A WORLD WITH MORE WATER:

THREE ESSAYS ON FLOOD DAMAGE AND CLIMATE CHANGE ADAPTATION BY U.S. LOCAL GOVERNMENTS

by

ROBERT HINES

(Under the Direction of Katherine Willoughby)

ABSTRACT

Unmanaged stormwater flows can threaten life, property, and the natural environment. Already damaging and deadly, flooding will only worsen as seas rise. Local governments are critical players in the inter-governmental effort to manage flooding and sea level rise. To adapt, local governments must invest in their infrastructure systems based on the complex risks and uncertainties underlying both flooding and sea level rise. This dissertation studies local governments' budgetary decision-making at the macro and micro scales through three empirical studies. The first study assesses local governments macro-budgeting decisions by modeling flood control investment based on the demand of the median voter. The first study tests if local governments invest in flood control infrastructure systems in response to either experienced damages, new information on their flood risks, or if they fail to invest in response to their risk at all. Results indicate that local governments decide to pursue flood control infrastructure in response to damages which they develop in response to new scientific information. The second study turns to the micro-level and investigates how local governments' public works directors would prioritize assets at risk of failure if seas were to rise through a decision-making experiment. Applying cumulative prospect theory, the second study argued that public works directors should be decreasingly sensitive to increases in assets' criticality and to changes in assets' probability of failure as the probability of failure departs from impossibility or certainty. However, the results show that works directors tended to exhibit risk aversion because they were decreasingly sensitive to both increases in assets' importance and probability of failure across the full range of failure probabilities. Finally, turning back to the macro-level, the third study developed cost-functions to test if systematic capital budgeting practices could improve local governments' cost-efficiency by improving the decisions surrounding stormwater investments. However, the third study indicates that while environmental and scale factors drive costs, neither master plans nor asset inventories improve cost-efficiency. Overall, investing in flood control, stormwater management, and sea level rise resiliency can improve public safety and water quality but requires the commitment of public and elected officials.

INDEX WORDS: Local government, Capital budgeting, Flood management, Risky decision-making, Sea level rise, Resiliency, Adaptation

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DEDICATION

Dedicated to Margaret Hines, Peggy Brice, and Luther Brice whose lifelong impact on students I can only hope to match.

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CHAPTER 1: INTRODUCTION AND LITERATURE REVIEW

Flood damages cost more each year than any other natural disaster in the United States and are only projected to worsen as seas rise (Government Accountability Office, 2021; National Academies of Sciences, Engineering, and Medicine, 2019). Even as floodwaters threaten life and property, untreated stormwater threatens our rivers, lakes, and other waters (National Research Council et al., 2009). Local governments manage stormwaters, mitigate floods, and, if they are near the coast, may be exposed to the risks of rising seas (Cigler, 2017; Grigg, 2013; Hines et al., 2022). Developing stormwater management infrastructure, flood mitigation measures, and investing in resiliency require local governments to finance capital projects. Theories of public budgeting have been framed as answers to V.O. Key's famous question, "On what basis shall it be decided to allocate x dollars to activity A instead of activity B?" (1940, pg. 1138). This three-essay dissertation seeks to explore the basis on which local governments choose to allocate financing to flood prevention, sea level rise resiliency projects, and stormwater management, examining resiliency decision-making at the organizational and individual levels.

First, this chapter reviews the literature on the responsibility of U.S. local governments for stormwater management and budgeting processes. Rubin's (2006) Real Time Budgeting is introduced as a framework for theory building that characterizes micro- and macro-level revenue, expenditure, balance, processes, and implementation outcomes as the result of individual actors making decisions in the context of their budgetary environment. The key distinguishing feature of budgeting for flood management and sea level rise is the probabilistic risk of future flood damage and the uncertainty that defines sea level rise. Within the context of this framework, voter demand, actor level, and process-based theories can help explain micro-and macro-based budgetary outcomes (Bartle, 2001; Bergstrom & Goodman, 1973; Holtz-Eakin, 1986; Rubin, 2016; Thurmaier & Willoughby, 2001; Wildavsky, 1964). Ultimately, the three essays in this dissertation offer three theoretical perspectives to help explain local governments' macro-level accumulation of stormwater and flood control infrastructure, individual public works directors' micro-level project prioritization decisions, and the macro-level stormwater management cost-drivers in local government budgetary environments.

The second chapter asks how local governments' macro-level decisions to accumulate flood control infrastructure are influenced by informational shocks. At the federal level, less is invested in disaster prevention than in response, despite the cost-efficiency of disaster prevention (Cigler, 2017; Congressional Budget Office, 2007). Voter myopia and informational asymmetries between voters and their elected officials have been blamed for this apparent pattern of underinvestment. However, because these two explanations produce observationally equivalent policy outcomes, it is not clear why voters fail to reward politicians who invest in disaster prevention rather than response (Gailmard & Patty, 2019; Healy & Malhotra, 2009). By modeling local governments' flood control capital stock acquisitions as the result of the median voters' demand for flood protection, this chapter tests whether local voters change their demand for flood protection in response to informational shocks that reveal their flood risks (Bergstrom & Goodman, 1973; Chen et al., 2019; Fisher & Wassmer, 2015; Holtz-Eakin, 1986).

Rational voters that invest in response to such new information may demand new infrastructure when Flood Insurance Studies (FIS) update the regulatory floodplain and reveal new flood risks (Government Accountability Office, 2021; Highfield et al., 2013). If voters are biased by their most recent experiences, flood damages may change their risk perceptions in the wake of a disaster, leading local governments to invest accordingly (Dumm et al., 2020;

Gallagher, 2014; Grether, 1980; Kahneman & Tversky, 1972; Volkman-Wise, 2015). Finally, voter myopia may prevent local governments from investing in response to either form of flood risk information. The second chapter develops a panel of Florida counties, from 2010 to 2019, to test for investments in new flood control and stormwater infrastructure due to 1) experienced flood damages or 2) new information from Flood Insurance Studies.

Turning to the micro-level, the third chapter explores how local government public works directors (hereafter PWDs) prioritize capital assets threatened by rising seas. PWDs, department leaders who formulate, prioritize, and ultimately implement their department's capital budgets (Felbinger, 1989), play a key role in micro-level resiliency investment decisions by working with elected officials during the budget process (Rubin, 2006). Taking a social judgment theory-based approach, this study, using an online experiment, asked public works directors to prioritize capital projects based on their key characteristics related to making adaptive investments. Assets at risk may have different levels of criticality, probabilities of failure if seas rise, future levels of adaptability, support from current elected officials, and alignment with strategic goals, and resiliency projects may have differing levels of cost efficiency. Across those criteria, PWDs will likely take either a more politically- or economically-oriented approach to decisions about investments (Thurmaier & Willoughby, 2001; Willoughby, 1991; Willoughby & Finn, 1996). However, the defining feature of sea level rise is its inherent uncertainty (Keenan, 2019; Price, 2019; Sweet et al., 2022)

A micro-foundations of project prioritization should be based on the ways that public works directors, in this case, navigate risk. Government assets carry different levels of sea level rise risk exposure and value. Tversky and Kahneman's (1992) cumulative prospect theory has emerged as a leading model of human decision-making under conditions of risk and uncertainty, explaining decision-makers' tendency to become decreasingly sensitive to the absolute size of gains and losses, and increasingly sensitive to probabilistic changes as they approach conditions of impossibility or certainty (Barberis, 2013; Ruggeri et al., 2020). It is not clear whether PWDs' risk preferences will 1) exhibit the non-linearities implied by prospect theory or 2) generate risk aversion, as has been observed in previous studies (Fennimore & McCue, 2021; McCue, 2000; Tversky & Kahneman, 1992). The Chapter 3 experiment tests if public works directors' risk preferences follow the predictions of cumulative prospect theory and characterizes their heterogenous preferences for project prioritization over those projects' degree of adaptability, cost-efficiency, strategic goal alignment, and level of support from current elected officials.

