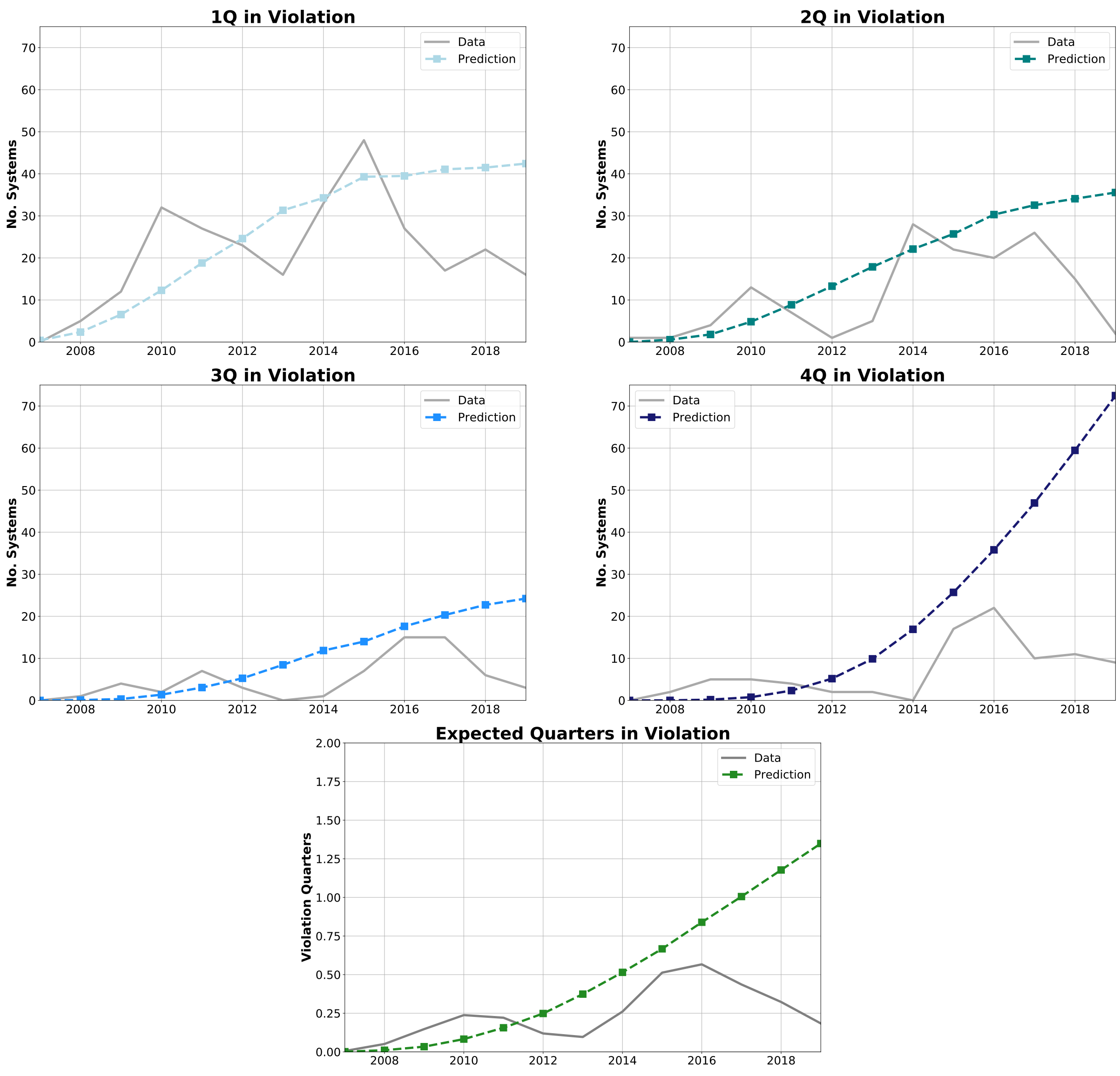
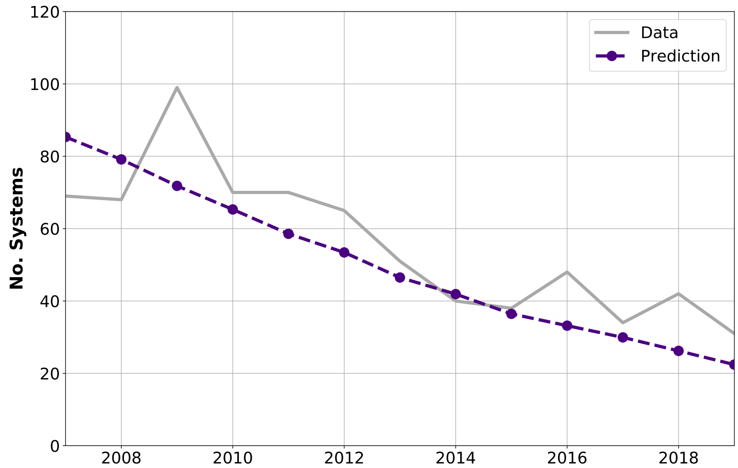
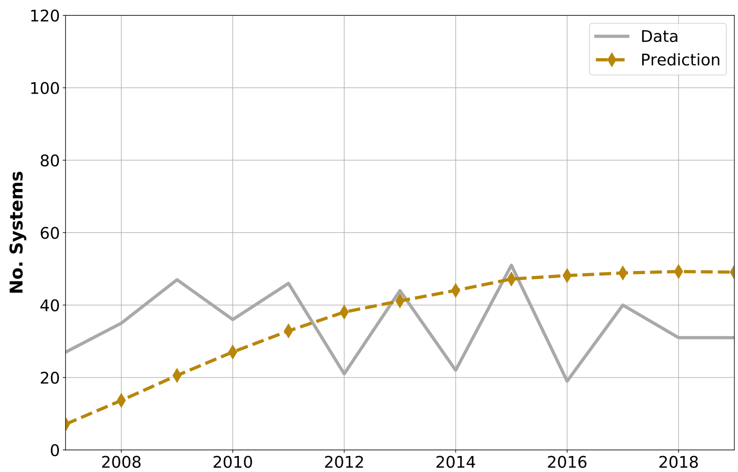