The fourth chapter investigates how the local government physical environment drives stormwater management costs, asking whether the engagement of systematic capital budgeting practices can improve cost-efficiency (Srithongrung et al., 2019). The normative capital planning literature considers master planning and asset inventories as key features of effective capital planning and budgeting processes (Ammar et al., 2001; Ebdon, 2004; Ermasova, 2020; Kim & Ebdon, 2020; Srithongrung, 2008; Srithongrung et al., 2019). Cost-efficiency for public organizations can be defined as their ability to achieve a given level of service using the fewest resources possible (Donahue, 2004; Duncombe & Yinger, 2011). With this in mind, this study develops public cost functions to test whether stormwater utilities with more complete asset inventories and stormwater master plans manage to reduce flood damages at a lower expense, given prices, service population, level of performance, and environmental conditions.

Finally, this dissertation concludes by reviewing the results of the three empirical chapters, before suggesting research implications for the politics of the budgeting process and flood control and stormwater management policy. The risk and uncertainty of stormwater management flood control differently impact local governments' budgetary decisions at the organizational and individual levels. Future research should address how scientific information impacts the sea level rise planning processes of local governments, and shift to evaluating local governments' responses to sea level rise.

Literature Review

Understanding stormwater management is critical: untreated stormwater pollutes water bodies and floods threaten human life and property (National Academies of Sciences, Engineering, and Medicine, 2019; National Research Council et al., 2009). The level of property damages caused by flooding can be severe. Major freshwater floods alone caused an annual average of $9 billion in damages between the years of 2004 and 2014 (National Academies of Sciences, Engineering, and Medicine, 2019). Yet, the challenge of flood management will only grow, as sea level rise exacerbates pressure on flood management systems in coastal areas and changing weather patterns complicate budgeting for flood prevention. In coastal areas, flood damages are expected to increase by two to three orders of magnitude by 2100, and substantial adaptive investments will be required to reduce regional risk exposure (Glavovic et al., 2022; National Academies of Sciences, Engineering, and Medicine, 2019; Oppenheimer et al., 2019). If communities fail to invest in adaptive measures, sea level rise may force millions of people along the U.S. coastline to migrate inland, potentially reshaping the nation's population (Hauer, 2017; Hauer et al., 2016). Due to these challenges, mitigating flooding and planning for sea level rise resilience matters more than ever.

Local governments are an integral part of the inter-governmental effort to mitigate stormwater pollution and flood damage (Cigler, 2017). The mission of local governments to drain urbanizing areas has led to modern stormwater management programs, which reduce the quantity and improve the quality of stormwater flows by engaging in stormwater best management practices (Environmental Finance Center, 2020; Grigg, 2013; National Research Council et al., 2009). In urban areas, improving stormwater quality is a legally delegated responsibility. Local governments classified as municipal separate stormwater systems (MS4s) have the responsibility to reduce stormwater pollution to the maximum extent possible (National Research Council et al., 2009). Local governments may complement drainage systems with a wider array of strategies for flood prevention, including 1) structural mitigation techniques and technologies like structural retention, channelization, and levees, and 2) soft mitigation techniques such as zoning codes, acquisition of public lands, and education (Brody et al., 2009). Such investments in flood mitigation programs can be highly effective. The Congressional Budget Office (2007) measured a 4:1 cost benefit ratio for FEMA's flood mitigation grant programs between 2004 and 2007; local governments investing in enough documented flood mitigation activities to increase their Community Rating System score reduced their average flood damages by $38,989 (Highfield & Brody, 2013).

Climate change will increase the challenge of stormwater and floodplain management for coastal local governments. As flood damages rise alongside sea levels, existing mitigation efforts may need to be redoubled. However, sea level rise represents challenges beyond flooding. Indeed, coastal local governments will need to consider sea level rise just to maintain current infrastructure systems. Critical buildings, stormwater drainage systems, water supply infrastructure, transportation networks, and other critical facilities may fail, or go insolvent, with rising tides (Allen et al., 2019; Fisk, 2019; Price, 2019).

The literature on local government investments in climate risk adaptations is relatively small, but growing. Early efforts to combat climate change centered around mitigating carbon emissions, to reduce the magnitude of future warming; now, however, as the impossibility of full mitigation becomes increasingly apparent, local and regional governments are, and will be, forced to adapt to localized threats (Moser and Boykoff, 2013; Mimura et al, 2014). Meanwhile, research on climate change adaptive planning is largely concentrated in the environmental planning literature. Given that Mimura and colleagues (2014) indicate much of the current investments in climate change adaptation have focused on large, physical adaptation projects, understanding the capital budgeting practices surrounding climate change will be useful.

A public finance literature has emerged on government response to climate change, based on the risks that sea level rise poses to localities' key capital assets and continued service provision (Akerlof et al., 2019; Allen et al., 2019; Fisk, 2018; Keenan, 2019). Adapting to sea level rise will require local governments to identify their risks, develop resiliency options, and eventually sequence adaptive actions for prioritization and funding in capital budgets (Hines et al., 2022). Fundamentally, local governments will need to allocate resources towards flood prevention and sea level rise resiliency through their budget process. The following section introduces a theory of budgeting for stormwater management, flood control, and sea level rise, to better illuminate local government resiliency investments.

A Framework for Budgetary Decision-making

The diverse set of theoretical perspectives offered to explain aspects of public budgeting can underpin theoretical explanations of local government decisions to finance flood and sea level rise resiliency. These perspectives have focused on voter demands, the individual human ability to process information, and the protocols that make up the public budgeting process. By capturing the political foundations of the budget process, voter demand models have successfully represented governments' overall and capital expenditures by the median voter's demand for public goods (Bartle, 2001; Bergstrom & Goodman, 1973; Holtz-Eakin, 1986; Salvino et al., 2012; Turnbull & Chang, 1998; Turnbull & Djoundourian, 1994). Such models have been extended to analyze capital budgeting decisions (Chen et al., 2019; Fisher & Wassmer, 2015). While median voter models well illustrate aggregate public spending and are easily estimated from commonly available data, their limited explanatory power fails to consider the institutions that ground budgetary processes, or the well-documented and rich interplay between boundedly rational public officials, departmental leaders, and budget examiners (Kearns & Bartle, 2001; Thurmaier & Willoughby, 200l; Wildavsky, 1964).

Incrementalist theories have demonstrated high empirical power by modeling budgets as the mostly stable result of routine budget processes, conducted by boundedly rational actors using prior budgets as reference points (Padgett, 1980; Wildavsky, 1964). Of course, budgets are not always stable; more modern theories, like punctuated equilibrium, have examined how institutional frictions, policy complexity, and organizational feedback can lead to periods of exceptional rather than incremental budget change (Epp & Baumgartner, 2017; Flink, 2017; Jones & Baumgartner, 2012). While these budget theories provide a political, behavioral, and institutional framework describing budgetary decision-making, they do little to track the unique characteristics of flood resiliency and sea level rise, as policy issues, across different budgetary outcomes. A larger theoretical framework is required to integrate the unique characteristics of stormwater management and sea level rise into broader theories of public budgeting.

Rubin's (2006) Real Time Budgeting (RTB) theory provides a framework for understanding budgetary decisions on the part of various relevant actors throughout the budget process. Rubin clarifies that budgets are open to the environment and influenced by shocks, changes in public opinion, and a government's economic environment. Budgetary outcomes are the result of actors making inter-related micro- and macro-decisions about expenditures, revenues, budgetary process, budgetary implementation, and budgetary balance. As the budget is prepared, approved, and eventually implemented, budgetary actors (e.g., department heads, members of budget offices, elected officials, citizens, and the courts) adjust their decisions about each stream while reflecting on past decisions and predicting future needs. Individual actors' decisions and strategies can be defined as micro-budgeting, influenced by broader revenue constraints, budget processes, and environmental conditions.