Figure 8: Model Fit for Violation Behavior

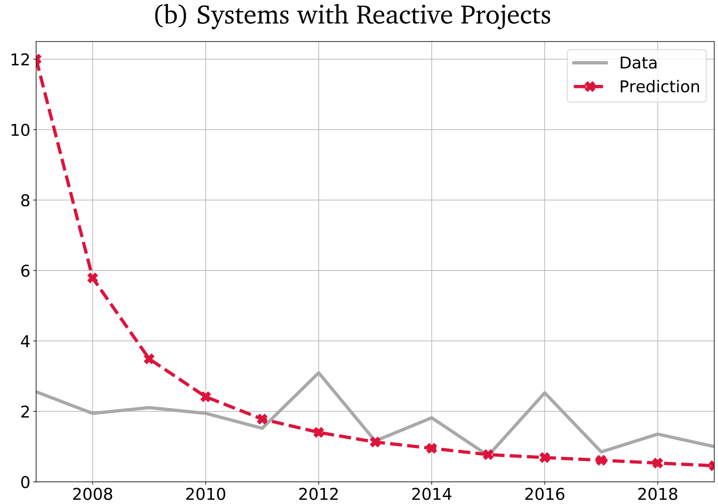
Notes: In the top four graphics, the gray lines indicate the number of systems observed in the data with the indicated quarters spent in violation. The dashed blue lines show the average number of predicted systems that spend the indicated quarters in violation. The final graph plots the expected amount of time spent in violation, with the solid gray line indicating the observed expected violation quarters and the green line indicating the predicted values. All predictions are calculated as the average of 100 simulations based on the parameter estimates.



(a) Systems with Proactive Projects



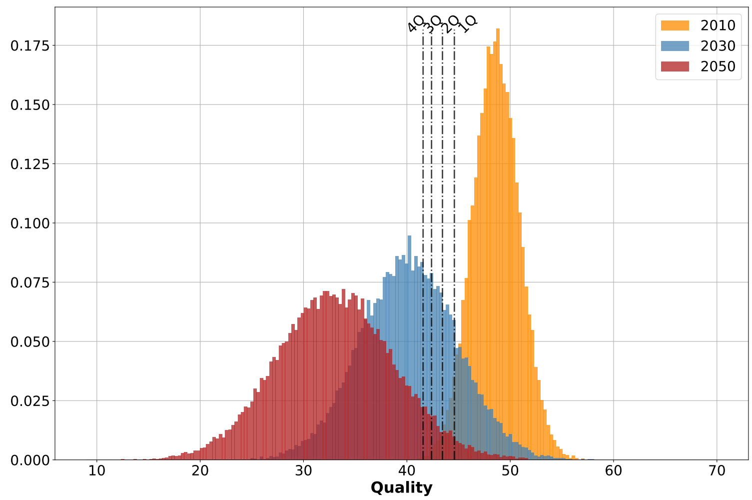
(b) Systems with Reactive Projects



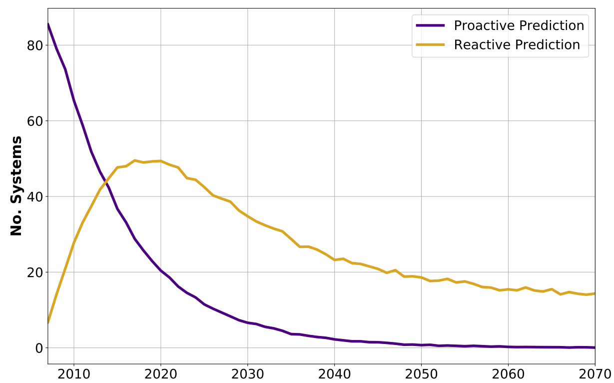
(c) Ratio of Project Types

Figure 9: Model Fit for Infrastructure Projects

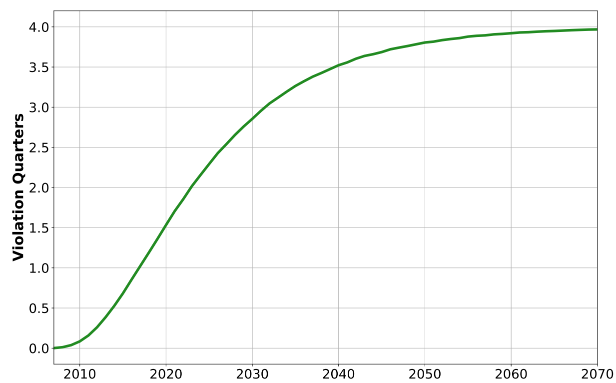
Notes: The solid gray lines indicate observed values in the data, dashed colored lines indicate the average results from 100 simulations using parameter estimates. The top graph depicts the annual number of systems with proactive projects, the middle graph depicts reactive projects, and the bottom graph depicts the annual ratio of proactive to reactive projects.



(a) Simulated Quality Distribution



(b) Long Run Project Trends



(c) Expected Quarters in Violation

Figure 10: Long Run Implications

Notes: The top histogram portrays the distribution of quality for 100 simulations of 353 systems in 2010, 2030, and 2050. Vertical lines indicate the estimated violation thresholds. The bottom left panel displays the predicted number and types of projects from 2007-2070. The bottom right panel displays the predicted average quarters each system spends in violation from 2007-2070.

5.5 System Manager Foresight

In the model presented in Section 4, I assume that managers are forward-looking. In order to justify investment decisions that have limited immediate benefits, system managers must value the future states of the system. I also assume that system managers make annual decisions considering the infinite horizon of possible future states of their infrastructure and that they discount the future at a rate of $\beta = 0.95$. In this section, I examine the results of alternative assumptions to assess the possibility that system managers are making decisions under different model specifications. I focus my evaluation on the changes in the effect of each type of project on quality, (α^p, α^r), and the weight that system managers place on consumer disutility, λ. The thresholds for violation and reactive projects are not identified by system manager decisions and therefore remain relatively unchanged in alternative estimations.

Table 9: Time Horizon Comparison

	Baseline	1 Year	5 Year	10 Year	15 Year
α^p	0.056	0.277	0.148	0.070	0.069
	(0.009)	(0.011)	(0.003)	(0.009)	(0.009)
α^r	0.039	0.343	0.027	0.023	0.033
	(0.005)	(0.003)	(0.001)	(0.003)	(0.005)
λ	10.029	29.786	27.100	23.501	15.566
	(1.029)	(0.827)	(0.192)	(2.479)	(1.969)
Neg. Log Likelihood					
ℓ	5734.504	5990.070	5752.430	5728.843	5731.397

Table 10: Discount Factor Comparison

	Baseline	$\beta = 0.8$	$\beta = 0.9$	$\beta = 0.99$
α^p	0.056	0.153	0.106	0.061
	(0.009)	(0.019)	(0.027)	(0.017)
α^r	0.039	0.018	0.052	0.075
	(0.005)	(0.004)	(0.011)	(0.023)
λ	10.029	27.784	10.447	3.896
	(1.029)	(1.014)	(1.481)	(1.003)
Neg. Log Likelihood				
ℓ	5734.504	5759.610	5739.565	5755.452

First, I analyze results from models in which system managers make one-shot decisions based on projections of the state of their infrastructure at a fixed number of years in the future. The main difference between these models and the baseline model is in the calculation of the probability that a system manager invests in an infrastructure project. I consider specifications where system managers are assessing their infrastructure state one, five, ten, or fifteen years in the future. The results of these estimations are presented in Table 9. The one-shot model with a one-year time horizon is the worst match to the data. This specification has the highest objective value, implying the worst fit, and overestimates both the effectiveness of projects and the weight placed on consumer disutility. As the time horizon for the one-shot specifications increases, the parameter estimates and the negative log likelihood function approach values that are close to the baseline specification. Both the ten-year and fifteen-year one-shot models perform slightly better than the infinite horizon model. However, the differences in objective functions are relatively minor, and the baseline model has smaller standard errors for the parameter estimates.

Second, I alter the rate at which system managers discount the future. The discount factor describes the relationship between current and future events. In the baseline specification, I hold this parameter fixed at 0.95, meaning that to a system manager a $1 expenditure tomorrow is only worth $0.95 today. To compare alternative discount rates, I consider specifications where the discount factor is held fixed at 0.8, 0.9, and 0.99. The result of these estimations are presented in Table 10. The baseline specification fits the data better than the alternative specifications, although the value of the negative log likelihood function is similar in all four models. In the specification with $\beta = 0.8$, the estimate for the weight system managers place on consumer disutility increases to compensate for the lower discount rate. Similarly, in the specification with an increased discount rate of $\beta = 0.99$, estimates for λ are lower as system managers in this model place a higher weight on the future. Across the model specifications I consider, I find little conclusive evidence that an alternative model for system manager decisions provides substantial improvement over the baseline infinite horizon model. The baseline model has the most believable estimates for the weight placed on consumer disutility, and this specification most precisely estimates the parameter values.

6 Counterfactual Simulations and Policy Implications

As presented in Section 5, the rate of project adoption and the size of infrastructure projects are currently too low to prevent system decline into an extended state of violation. In this section, I examine outcomes under alternative policies targeting increased proactive or reactive investment and the ability of these policies to combat quality decline. I first assess the efficacy of policies designed to increase the number of projects; I then explore policies that increase the size of a project; lastly, I consider a combination of these two policies.

6.1 Project Incentive Policy Simulations

First, I simulate scenarios where the state or federal government institutes a multiplicative penalty to water systems for any time spent in noncompliance. The EPA does currently use penalties to incentivize compliance behavior, but penalties are generally applied only to the most egregious offenders.[28] An alternative way of achieving a similar goal is to institute a policy that decreases the cost to water utilities from investing in infrastructure. The Drinking Water State Revolving Fund (DWSRF) is an existing government assistance program designed to financially aid water systems in meeting federal health-based water quality standards. As part of this program, states are able to institute their own criteria for receiving funds. In the second set of simulations, I simulate scenarios where either proactive or reactive projects are fully subsidized.

Figure 11 graphs the expected time in violation as predicted by the model estimates (the solid black line), and in the proposed counterfactual scenarios over 2007-2057. The blue dashed lines indicate the predicted average quarters spent in violation for a multiplicative penalty of two (the

[28] See Blundell et al. (2020) for an analysis of the dynamic application of penalties by the EPA.