In the case of managing and implementing flood control, sea level rise resiliency, and stormwater management infrastructure, voters, elected officials, and public works directors will need to react to the changes in their environment. For instance, an elected official looking to make flood control or stormwater management improvements may also face an economic downturn, causing them to punt necessary, but easily delayed, investments. A damaging flood occurring mid-way through a budgetary cycle may alter actors' perceptions of flood risks, causing them to revisit the need for new flood control expenditures and rethink finance solutions by changing their balance decisions (by issuing debt) or revenue decisions (by increasing taxes or fees). Similarly, a flooding disaster may inspire a government to change its process decisions and invest in systematic capital budgeting practices like master plans and asset inventories. In each of the above examples, environmental conditions shocked budget actors into changing their perception of flood risks' importance, relative to 1) other budgetary decisions, 2) expectations for future flooding, and 3) their final budgetary decisions, in the streams described by Rubin (2006). Perceptions of flooding risks and future sea level rise are based on budgetary actors' decisions in conditions of risk and uncertainty. Ultimately, what differentiates explanatory budgeting theories for sea level rise and resiliency from general theories explaining the budgetary process are the environmental factors which define flood risks and the uncertainty of future sea level rise.

Drawing from Rubin's (2006) RTB model, governments' flooding-, and sea level rise-related budgetary decisions are framed by their environmental operating conditions. Flooding and sea level rise, as policy issues, are defined by conditions of risk and uncertainty likely to differently impact local governments decision-making at the macro, micro, and process-based levels. At the macro-level, local governments' aggregate capital expenditures are likely influenced by information on environmental flood risks. At the micro-level, public works directors play a key role in proposing, prioritizing, and protecting infrastructure systems that may be exposed to sea level rise, and will be forced to make risky decisions regarding threatened pieces of infrastructure (Felbinger, 1989). Similarly, local governments must plan for adequate infrastructure systems based on the physical nature of their environment. Expenditures on stormwater management systems depend on the physical conditions within which a government operates; its ability to cost-effectively deliver infrastructure may be improved by the real deployment of systematic capital budgeting processes (Srithongrung et al., 2019).

Political Representation and Macro-Budgetary Decision-making

At a macro-level, local government capital expenditure decisions can be modeled based on the demands of the median voter because they are decisive in local elections (Bergstrom & Goodman, 1973; Chen et al., 2019; Fisher & Wassmer, 2015; Holtz-Eakin, 1986). This model can be modified to include the unique nature of flood prevention as a risk. In the context of sea level rise, the demand for flood protection may result from the median voter's perception of flooding as a damage worth preventing. However, there is reason to believe that voters may not demand investments in flood mitigation. In what she calls the intergovernmental paradox of disaster management, Cigler (2007, 2017) notes that while local governments have the most responsibility for responding in the wake of a disaster, competing priorities and a lack of financial resources may cause their mitigation efforts to lag. While disasters or floods cannot be entirely prevented, some of their worst effects can be mitigated (Congressional Budget Office, 2007; Highfield & Brody, 2013). However, much more is spent at the federal level on response then prevention (Cigler, 2017).

Voter preferences may influence this lack of support for local-level preventative spending. As demonstrated by Healey and Malhotra (2009), voters tend to reward politicians for relief spending for disaster response, but not for disaster prevention. While Healey and Malhotra (2009) attribute this to voter myopia, Gailmard and Patty (2019) suggest that voters who want to prevent disaster and unnecessary, rent-seeking mitigation projects face an information asymmetry problem such that they cannot evaluate the efficacy of preventative infrastructure. Thus, their model suggests, voters ultimately thwart prevention by failing to support elected officials who invest current dollars to avert some future disaster (Gailmard & Patty, 2019). At the local level, the median voter may fail to support flood control measures due to either myopia or fears of the misappropriation of local funds.

However, underinvestment in flood control infrastructure may be based on voters' underweighting of low probability events. Making decisions under risk is challenging, and decision-makers are often subject to cognitive biases (Camerer & Kunreuther, 1989; Meyer & Kunreuther, 2017). When decision-makers' risk perceptions are based on experience, they tend to underweight the probability of rare events (Hertwig et al., 2004). This may be the result of the representativeness heuristic, whereby the occurrence of a disastrous event spikes decision-makers' perceptions of its likelihood, which fades over time (Dumm et al., 2020; Grether, 1980;

Volkman-Wise, 2015). Recency biases may contribute to an organization's relative lack of preparation for disaster, just as individuals tend to buy flood insurance policies in the wake of a damaging flood, only to cancel them as their memories fade (Gallagher, 2014; Volkman-Wise, 2015; Zhang & Maroulis, 2021). Similarly, flood events may spike the median voter's perception of flood risks and lead their government to invest in new flood control infrastructure.

Public Officials and Micro-Budgetary Decision-making

At a micro-scale, local governments must sequence adaptive projects into capital improvement plans for financing in annual budget cycles (Ermasova, 2020; Hines et al., 2022; Srithongrung et al., 2019). While high-level public budgetary negotiations set macro-level budgetary targets, decisions about specific capital outlays or line items are the result of complex interplay between elected and public officials (Thurmaier & Willoughby, 2001; Wildavsky, 1964; Willoughby, 1991; Willoughby & Finn, 1996). In the context of local governments adapting to sea level rise, public works departments' budgetary decisions are particularly important: these departments are responsible for potential threats to drainage, transportation, and water supply infrastructure systems (Allen et al., 2019; Fisk, 2019; Price, 2019). Local governments in Florida and across the southeast are beginning to invest in understanding their exposure to sea level rise risk and develop adaptive options (Grandage et al., 2023; Hines et al., 2022). However, it remains to be seen how governments will prioritize and sequence those policy options to preserve their infrastructure systems.

As department leaders, public works directors' risk perceptions and preferences will influence project selection (Felbinger, 1989). While decision-makers, when making decisions based on experience, tend to underweight the likelihood of rare events, basing those decisions on stated probabilities will likely lead them to overweight these odds (Hertwig et al., 2004).

Normatively, PWDs may use formal cost-benefit analysis to attempt to preserve the most important and vulnerable projects first. However, the uncertainty inherent in future levels of sea rise make this proposition difficult; further, decision-makers do not tend to make decisions from straightforward probabilistic calculations (Price, 2019).

Decision-makers tend to display non-linear preference patterns when making risky decisions (Price, 2019; Tversky & Kahneman, 1992; Wakker, 2010). Cumulative prospect theory integrates Kahneman and Tversky's (1979) insights from prospect theory with Quiggin's (1982) cumulative representation of uncertainty to capture decision-makers' tendency to 1) be risk averse for gains and low probability losses, 2) be risk seeking for high probability losses and high probability gains, and 3) exhibit a desire to avoid losses. Tversky and Kahneman (1992) captured this fourfold risk pattern by parametrizing decision-makers' non-linear preferences, with an S-shaped curve weighting the value of a risky outcome (convex for losses and concave for gains) and an inverse S-shaped curve for the probability of a risky outcome (concave for low probability outcomes and convex for high probability outcomes).

While prospect theory can thus capture risky decision-making, the unique nature of the public sector needs to be considered. Fennimore and McCue (2021) and McCue (2000) indicate that public financial managers tend to be strictly risk averse. Indeed, individual decision-makers often deviate from prospect theory, making choices best described by strictly convex, concave, linear, and inverse S-shaped probability weighting curves (Abdellaoui, 2000; Bruhin et al., 2010; Harrison & Swarthout, 2020; Quiggin, 2012; Van De Kuilen & Wakker, 2011). Thus, it is not clear how public works directors will approach risky project prioritization decisions.

Public Budgeting and the Natural Environments of Governments

Local government stormwater management macro-level outlays are based on the physical and economic features of the budgetary environment that drives their costs. As applied to the public sector, cost functions seek to uncover the minimum cost of delivering public services, at a certain level of quality to a given population, based on the environmental conditions driving costs and prices for labor, capital, and other critical inputs (Donahue, 2004; Duncombe, 1989, 1992; Duncombe & Yinger, 1993, 2011). While scholars have widely applied cost functions to understand the costs of fire prevention and education in the public sector, these have not been extended to stormwater management programs (Donahue, 2004; Duncombe, 1989, 1992; Duncombe & Yinger, 1993, 2011).

Cost functions can help explain how environmental factors impact stormwater utility costs. Stormwater utilities work to reduce public flooding and stormwater pollution caused by untreated stormwater flows (Grigg, 2013; National Research Council et al., 2009); regulated MS4s must work to reduce stormwater pollution to the maximum extent practical (National Research Council et al., 2009). Therefore, stormwater utilities with a higher proportion of property located in floodplains may face more intense stormwater flows and higher costs. Similarly, more urbanized regions with more impervious surfaces may deal with worse stormwater flows and quality, because pervious surfaces are not available to absorb excessive stormwater runoff (Arnold & Gibbons, 1996; Chabaeva et al., 2009; National Research Council et al., 2009; Sohn et al., 2020).