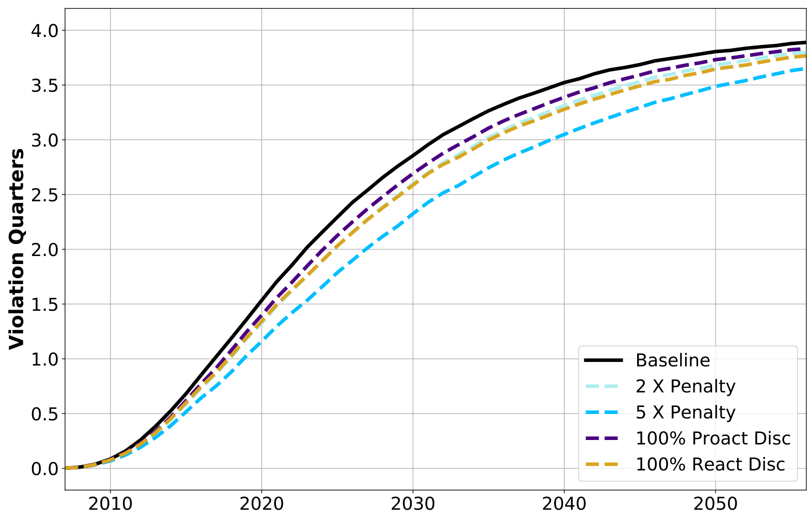


Figure 11: Counterfactual Expected Violation Quarters

Notes: Black lines depict the predicted average number of quarters spent in violation across all public water systems over 2007-2057 implied by the parameter estimates. The dashed blue lines portray the average number of violations expected under a penalty of two and five times the disutility to consumers respectively. The purple dashed line indicates the effect of fully subsidizing proactive projects, and the gold line indicates the effect of fully subsidizing reactive projects.

light blue dashed line), and five (the blue dashed line). There is little increased benefit from multiplicative penalties above five. At these penalty levels, any increase in the cost of spending time in violation no longer serves as an effective incentive to induce system managers into undertaking additional projects. Due to the average change in quality from an infrastructure project, the manager is not incentivized to invest in additional projects even under severe penalties because the expected effect of a project insufficiently reduces the amount of time in violation. This simulation indicates that, holding all else fixed, there is an upper bound on the ability of penalties imposed by the EPA to increase system managers' investment in infrastructure projects.

To explore the possible benefits of a reduction in project costs, I run simulations where the cost to a system manager from investing in a proactive or reactive project are eliminated while keeping the investment size the same. The effect of fully subsidizing proactive projects (the purple dashed line) and fully subsidizing reactive projects (the gold dashed line) are also graphed in Figure 11. The least effective policy is the complete subsidization of proactive projects. Making proactive projects free only provides a slight improvement over the baseline conditions. This is due to the overall decline in proactive investments as system quality falls to lower and lower levels. Free reactive projects are more effective at reducing the expected time systems spend in violation. As demonstrated in Section 5.3, it is optimal for system managers to invest in infrastructure just prior to entering into violation, at roughly $q = 47$. By subsidizing reactive infrastructure projects, managers undertake more projects close to optimal investment levels as they no longer face the costs from investing reactively. Over time, due to the low effect of investment on system quality, infrastructure continues to decay and managers slowly stop investing in reactive projects. Similar to the effect of increasing penalties for violations, eliminating project costs to incentivize investment

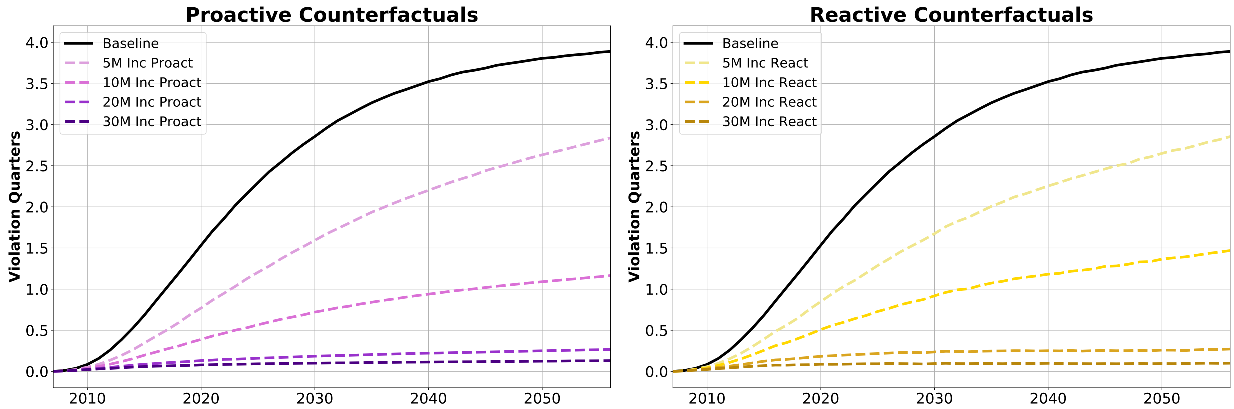


Figure 12: Counterfactual Expected Violation Quarters, Increased Investment

Notes: The left panel displays the expected violation quarters from 2007-2057 for different proactive investment levels, discounted to be free to system managers. The right panel displays the same information for reactive investments. The black solid line depicts the expected violation quarters in the baseline model.

is also unable to prevent system quality decline.

6.2 Altered Project Investment Levels

In the next set of simulations, I examine policies that increase the investment level for reactive and proactive projects, which I implement as an additive increase to the existing project size distributions. I first assess the effect of increasing project size on its own. For larger project investments, a single project increases infrastructure quality by a larger amount. But, without any additional incentives, system managers make fewer project investments. The increased expected benefit from making an investment is overshadowed by the increased cost to system managers. I then consider policies that combine increased project size with government subsidies that together increase the expected effectiveness of projects and induce additional investment.

Figure 12 graphs the expected quarters in violation under different levels of increased project size, with all investments completely subsidized. The left panel displays the anticipated average violation quarters resulting from increasing proactive project size by $5 million, $10 million, $20 million, and $30 million; the right panel displays the same for reactive projects. On average, policies targeting either proactive investment or reactive investment both appear to have similar effects. As the size of the project increases, the average expected time in violation across all systems declines. For a $30 million increase in proactive project size systems spend on average 0.09 quarters in violation each year over 2007-2057, or about eight days in violation annually. A $30 million increase in reactive project size results in systems spending on average 0.08 quarters in violation each year over 2007-2057, or about seven days in violation annually. Although these effects appear to be similar in aggregate, further examination of the distributional effects of these policies reveals that these policies can produce disparities in outcomes across systems.

Figure 12 depicts histograms for the number of systems that spend any years in violation over 2007-2057 under the proactive and reactive policies that increase project size by $30 million and fully subsidize costs. The left panel depicts the outcomes for systems under the proactive policy. In my simulations for a proactive investment-promoting policy, only a few systems spend time in violation. However, if a system spends any years in violation, they are likely to spend many years in violation—systems with violation years spend an average of 29 years with some time in violation of the simulated 50 years of data. The right panel depicts the same outcomes across all systems under the reactive policy. In this case, most systems spend some time in violation, but the average number of years with violations that any one system experiences is just over three out of 50 simulated years.

Proactive and reactive targeted policies have diverging distributional effects. By promoting only proactive investment, system managers are only incentivized to invest when the probability of a proactive project is high and the resulting change in quality level reduces future time spent in violation. Under this policy, system managers on average invest at quality levels around 50.1, which is slightly higher than the optimal timing for investment. This results in many systems maintaining infrastructure quality well above required levels. Unfortunately, if a system receives a particularly negative shock to quality managers are unable to recover through investment. Because reactive projects are still relatively small, even if managers continually invest after receiving a negative shock, they are unable to restore the equality of their system. In these conditions, systems are left unprotected against possible disasters. The results of my simulation are also based on an initial point in which very few systems are in a state of violation. If more systems start at lower qualities, then more systems spend long periods of time at very low levels of quality.

Under the policy that targets reactive investment, systems are incentivized to delay infrastructure projects until they are most likely to be reactive. The average quality at the time of investment under the reactive policy is 46.7, which is close to the optimal investment level of 47.3. However, under the reactive policy systems maintain quality levels that are also close to the first violation threshold, 44.6, which results in system qualities periodically dipping below this threshold, resulting in time spent in violation. For any system that experiences a drop in system quality, the effectiveness of an infrastructure project is now sufficient to bring quality levels back into compliance.

The primary difference between the two policies is in the distribution of violation risk. In the proactive focused policies, the risk of entering into a state of violation is concentrated in a few systems that are unable to escape long run states of violation. In the reactive focused policy, the risk of violation is distributed across all systems. Figure 14 plots the outcomes for two systems under the proactive and reactive policies. The conditions faced by these systems are the same in both simulations, the only difference is the subsidy policy offered to the system manager. In the top left panel, the manager invests proactively from the beginning of the simulation and remains at a high quality. In the top right panel, the system manager delays investment and ends up spending time in violation. In the bottom left panel, the system receives a negative system shock and is unable to repair the infrastructure damage with reactive projects. The bottom right panel shows that under the reactive promoting policy, the same system makes an effective reactive investment and spends almost no time in violation.

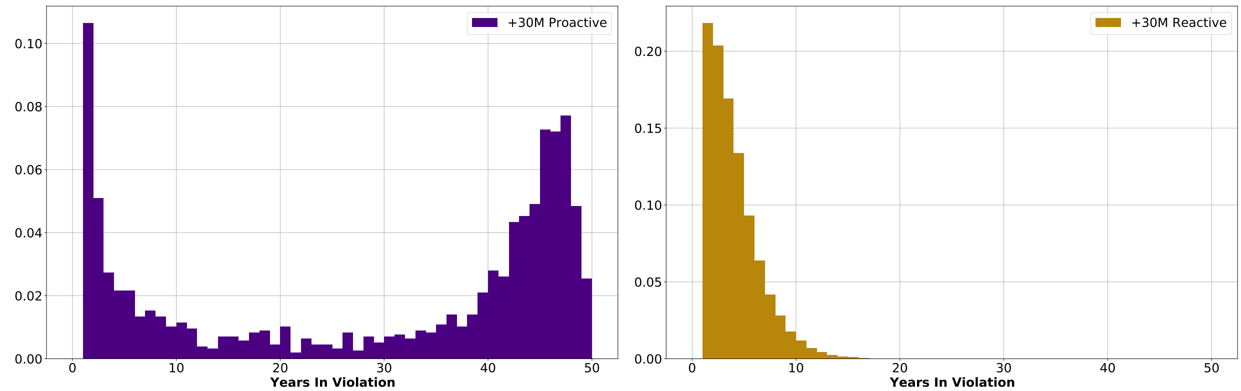


Figure 13: Counterfactual Systems with Violation Years

Notes: Both panels depict histograms for systems that spend any number of years in violation over 2007-2057. The left panel displays the outcome under a policy that focuses on proactive investment by increasing project size by $30M and subsidizing investment, the right panel displays the same for reactive projects. Under the proactive policy fewer systems spend time in violation, but the average system has 28.92 years with any time in violation. Under the reactive policy most systems spend time in violation, but the average system has 3.54 years with any time in violation.