Local governments are not alone in their effort to mitigate stormwater pollution. Stormwater credits, which provide an incentive for citizens to reduce their own contribution to stormwater pollution, may reduce costs for local governments (Kertesz et al., 2014; Zhao et al., 2019). Cost functions provide a theoretical framework for modeling the impact of environmental factors, like impervious surfaces, on the cost of providing stormwater management programs, and allow for the identification of organizational cost-inefficiency as an organization's spending above the minimum cost of providing stormwater services (Donahue, 2004; Duncombe & Yinger, 2011).

It is possible that governments making better capital projects decisions at the micro-level can improve their cost-efficiency, achieving higher levels of performance while spending less (Donahue, 2004; Duncombe & Yinger, 2011). The systematic capital budgeting literature recommends 1) the use of master plans to sequence capital investments over time and 2) the development of complete asset inventories to guide both project selection and maintenance decisions over time (Ammar et al., 2001; Ermasova, 2020; Kim & Ebdon, 2020; Srithongrung, 2008; Srithongrung et al., 2019). While these practices are commonly recommended, relatively little literature directly examines their impact on economic or organizational outcomes, with the notable example of Srithongrung's (2008) paper. Theoretically, systematic capital budgeting practices should improve organizational cost-efficiency by guiding budgetary decision-making. However, there is not sufficient empirical evidence to say that they do so in reality.

Conclusion

Local government decisions to invest in flood control, stormwater infrastructure, and sea level rise resiliency depend on their navigation of risk and uncertainty. This dissertation seeks to explore the impact of local governments' environmental characteristics on their micro- and macro-budgeting decisions by applying three different theoretical perspectives on budgetary decision-making (Rubin, 2006). The second chapter studies how local governments invest in aggregate flood control infrastructure acquisitions decisions in response to the median voter's perception of flood risks. The third chapter studies how individual public works directors prioritize individual resiliency projects based on their risky characteristics. Finally, the fourth chapter explores how the physical conditions of local governments change the cost of providing stormwater services, and asks if systematic capital budgeting practices can improve micro-level budgetary decision-making sufficiently to reduce macro-level costs. Taken together, the three essays affirm the importance of studying budgetary decision-making from multiple angles to understand the diverse influences of the public, elected officials, departmental leaders and staff, and policy problems on budgetary outcomes.

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CHAPTER 2: LEARNING TO LIVE WITH FLOOD RISK: FLORIDA COUNTIES' ACCUMULATION OF FLOOD CONTROL INFRASTRUCTURE[1]

[1] Hines, R.E. To be submitted to the *Policy Studies Journal*.

Abstract

Flooding disasters are a leading cause of weather-related damage that federal, state, and local agencies and governments work to mitigate. Too often, however, governments seem to aim their efforts at flood recovery rather than flood prevention. Voter myopia and informational asymmetries between the public and the politicians who serve them have been blamed for the tendency to underinvest in flood mitigation. This study argues that governments adaptively invest in flood prevention by learning both from their own experiences with flooding and through the Federal Emergency Management Agency's Flood Insurance Studies (FIS). The results suggest that governments' ability to learn from scientific information is limited. While Flood Insurance Studies were associated with increased investment for counties which choose to invest in flood control infrastructure, experienced flooding, rather than Flood Insurance Studies, influenced counties' decisions to initially pursue flood control infrastructure investments.

Introduction

Disaster mitigation projects are highly cost-effective ways to save lives and property before disaster strikes (Cigler, 2017; Congressional Budget Office, 2007). However, substantially more is spent at the federal level on disaster response than prevention (Cigler, 2017). Voters seem to reward politicians who respond to disaster, but fail to provide that same support for prevention efforts (Healy & Malhotra, 2009). The apparent under-provision of disaster mitigation projects remains an ongoing puzzle. Is disaster mitigation consistent with a rational, biased, or myopic pattern of decision-making (Gailmard & Patty, 2019; Healy & Malhotra, 2009; Volkman-Wise, 2015)?

While floods are responsible for more damage and death than any other form of natural disaster, they can be managed through highly cost-effective flood mitigation efforts (Cigler, 2017). In fact, the U.S. Congressional Budget Office found that pre-disaster mitigation programs targeting floods and coastal storms from 2004-2007 prevented about four and a half dollars in future damages for each dollar invested (2007). Given the potential benefits of flood control projects, this paper sets out to understand if local governments' efforts to prevent flooding appear to be rational, biased, or myopic, by studying how they learn about their flood risk.

Governments can learn about their flood risk in several ways. First, the Federal Emergency Management Agency (FEMA) publishes Flood Insurance Rate Maps (FIRMS) for participating communities; these maps delineate flood risks and regulate floodplain management decisions (Highfield et al., 2013). The production of an updated FIRM occurs through a Flood Insurance Study (FIS) (Government Accountability Office, 2021). If governments plan their flood control investments rationally, an FIS, which produces new regulatory flood information, should serve as an informational shock, prompting new investments in flood mitigation that prevent newly delineated flood risks. Second, governments may learn about their risk of flooding through their accumulated experiences with disaster (Zhang et al., 2018; Zhang & Maroulis, 2021; Lee & Chen, 2021). However, such learning processes may be biased by the representativeness heuristic if governments overweight their most recent experiences (Dumm et al., 2020; Gallagher, 2014; Grether, 1980; Kahneman & Tversky, 1972; Volkman-Wise, 2015). If governments primarily invest based on their most recent and damaging flood experiences, they should react to instances of damaging flooding with additional flood control and stormwater investments. Third, governments may simply be myopic, failing to invest in response to either objective information on their flood risks or experienced damages (Healy & Malhotra, 2009).

This paper assesses how Florida's counties invest in flood control infrastructure capital stocks based on the demands of the median voter (Bergstrom & Goodman, 1973; Chen et al., 2019; Fisher & Wassmer, 2015; Holtz-Eakin, 1986). Counties' decision to acquire flood control infrastructure, or not, precedes their decision about how much infrastructure to acquire. The results of the study show that counties which flood more frequently, have more property at risk, and recently received updated flood maps were not more likely to have flood control infrastructure. Because counties with recent, damaging floods are more likely to have flood control infrastructure than those without, the median voter may be biased by the representativeness heuristic (Dumm et al., 2020; Gallagher, 2014; Grether, 1980; Kahneman & Tversky, 1972; Volkman-Wise, 2015). However, these results do not suggest that the median voter cannot make rational decisions. Among counties that choose to develop capital stocks, FISs tended to prompt renewed investments in flood control. Ultimately, counties appear to be responding to a two-part learning process, such that 1) instances of damaging flooding increase the median voter's perception of their flood risk, which 2) they update in response to new, objective information on the extent of their risks.

Literature Review

Managing Flooding at the Local Level

Studying local governments' investment patterns is critical, because they have the ability to implement cost-effective flood mitigation programs. While the federal government originally built and continues to operate many of the active primary flood control infrastructure systems in the United States and provides flood insurance through the National Flood Insurance Program (NFIP), localities play a critical role in mitigating flood damages (Cigler, 2017; Brody et al., 2010). Local governments build flood control infrastructure that directly reduces flood damages, can direct construction away from flood prone areas through zoning, and manage Community Rating System (CRS) programs that reduce flood risk (Cigler, 2017; Brody et al., 2010). Indeed, local mitigation can provide substantial protection against flooding. For example, communities that invested in CRS 530 activities, which include floodproofing individual buildings and building flood control systems, averaged approximately $320,000 in reduced flood claims in A-V flood zones in 2009 (Highfield & Brody, 2013).

The extent of local governments efforts to reduce flooding varies substantially. Brody and colleagues' (2009) survey of jurisdictions in Texas and Florida showed that local governments invest in a mix of structural and non-structural mitigation activities.[2] In terms of structural techniques, 72% of surveyed governments used structural retention, 50% used channelization, and 93% cleared debris from waterways to reduce flooding. A handful of governments went further, with approximately 15% reporting using their own dams and levees, and others using significant non-structural mitigation techniques that include planning, zoning, land use codes, and other outreach programs. Since local governments may develop multiple strategies to combat disastrous flooding, how do they learn what structural and non-structural mitigation techniques to build, adapt, or engage?

The Rare Event Problem

Different rational and irrational learning patterns have been used to describe how governments respond to the challenge to protect life and property before disaster strikes. While it seems natural to expect that governments plan for disasters based on rationally-derived expectation of potential future damages, it seems that, instead, they learn from their own experiences of disaster, through processes that are subject to bias (Berkhout, 2012; Camerer & Kunreuther, 1989; Zhang et al., 2018; Zhang & Maroulis, 2021). Risk and uncertainty challenge

[2] Structural flood control mechanisms involve engineered structures that reduce flood risk, such as traditional dams and levees. Non-structural (non-physical) interventions include land use controls, open space preservation, and green infrastructure solutions that increase natural on-site water storage during floods (Cigler, 2017; Brody et al., 2010).

human decision-making, and a wide number of cognitive biases and heuristic shortcuts have been shown to explain the idiosyncratic policies that sometimes emerge from decision-making conducted under conditions of risk and uncertainty (Camerer & Kunreuther, 1989; Meyer & Kunreuther, 2017). However, the conditions under which a government would take a forward-looking, rational approach to disaster prevention, learn from their experiences, or work towards adaptation through a biased lens are not clear.

Expected utility theory is the classic rational explanation for decisions made under risk and uncertainty. Normatively, the value of a probabilistic outcome can be determined by its expected value (Camerer & Kunreuther, 1989). If governments were to invest in disaster mitigation rationally, the value spent on mitigation should scale with future disasters' expected damages. Indeed, aggregated general capital investment decisions by local governments appear to be consistent with a rational model of decision-making. Governments appear to smooth their investments in capital infrastructure based on their expectations of future revenue levels (Holtz-Eakin & Rosen, 1989, 1993). Furthermore, local governments are more likely to participate in the CRS when the flood risks in their environment are greater (Landry & Li, 2012).

Learning-based theories of disaster mitigation begin by recognizing that organizations are constrained and may be unable to comprehensively identify and respond to risks. Generally, organizations with histories of disaster damage tend to expend the energy to mitigate future disaster, if they perceive their vulnerability and have the capacity to adapt and respond (Zhang et al., 2018; Zhang & Maroulis, 2021; Lee & Chen, 2021). Governments with histories of flood damages have been shown to invest in additional mitigation measures (Brody et al., 2010; Landry & Li, 2012; Li & Landry, 2018). Governments' constituencies can learn as well. Surveys show that people will tolerate taxes for enhanced disaster preparedness, and that those previously affected by hazards are more likely to be aware of and prepared for their general level of overall risk (Donahue, 2014; Donahue et al., 2014).

However, learning from disaster may require governments to overcome a great number of documented cognitive biases. Myopia, which can be defined as an irrational disregard for the future, and recency biases are particularly relevant for flood management: investments in flood mitigation pay dues to prevent future uncertain flooding, and floods are relatively infrequent events that may be forgotten over time (Camerer & Kunreuther, 1989; Meyer & Kunreuther, 2017). Humans have a fascinating tendency to overweight low probability events when making decisions based on stated probabilities, and underweight low probability events when making decisions from experience (Hertwig et al., 2004). A good way of thinking about recency biases is through the representativeness heuristic; this framework, introduced by Kahneman and Tversky (1972), argues that decision-makers subjectively evaluate events by overweighting the factors that make the event more representative of the population the event is drawn from. Testing this theory, Grether's (1980) experiments demonstrated that decision-makers can be thought of as biased Bayesians who weight new information over their accumulated experiences. It has been long noted that flood insurance markets experience cycles of low demand prior to disasters and high demand after (Gallagher, 2014; Volkman-Wise, 2015). Studies have successfully applied the representativeness heuristic to explain the demand for flood insurance and may explain decisions surrounding flood mitigation (Volkman-Wise, 2015; Dumm et al., 2020). Recent flood experiences seem to have a direct effect on mitigation activities, but their effect may be relatively slight or short-term (Brody et al., 2010; Li & Landry, 2018).

Governments have displayed elements of rational planning, adaptation, and bias in flood planning. Local governments across the United States work to mitigate flooding through the CRS and through their own initiatives (Brody et al., 2009; Highfield & Brody, 2013). Yet, there is evidence that voters tend to disregard preventive spending and may be myopic, or unable to discern appropriate investments in disaster prevention from unnecessary projects (Healy & Malhotra, 2009; Gailmard & Patty, 2019). Organizations seem to be able to learn from their experiences of disaster; while flood mitigation does scale, to a degree, with recent experiences, there may be a fading effect to experienced disaster (Brody et al., 2010; Landry & Li, 2012; Li & Landry, 2018; Zhang et al., 2018; Zhang & Maroulis, 2021). Rational voters' willingness to support politicians who invest in prevention, governments' ability to adapt to risks, and individuals' willingness to pay for flood protection all begin with their perception of flood risk (Gailmard & Patty, 2019; Zhang et al., 2018; Zhang & Maroulis, 2021; Zhai et al., 2006). The following section argues that governments are responsive to voters' demand for flood protection based on the median voter demand model of capital stock acquisition, and aims to test whether local investment patterns appear rational, biased, or myopic.

Theory and Hypotheses

The median voter demand model argues that governments' investments in capital infrastructure resolve to the demand function of the median income voter because their vote is decisive (Bergstrom & Goodman, 1973; Holtz-Eakin, 1986; Meltzer & Richard, 1981). Recent work has applied the median voter demand model to aggregate governmental capital expenditures and capital expenditures in different functional areas such as roads and water utilities (Fisher & Wassmer, 2015; Chen et al., 2019). If the median voter is myopic, or rationally demands underinvestment to prevent rent-seeking investments, they may demand that governments not invest in flood control infrastructure at all (Healy &Malhotra, 2009; Gailmard & Patty, 2019). This would represent a corner solution, whereby governments' total lack of investment maximizes the utility of the median voter who either does not care about future levels of flood risk or is attempting to prevent dishonest investments. Alternatively, voters may recognize the risk of flooding and demand that their governments invest in preventative measures allowing governments to pursue flood control projects (Gailmard & Patty, 2019). Either way, the supply of flood control infrastructure hinges on public perceptions of flood risk.

Willingness-to-pay studies show that a person’s willingness to invest in disaster risk mitigation, in general, and flood prevention, in particular, depends on their perception of risk (Zhai et al., 2006). In the case of flooding, the median voter must perceive flooding as a risk worth mitigating to demand it. Voters can become rationally informed about their susceptibility to flooding risk. FEMA publishes Flood Insurance Rate Maps (FIRMs) which delineate properties’ risks of flooding. Because flood risks are published in official sources, it is possible for citizens to rationally use the scientific information available to them to evaluate their flood risk (Gallagher, 2014; Volkman-Wise, 2015). If voters recognize their risk from flooding based on officially published information, then governments more at risk should be more likely to develop flood control infrastructure systems.

H1: Governments that are more exposed to flood risks are more likely to have flood control infrastructure.

Strategic governments should invest in capital stocks in proportion to the level of risk in their environment, based on the median voter’s demand. A FEMA Flood Insurance Study (FIS), as the basis for the community’s Flood Insurance Rate Map (FIRM), establishes an objective measure of flood risk for a county (Government Accountability Office, 2021). The FIRM establishes the Special Flood Hazard Area (SFHA), as well as other areas with different flooding risks (Government Accountability Office, 2021). FIRMS are especially likely to inform voters’ risk perceptions: the SFHA is the regulatory floodplain in which insurance purchase or floodplain management regulations apply (Government Accountability Office, 2021). However, flood maps are not updated on an annual basis and can become inaccurate in the years between updates (Highfield et al., 2013; Government Accountability Office, 2021).