7 Conclusion

In this paper, I provide a framework for analyzing infrastructure investment decisions and the effectiveness of proactive and reactive expenditures. I first establish that proactive and reactive projects are different and reduce the probability of a future health-based violation in distinct ways. I use empirical findings from a new dataset to motivate and estimate a dynamic discrete choice model of water system manager infrastructure investment. I find that smaller proactive investments are required to have the same increase in quality as larger reactive expenditures, implying that proactive investments are more efficient. I simulate the future expected outcomes for water systems and determine that at the current levels of investment, water systems will increasingly violate health-based quality standards. I find that policies targeting system manager investment behavior have different risks. Increased and subsidized proactive investment can enable managers to maintain quality levels well above standards but leads to overinvestment. At the same time some systems face dramatic, unrecoverable emergencies. Increased and subsidized reactive investment leads to all systems maintaining a constant low level of violation risk but reduces overspending and provides a safety net against massive system disasters.

My research has contemporary policy implications. On November 15, 2021, the Infrastructure Investment and Jobs Act of 2021 was signed into law. The Act provides $550 billion in federal support for public transportation development, passenger rail, highways and bridges, drinking and wastewater infrastructure, high-speed internet, power generating infrastructure, and electric vehicle charging stations. Much of this federal assistance will be used to upgrade existing infrastructure systems, yet the difference between reactive and proactive spending is neither mentioned nor considered in the Act. My results indicate that any policies targeting this distinction in system managers' investment decisions have important implications. A better understanding of this distinction could help policymakers to implement the funds allocated in the Act more effectively.

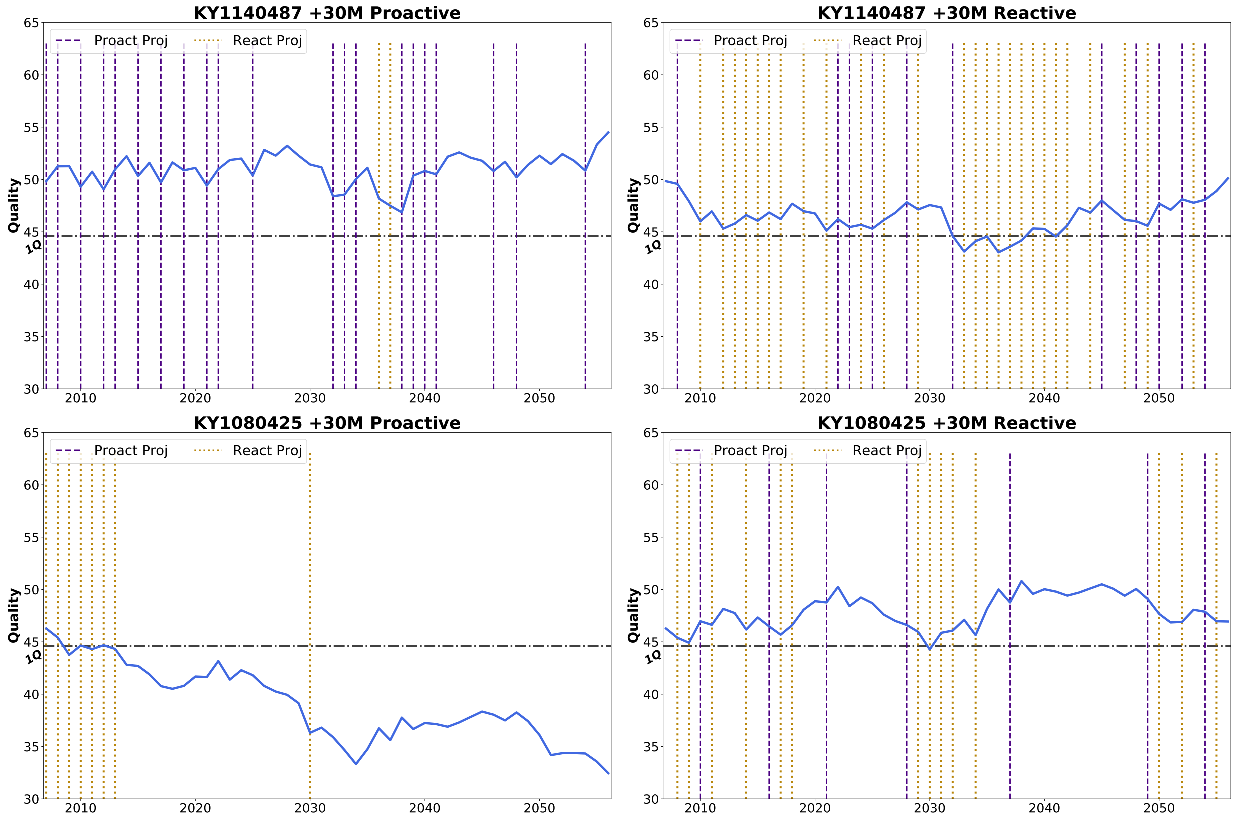


Figure 14: Counterfactual Quality and Timing of Projects

Notes: Solid blue lines plot simulated quality values, gold lines indicate reactive projects, purple lines indicate proactive projects. The horizontal gray line indicates the first threshold for a health-based violation. The left figures plot the projects and qualities for two different systems when subsidizing and increasing proactive project size by $30M. The right figures depict the outcomes for the same systems when faced with a policy that subsidizes and increases reactive project size by $30M. The top system remains above violation levels under the proactive policy, and occasionally experiences violations under the reactive policy. The bottom system receives a bad shock under the proactive policy and the system manager is unable to prevent the system's decline. Under the reactive policy, the same system recovers from the negative shock by investing in larger, effective reactive projects.