FEMA has a statutory obligation to determine whether an area needs a new FIRM every five years, and works with state and local stakeholders to prioritize the most-needed investments (Government Accountability Office, 2021). Typically, areas with higher flood risks are more likely to receive a FIS (Government Accountability Office, 2021). Because FIRMs may reveal unmapped flood risk and can change the regulatory floodplain, FISs should act an informational shock that increases the public's perception of their flood risks. If the median voter informs themselves of their flood risk using scientific, official information, then the occurrence of an FIS should increase the probability that they demand infrastructure systems and lead to larger investments in flood control.

H2a: Governments' likelihood of investing in flood control infrastructure increases after experiencing an FIS.

H2b: Governments make larger investments in flood control infrastructure after experiencing an FIS.

Alternatively, governments may fail to behave in strategic ways. Given apparent underinvestment in prevention efforts relative to their cost efficiency, and voters' tendency to reward federal politicians more for relief than local disaster spending, the process of adaptation may be biased. According to Healey and Malhotra (2009), this tendency may be explained by voters' myopic disregard for the potential future benefits of protective infrastructure. However, as argued by Gailmard and Patty (2019), there is a notable potential for information asymmetries between political representatives and voters. These scholars lay out a model where voters are uncertain about the future probability of disaster and are unable to distinguish needed disaster prevention investments from unnecessary investments. Uncertain voters might select politicians who do not provide flood control infrastructure to avoid those who support unnecessary and potentially rent-seeking capital investments. Since informational asymmetries and voter myopia both result in disinvestment, they are indistinguishable unless disaster is almost certain or voters' risk perceptions are observable (Gailmard and Patty, 2019).

Some locations are much more flood prone than others and may have populations with different perceptions of potential flood damage. In some regions, flooding is a frequent occurrence, which might prompt investments in future flood protection. Countries that have a high propensity to experience disaster realize both fewer deaths and economic losses from the event (Neumayer et al., 2014), and regions that have experienced flooding tend to develop flood mitigation strategies (Brody et al., 2009; Landry & Li, 2012; Li & Landry, 2018). In places with historically high flood frequencies, voters will likely perceive the risk of flooding because they have experienced it themselves. If voters are myopic, governments will not invest in flood prevention even when their history of experienced disaster is high (Gailmard and Patty, 2019). Alternatively, if voters learn from their experiences of flooding, they will demand flood control infrastructure. Therefore, governments serving areas with histories of frequent flooding will invest in flood control infrastructure, thereby avoiding a corner solution in which flood control infrastructure is not provided.

H3: Governments that flood frequently are more likely to have flood control infrastructure.

Myopia is not the only bias that may drive investments aimed at reducing flood risks. Recent flood events have been shown to have small but independent effects on CRS flood mitigation activities, and insurance markets seem to feature under/over investment dynamics whereby populations seem to learn from their experiences of flooding before discounting them (Li & Landry, 2018; Dumm et al., 2020; Gallagher, 2014; Volkman-Wise, 2015). It is possible that voters experience a cognitively-biased learning process that can be modeled by the representativeness heuristic.[3]

The representativeness heuristic, as introduced by Kahneman and Tversky (1972) and refined by Grether (1980), argues that individuals tend to overweight prior information when making decisions about an events likelihood. Building on Grether's (1980) work, Volkman-Wise (2015) explains that a rational person might develop their beliefs about disaster through their experiences, in lines with Bayes' Rule, whereas a person biased by the representativeness heuristic would overweight their recent experiences when updating their beliefs. Given that the true probability of a disaster does not change from year to year, a Bayesian individual's beliefs about its likelihood should not change overmuch from year to year, as their accumulated prior experiences are weighted more heavily than recent flooding instances (Volkman-Wise, 2015). Alternatively, a person biased by the representativeness heuristic would overreact to recent experienced flooding (Volkman-Wise, 2015).

If voters' expectation of future flooding is partially based on experienced flooding, then observed flood damages should prompt capital investments, and the effect of those observed flood damages should fade over time. Given that flood insurance demand can be explained by

[3] The representativeness heuristic and the availability heuristic have both been used to describe time-based forgetting processes in different literatures because they describe similar concepts (Gallagher, 2014). In this case, the definition offered by Grether (1980) and Volkman-Wise (2015) is used for the representativeness heuristic.

the representativeness bias, and governments have been observed to underinvest in disaster mitigation, it is likely that expected flood damages are influenced by more recent flooding events (Dumm et al., 2020; Gallagher, 2014; Volkman-Wise, 2015). Therefore, flooding should lead to a period of increased flood control capital stock acquisition that fades over time, similar to the process by which organizational risk perceptions decay in the periods after a disaster (Zhang & Maroulis, 2021). If voters are biased by their recent experience, then a damaging flood should decrease the probability that governments fail to invest as a corner solution, and should increase governments' level of flood control infrastructure.

H4a: Governments likelihood of investing in flood control infrastructure increases after experiencing a damaging flood.

H4b: Governments make larger investments in flood control infrastructure after experiencing a damaging flood.

To differentiate between rational, biased, and myopic explanations of flood mitigation, this study analyzes how Florida's county governments acquire capital stocks in response to their level of objective risk, experienced FISs, flood damages, and flooding propensity. If counties' investments are rational and based on scientific information, then FISs should inform flood control investment decisions, and hypotheses H1 through H2 should not be rejected. Alternatively, if governments' investments in flood protection are based on experience, and the effect of past floods decline over time in line with the representativeness heuristic, hypotheses H3 through H4 should fail to be rejected. If hypotheses H1 through H4 are all rejected, then neither scientific information nor experienced flooding are sufficient to prompt investment. This outcome would imply that either voters are myopic or that an alternative factor prevents flood control investments.

Empirical Strategy

This study analyzes county governments in the state of Florida, which features a mix of urban and rural areas and coastal and non-coastal counties facing different types of flood risks. The state provides rich information on counties' flood control capital expenditures over time, and flood insurance claims, insurance policies, and weather events can all be reliably aggregated at the county level, making it possible to build a detailed and accurate statistical model (Dombrowski et al., 2020).[4] The median voter demand model for capital expenditures posits that communities' demographic, economic, fiscal, and political conditions influence their accumulation of capital stocks (Bergstrom & Goodman, 1973; Chen et al., 2019; Fisher & Wassmer, 2015; Holtz-Eakin, 1986). This study modifies the basic model by adding variables that capture the median voter's risk perceptions, driven by either available objective information on flood risk or experienced disaster. If voters are rational and governments invest strategically, flood control investments should be based on the objective level of flood risk in the county. Alternatively, biased investment patterns may be based on voters' shifting risk perceptions, as driven by their recent experiences.

In each period, the median voter may demand, or fail to demand, flood control infrastructure. Some counties choose to invest in flood control infrastructure capital stocks over time, but other counties may fail to invest in any infrastructure at all (Chen et al., 2019; Fisher & Wassmer, 2015). To capture counties' complete investment decision, flood control capital stocks should be modeled as the result of a non-linear process in which counties first choose whether to develop capital stocks, before investing, to match the extent of flood control protection demanded by the median voter (Wooldridge, 2010). In this context, corner solutions should be

[4] Multiple datasets were combined in R for this study using data.table, readxl, dplyr, and tidyr (Dowle & Srinivasan, 2022; Wickham, François, et al., 2023; Wickham, Vaughan, et al., 2023; Wickham & Bryan, 2022).

observed as the result of voter myopia or rational underinvestment. Counties which invest, and do not have a corner solution outcome, should invest and adjust their capital stocks to reflect the level of flood protection demanded by the median voter. Therefore, a hurdle model was used to first predict counties' decision to invest or not invest in flood control infrastructure and then predict counties' decision to select an appropriate level of infrastructure (Cragg, 1971; Wooldridge, 2010). As noted by prior studies on capital stock acquisition, governments respond to differing levels of demand for public services based on the characteristics of their communities and operate in diverse fiscal environments (Chen et al., 2019; Fisher & Wassmer, 2015). Therefore, this study controlled for the demographic factors driving the demand for flood protection, as well as governments' fiscal, economic, and policy environments.

Governments' flood control capital stocks were estimated at the county level, using the depreciated sum of each county's prior capital investments (Chen et al., 2019; Fisher & Wassmer, 2015). Florida's Local Government Financial Reporting Database consists of standardized accounting data submitted by local governments linked to specific account descriptions. Counties' capital outlays for stormwater management and flood control, pooled in the financial reporting dataset, were collected for the years 1993-2019 (Bureau of Financial Reporting, 2022; Florida Department of Financial Services, n.d.). Following Chen and colleagues (2019), flood control capital stocks were calculated as the sum of depreciated flood control capital expenditures, as shown in Equation 1.1.[5] The depreciation rate of flood control infrastructure was set to 1.52%, corresponding to the Bureau of Economic Analysis's estimated rate for non-building water, sewer, and other local government infrastructure systems (2003). For

[5] Flood control and stormwater capital stocks serve two purposes. This study is focused on local governments' response to flooding, but these systems also serve the important function of reducing pollution. The capital stock measure does also reflect the demand for pollution control, because these expenditures are sometimes made to accomplish both objectives.

each i government in fiscal year t, capital expenditures from the current year and the previous 14 years were used in the creation of the stock variable. This approximation works well: flood control systems may be long lived, and the aggregation allows for the estimation of flood control capital stocks from years 2007 on. Some governments choose not to invest in flood control infrastructure. As of 2019, 31 of Florida's 67 counties had no flood control capital stocks.

$$\text{Capital Stock}_{i,t} = \sum_{j=0}^{14} \text{Flood Control Capital Expenditure}_{t-j} \left(1 - .0152\right)^{j} \tag{1.1}$$

This study leveraged FEMA's published flood maps to calculate a risk index for the year 2019, and assessed counties' response to change in publicly-available risk information by studying their reaction to FEMA's FISs. The Special Flood Hazard Area (SFHA), made available for the entire state of Florida through the Florida Geographic Data Library's National Flood Hazard Layer (Federal Emergency Management Agency, 2019), is the extent of the 100-year floodplain with an expected 1% chance of flooding in any given year (Government Accountability Office, 2021). A flood risk index was calculated by overlaying the SFHA onto counties (Landry & Li, 2012; Li & Landry, 2018). In this case, the University of Florida's GeoPlan Center and the Department of Revenue provided a GIS file containing all the parcels in the state (Department of Revenue, 2021). For each county in 2019, QGIS was used to extract parcels touching or within the SFHA, and their just value was aggregated to give a measure of the property value at risk of flooding in each county. The property value at risk was normalized into per capita terms for comparability across counties and logged to adjust for skew. Since the occurrence of an FIS can change counties' estimated risk of flooding, FISs' effective dates were collected from FEMA's Map Service Center, and a binary indicator was generated, with a value of one, for each fiscal year in which a new FIS became effective for each county.

Governments' experience with disasters includes both flooding over time and the damage caused by destructive floods. Floods for each county in each year were aggregated from National Oceanic and Atmospheric Administration's Storm Events Database (n.d.). Each county's flood history was calculated as the average number of floods it experienced in the past ten years (Zhang & Singh, 2005). Not all floods are equally destructive, and it is reasonable to presume that voters would be more reactive to destructive floods.

The NFIP Flood Insurance Claims and Policies datasets were used to create a measure of flood damage exposure.[6] Each county's building and contents flood insurance claim payouts were aggregated per fiscal year to get a measure of flood damages per year (Dombrowski et al., 2020). To normalize the amount of flood claims per year to make damages comparable between counties, claims were divided by population to give a per capita measure. In many cases, counties experienced no flood damages in some years and extreme damages in others. The inverse hyperbolic sign (IHS) transformation approximates the log transformation while allowing for zeros (Bellemare & Wichman, 2020). To preserve the zeros while adjusting for skew, claims per capita were given the IHS transformation. Counties with a higher proportion of owners of flood insurance policies may invest in flood protection to reduce their constituents' premiums. Including flood insurance take up is critical, because counties may receive CRS points, which provide flood insurance discounts, for investing in flood mitigation infrastructure (Cigler, 2017; Brody et al., 2010). The NFIP Policies dataset was used to aggregate total building and contents coverage. The total value covered by NFIP policies was normalized into per capita terms and logged for skew.

[6] Flood policies and claims were bulk downloaded from FEMA. Note that, "This product uses the Federal Emergency Management Agency's OpenFEMA API, but is not endorsed by FEMA. The Federal Government or FEMA cannot vouch for the data or analyses derived from these data after the data have been retrieved from the Agency's website(s)" (FEMA, n.d.).

Supplemental variables were added to model each county's policy and fiscal environment. First, presidentially-declared disasters may make communities eligible for Hazard Mitigation Grant Program funding, which provides for future investments aimed at reducing disaster damages (FEMA, 2015). This study controlled for the number of active Hazard Mitigation Grant Programs, gathered from FEMA's Disaster Declarations Summary Dataset, to ensure that investments made due to flood damage were not the product of shifting grant funding availability. Similarly, the state of Florida provides stormwater grants to local governments, as recorded in the Local Government Financial Reporting Database (Florida Department of Financial Services, n.d.). Stormwater grants were given the IHS transformation for skew while allowing for zeros.

Local governments with poor fiscal health may be unable to invest in new stormwater and flood control infrastructure systems. Because balance sheet information over the panel period was unavailable, proxies were used to control for local governments' debt burden and reliance on intergovernmental aid. Following Chen (2019), who considered how local governments' own source revenue capacity and reliance on intergovernmental aid influenced their investment decisions, intergovernmental revenues as a percentage of all revenues were used to measure the county's dependence on external revenue sources outside of its control (Kioko & Marlowe, 2016). The effect of this variable is ambiguous. On one hand, governments dependent on external revenues may be unable to redirect their own resources to mitigation projects (Chen et al., 2019). On the other hand, grants and other sources of intergovernmental revenue may increase flood control capital stocks, because intergovernmental revenues tend to increase expenditures and are especially likely to be directed towards capital projects (Chen et al., 2019; Fisher & Wassmer, 2015; Wallin, 1996). Intergovernmental revenue dependency was measured by dividing the sum of each county's intergovernmental revenues by the sum of each county's total revenues.

As a measure of fiscal health, intergovernmental revenue dependency was supplemented with a measure of each counties' debt burden. Each county's total debt service as a percentage of expenditures was used as a coverage ratio measuring the extent to which the county is burdened by debt payments (Kioko & Marlowe, 2016).Theoretically, governments with existing high debt service burdens may face additional budgetary pressure, due to their need to pay more in principal and interest and avoid issuance of new debt and its future payment requirements. Nationally-representative survey evidence shows elected officials' concerns over debt affordability and potential future rate increases when deciding whether to invest in water infrastructure (Hansen & Mullin, 2022), which may extend to flood control infrastructure. This measure was calculated by dividing all debt service payments by total expenditures, using data from the Local Government Financial Reporting Database.

Socio-economic and demographic predictors follow from the literature on median voter demand models. Median income was included: the demand for flood control likely rises with income, and the property tax share of the median voter represents their tax price paid for increase in public services (Bates & Santerre, 2015; Bergstrom & Goodman, 1973; Chen et al., 2019; Holtz-Eakin, 1986). Higher tax shares indicate that the median voter must pay relatively more for new spending, and is therefore expected to lower the demand for flood protection. The tax share of the median voter follows from Chen (2019), measured as the median house value as a percent of the total just value of properties in that city (Florida Department of Revenue, n.d.; Manson et al., 2021). Data on median house value and median income (from the National Historic

Geographic Information System) were calculated using the American Community Survey's five-year moving averages which are available for all counties (Manson et al., 2021).

Demographic variables are commonly included in median voter demand models to capture the differences in diverse communities' tastes for public goods. This study includes the percent of the county population which 1) is white and not Hispanic, 2) is over age 65, 3) holds a bachelor's degree or higher, and 4) is in poverty (Bates & Santerre, 2015; Bergstrom & Goodman, 1973; Chen et al., 2019). Demographic data were sourced from the National Historic Geographic Information System and are again calculated from the American Community Survey's five-year moving averages (Manson et al., 2021).