Some caveats to my results suggest directions for future research. I estimate my model using the water infrastructure investment decisions in Kentucky. Additional research can shed light on the applicability of my findings to other geographies and sectors, where managers may face different trade-offs. Furthermore, system managers are not the only decision makers involved in the infrastructure investment process. Through the DWSRF, states decide how to allocate federal assistance. Future research into the relationship between state and system manager decisions could provide a more complete picture of the entire investment cycle.

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Appendix

A Recursive Likelihood Algorithm Details

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

$$L_T(\theta) = \int \ldots \int p_q(q_0;\theta) P_{iy_rk_pk_ry_vq}\Big(\{i_t, y_{rt}, k_{pt}, k_{rt}, y_{vt}, q_t\}_{t=1}^{T} | \{i_0, y_{r0}, k_{p0}, k_{r0}, y_{v0}, q_0\};\theta\Big) dq_0 dq_1 \ldots dq_T \tag{A.1}$$

All transitions except for the progression of q, are independent, and the progression of q is determined by equation (2). As a result, the joint probability can be rewritten as follows.

$$\begin{aligned} &P_{iy_rk_pk_ry_vq}\Big(\{i_t, y_{rt}, k_{pt}, k_{rt}, y_{vt}, q_t\}_{t=1}^{T}|\theta\Big) = \\ &\prod_{t=1}^{T} p_{iy_rk_pk_ry_vq}(i_t, y_{rt}, k_{pt}, k_{rt}, y_{vt}, q_t | i_{t-1}, y_{rt-1}, k_{pt-1}, k_{rt-1}, y_{vt-1}, q_{t-1};\theta) \end{aligned} \tag{A.2}$$

$$\begin{aligned} &p_{iy_rk_pk_ry_vq}(i_t, y_{rt}, k_{pt}, k_{rt}, y_{vt}, q_t | i_{t-1}, y_{rt-1}, k_{pt-1}, k_{rt-1}, y_{vt-1}, q_{t-1};\theta) = \\ &p_{i|q}(i_t|q_t;\theta) p_{y_r|q}(y_{rt}|q_t, i_t;\theta) p_{y_v|q}(y_{vt}|q_t;\theta) p_{k_p}(k_{pt};\theta) p_{k_r}(k_{rt};\theta) p_q(q_t|i_{t-1}, y_{rt-1}, k_{pt-1}, k_{rt-1}, q_{t-1};\theta) \end{aligned} \tag{A.3}$$

Note that $p_{k_p}(k_{pt};\theta)$ and $p_{k_r}(k_{rt};\theta)$ are independent of q and are therefore pre-estimated and omitted from future representations of the likelihood function.

Incorporating the assumptions into the model, the likelihood becomes:

$$\begin{aligned} L_T(\boldsymbol{\theta}) = \int \ldots \int \prod_{t=1}^{T} \Big(&p_{i|q}(i_t|q_t;\boldsymbol{\theta}) p_{y_r|q}(y_{rt}|q_t, i_t;\boldsymbol{\theta}) p_{y_v|q}(y_{vt}|q_t;\boldsymbol{\theta}) p_q(q_t|i_{t-1}, y_{rt-1}, k_{pt-1}, k_{rt-1}, q_{t-1};\boldsymbol{\theta}) \Big) \times \\ &p_{i|q}(i_0|q_0;\boldsymbol{\theta}) p_{y_r|q}(y_{r0}|q_0, i_0;\boldsymbol{\theta}) p_{y_v|q}(y_{v0}|q_0;\boldsymbol{\theta}) p_q(q_0;\boldsymbol{\theta}) dq_0 dq_1 \ldots dq_T \end{aligned} \tag{A.4}$$

Rewriting the likelihood function:

$$
\begin{aligned}
&L_T(\theta) = \\
&\int \dots \int \prod_{t=1}^{T-1} p_{i|q}(i_t|q_t;\theta) p_{y_r|q}(y_{rt}|q_t, i_t;\theta) p_{y_v|q}(y_{vt}|q_t;\theta) p_q(q_t|i_{t-1}, y_{rt-1}, k_{pt-1}, k_{rt-1}, q_{t-1};\theta)\times \\
&p_{i|q}(i_0|q_0;\boldsymbol{\theta}) p_{y_r|q}(y_{r0}|q_0, i_0;\boldsymbol{\theta}) p_{y_v|q}(y_{v0}|q_0;\boldsymbol{\theta}) p_q(q_0;\boldsymbol{\theta})\times \\
&\left(\int p_{i|q}(i_T|q_T;\theta) p_{y_r|q}(y_{rT}|q_T, i_T;\theta) p_{y_v|q}(y_{vT}|q_T;\theta) p_q(q_T|i_{T-1}, y_{rT-1}, k_{pT-1}, k_{rT-1}, q_{T-1};\theta) dq_T\right) dq_1 \dots dq_{T-1}
\end{aligned}
\tag{A.5}
$$

Define the following at time $t = T$:

$$
\begin{aligned}
&E\Big[p_{i|q}(i_T|\tilde{q}_T;\theta) p_{y_r|q}(y_{rT}|\tilde{q}_T, i_T;\theta) p_{y_v|q}(y_{vT}|\tilde{q}_T;\theta)\Big| i_{T-1}, y_{rT-1}, k_{pT-1}, k_{rT-1}, q_{T-1};\theta\Big] = \\
&\quad \int p_{i|q}(i_T|q_T;\theta) p_{y_r|q}(y_{rT}|q_T, i_T;\theta) p_{y_v|q}(y_{vT}|q_T;\theta) p_q(q_T|i_{T-1}, y_{rT-1}, k_{pT-1}, k_{rT-1}, q_{T-1};\theta) dq_T
\end{aligned}
\tag{A.6}
$$

and at time $t = T - 1$:

$$
\begin{aligned}
&E\Big[\prod_{t=T-1}^{T} p_{i|q}(i_T|\tilde{q}_T;\theta) p_{y_r|q}(y_{rT}|\tilde{q}_T, i_T;\theta) p_{y_v|q}(y_{vT}|\tilde{q}_T;\theta)\Big| i_{T-2}, y_{rT-2}, k_{pT-2}, k_{rT-2}, q_{T-2};\theta\Big] = \\
&\int E\big[p_{i|q}(i_T|\tilde{q}_T;\theta) p_{y_r|q}(y_{rT}|\tilde{q}_T, i_T;\theta) p_{y_v|q}(y_{vT}|\tilde{q}_T;\theta)\big| i_{T-1}, y_{rT-1}, k_{pT-1}, k_{rT-1}, q_{T-1};\theta\big]\times \\
&\qquad \Big(p_{i|q}(i_{T-1}|q_{T-1};\theta) p_{y_r|q}(y_{rT-1}|q_{T-1}, i_{T-1};\theta) p_{y_v|q}(y_{vT-1}|q_{T-1};\theta)\times \\
&\qquad\qquad p_q(q_{T-1}|i_{T-2}, y_{rT-2}, k_{pT-2}, k_{rT-2}, q_{T-2};\theta) dq_{T-1}\Big)
\end{aligned}
\tag{A.7}
$$

Using this notation and working backward from $t = T$, the likelihood can be represented as:

$$
\begin{aligned}
L_T(\theta) = \int \Bigg(&E\Big[\prod_{t=1}^{T} p_{i|q}(i_t|\tilde{q}_t;\theta) p_{y_r|q}(y_{rt}|\tilde{q}_t, i_t;\theta) p_{y_v|q}(y_{vt}|\tilde{q}_t;\theta)\Big| q_0;\theta\Big]\times \\
&p_{i|q}(i_0|q_0;\theta) p_{y_r|q}(y_{r0}|q_0, i_0;\theta) p_{y_v|q}(y_{v0}|q_1;\theta) p_q(q_0;\theta)\Bigg) dq_0
\end{aligned}
\tag{A.8}
$$

B Identification Simulations

I simulate data to determine the robustness of the recursive likelihood integration (RLI) algorithm. First, I use simulations to generate a sample dataset for the 353 water systems over 50 years with known parameters of interest. Then I use the RLI algorithm on the simulated data to determine if the program is capable of recovering the true parameters. I also ran the algorithm on the data when holding the parameters of the initial q_0 distribution fixed but at incorrect values to investigate possible identification issues. Table B.1 contains a summary of my results.

Table B.1: Simulation Parameter Estimates

Parameter		True Values	Baseline	High Mean	Low Mean
Delay Consequences					
Consumer Disutility Weight	λ	10	9.707	8.061	13.602
			(1.000)	(0.301)	(0.999)
No Violation Threshold	q^*_{v0}	45	44.491	62.440	24.155
			(0.665)	(0.080)	(0.760)
1Q Violation Threshold	q^*_{v1}	44	43.185	61.440	23.147
			(1.000)	(0.078)	(0.665)
2Q Violation Threshold	q^*_{v2}	43	41.843	60.440	22.117
			(0.937)	(0.075)	(0.622)
3Q Violation Threshold	q^*_{v3}	42	40.557	59.441	21.061
			(0.916)	(0.076)	(0.602)
Reactive Project Threshold	q^*_r	47	47.156	65.307	26.843
			(1.045)	(0.091)	(1.720)
Project Effect on Quality					
Proactive Investment	α^p	0.1	0.120	0.158	0.097
			(0.025)	(0.006)	(0.026)
Reactive Investment	α^r	0.05	0.054	0.081	0.026
			(0.006)	(0.003)	(0.005)
Initial Quality Distribution					
Initial Quality Variance	σ^2_q	1.5	1.393	2.296	1.740
			(1.002)	(0.157)	(1.333)
Fixed Parameters					
Initial Quality Average	μ_q	50	50	70	30
Deterioration Rate	α^q	0.99	—	—	—
Neg. Log Likelihood					
ℓ		17177.967	16967.529	16917.805	17184.885

Notes: The estimation dataset simulates the behavior for 353 community water systems over 50 years.

The "Baseline" column depicts the results of the estimation when holding μ_q fixed at the same value used to generate the data. Under these conditions, the RLI algorithm is able to recover the remaining parameters. The algorithm slightly underestimates the threshold parameters but overall the estimates are close to the true values. In the other specifications, I hold μ_q fixed above the true value, and below the true value to determine the effect on the parameter estimates. Based on these tests, I conclude that the mean of the q_0 distribution determines the values of all the other parameters in the model. When holding the mean of the q_0 distribution fixed at 70, the thresholds for violation duration and reactive projects increase. Similarly, when holding the mean of the q_0 distribution fixed at 30, the thresholds for violation duration and reactive projects decrease. Additionally, the estimates for the effects of infrastructure projects on quality also follow the change in the initial quality level and the consumer disutility weight moves in the opposite direction. Based on this evidence, I conclude that μ_q is not identifiable, and hold this value fixed in the estimation of the model.

C Open Source Software

I use many open source resources in the completion of this project. I host my data locally in a postgreSQL database using the DBeaver client. The EPA data on water quality violations are sourced using the Enforcement and Compliance History Online (ECHO) API and converted to database tables. Most of the data cleaning and analysis is completed in python, using packages *numpy*, *scipy*, *pandas*, and *joblib* for parallelization. I employ *pyPDF2* and *selenium* in the WRIS data collection performed via web scraping and the reading of the subsequent pdf data.