Population density and the population growth rate are additional commonly included taste variables (Bergstrom & Goodman, 1973; Chen et al., 2019). In this case, they are likely to increase the demand for stormwater infrastructure, because denser areas likely benefit more from flood control systems and because growing areas likely require new flood control infrastructure for new developments. Population density was calculated as people per square mile; the growth rate was assessed as the percent change in population for that year. Similarly, since coastal counties' exposure to storm surge may drive a higher demand for flood control infrastructure, a dummy variable was included to capture counties' coastal status. Population density and growth rates were calculated from the University of Florida's Bureau of Economic and Business Research estimates and the United States Census' land area data (2010).

Finally, the political orientation of voters in each county may impact their taste for local flood control infrastructure. For example, local government officials in Michigan whose constituents were more likely to support the Democratic candidate for president were more supportive of climate policies; such voters may support flood control policies as way of improving resilience. Conversely, surveyed elected officials who were Republicans were less concerned about water supply infrastructure and skeptical of capital investments (Gerber, 2013; Hansen & Mullin, 2022). Therefore, this study used the share of votes received by the Democratic candidate for president in the last general election to measure the level of partisanship in the county, as provided by the MIT Election Data and Science Lab (2018). Table 1 contains descriptive statistics for the panel.

First, hypotheses 1 and 3, which argue that counties with more risk of flooding and more extensive flood histories should be more likely to have flood control capital stocks, were tested using a probit regression that models governments' acquisition of flood control infrastructure as of 2019. This model (shown in Equation 1.2 following the notation in Greene (2008)) is static: the complete National Flood Hazard Layer was unavailable for all years in the complete panel. The probability that each i indexed county has flood control infrastructure (y) is given by the logged value of property at risk of flooding per capita (r), historic flood frequency (f), the logged value of flood insurance policies per capita (n), the number of active hazard mitigation programs (h), intergovernmental revenue dependency (i), inverse hyperbolic sine transformed stormwater infrastructure grants (g), debt coverage (c), the tax share of the median voter (x), the median income (m), the percent of people in poverty (p), the percent white alone (w), the percent of people over 65 (s), the percent of people with a bachelor's degree or higher (b), the population density (d), the population growth rate (v), the democratic vote share (l), and coastal status (k). Each variable's impact is given by *B*, as indexed by the order of the variables in the model.

$$pr(y=1) = \text{probit}\begin{pmatrix} a + B_1 r_i + B_2 f_i + B_3 n_i + B_4 h_i + B_5 i_i + B_6 g_i \\ +B_7 c_i + B_8 x_i + B_9 m_i + B_{10} p_i + B_{11} w_i + B_{12} s_i + B_{13} b_i \\ +B_{14} d_i + B_{15} v_i + B_{16} l_i + B_{17} k_i \end{pmatrix} \tag{1.2}$$

Hypotheses 2a, 2b, 4a, and 4b were tested using a two-part model. Tobit or Cragg models, traditionally used for corner solution outcomes, rely on the strong distributional assumptions of normality and homoscedasticity for consistency (Wooldridge, 2010). To avoid relying on these assumptions, a more general two-part model was employed. First, a pooled probit regression was used to predict whether a county has flood control infrastructure in each year. Second, a pooled generalized linear model with a log link in the Poisson family was used to predict each county's level of acquired flood control infrastructure. Unlike the Tobit or Cragg model, the Poisson model is consistent so long as the independent variables correctly predict the expected level of capital stock (Wooldridge, 2010). While pooled models are less efficient than random effects formulations and do not allow for controlling time invariant unobservable effects, they are consistent even if lagged terms are included (Wooldridge, 2010). Cluster robust standard errors can be used to correct for serial correlation in the error term (Wooldridge, 2010).

The two-part model is shown in Equations 1.3 and 1.4, whereby each county is indexed by i and each year by t. In each case, capital stocks (y) were predicted by lagged flood damages (f) and their corresponding impacts (F), and lagged flood insurance studies (z) and their corresponding (Z) effects. The controls in Equation 1.3 follow Equation 1.2, except 1.3 and 1.4 exclude historic flood frequency, because flood events were captured through the lagged flood damage terms and include time effects (*t*). Stata's twopm package was used to estimate the two-part models (Belotti et al., 2015).

$$pr(y_{it} > 0) = \text{probit}\left(\begin{array}{l} \sum_{l}^{L}\left(F_l f_{i,t-l}\right) + \sum_{l}^{L}\left(Z_l z_{i,t-l}\right) + B_1 n_i + B_2 h_i + B_3 i_i + B_4 g_i \\ + B_5 c_i + B_6 x_i + B_7 m_i + B_8 p_i + B_9 w_i + B_{10} s_i + B_{11} b_i \\ + B_{12} d_i + B_{13} v_i + B_{14} l_i + B_{15} k_i + t_t \end{array} \right) \tag{1.3}$$

$$y_{it} \mid y_{it} > 0 = \exp\begin{pmatrix} \sum_{l}^{L}\left(F_l f_{i,t-l}\right) + \sum_{l}^{L}\left(Z_l z_{i,t-l}\right) + B_1 n_i + B_2 h_i + B_3 i_i + B_4 g_i \\ + B_5 c_i + B_6 x_i + B_7 m_i + B_8 p_i + B_9 w_i + B_{10} s_i + B_{11} b_i \\ + B_{12} d_i + B_{13} v_i + B_{14} l_i + B_{15} k_i + t_t \end{pmatrix} \tag{1.4}$$

The two-part model presented in Equations 1.3 and 1.4 may have several limitations. Primarily, it does not control for unobservable effects. Second, there may be a simultaneous relationship between flood control capital stocks and flood damages. High quality flood control stocks should prevent flood damages. If governments fail to invest, then there may be an observed negative relationship between flood damages and capital stocks, because observed damages are higher when capital stocks are underdeveloped. However, with a valid instrument that explains flood damage, but not infrastructure acquisition, testing for and correcting endogeneity is possible via the two-stage residual inclusion method.

Results

Testing for Endogeneity

Two-stage residual inclusion can be used to test and correct for endogeneity. Terza (2008) suggests that endogeneity in a second stage linear or non-linear regression can be consistently corrected by including the endogenous variable alongside a residual from a linear or non-linear first stage regression with a valid instrument. Endogeneity arises due to the correlation of the endogenous variable with the error term. Including the residual from the first stage regression controls for this endogeneity (Terza et al., 2008; Wooldridge, 2015). While two-stage residual inclusion and two-stage predictor substation are identical in linear models, only two-stage residual inclusion methods are generally consistent for non-linear models (Terza, 2008).

Two-stage residual inclusion provides a robust test for endogeneity. If the included residuals are significant in the second stage regression, then the null hypothesis that there is no endogeneity is rejected and correction for endogeneity is required (Terza et al., 2008; Wooldridge, 2014, 2015). This endogeneity test is robust, in the sense that correction for the two-stage nature of the estimation is not required, the test can be made robust to heteroskedasticity, and the first-stage model for the endogenous variable need not be correctly specified for the specification test to be valid (Wooldridge, 2014). If a linear functional form is available in the first stage, the residual from an ordinary least squares equation can be used (Wooldridge, 2014). However, if there is discreteness in the endogenous variable such that the endogenous variable is the result of a corner solution, then a more powerful test can be based on the generalized residual from a Tobit model (Gourieroux et al., 1987; Vella, 1993; Wooldridge, 2014). If the correction for endogeneity is required, then the generalized residual from the first-stage Tobit model can be used to correct for endogeneity, and bootstrapping can be used to correct for the two-stage nature of the estimation (Wooldridge, 2014).

The occurrence of hurricanes and tropical storms were used as instruments to predict current and lagged flood damages. Hurricanes cause flood damages but should not independently impact the median voter's demand for flood control infrastructure. If hurricanes cause damage, the median voter's perception of flood risks should rise because they experienced the impact of flooding on their community. However, if the hurricane fails to cause flooding, then the median voter's perception of flooding risks in their community should not change, since there would be no associated damage to change their perception of flooding risks. The current study used the count of hurricanes experienced by a county in each year, according to National Weather Service records, as an instrument.

There must first be a flood for there to be flood damages. Of the 666 observations for each county in each year of the panel, approximately 35% failed to experience flood damages. Therefore, the first-stage regression should take the form of a Tobit, because damages are partially discrete. While a linear first-stage model can be used to construct a valid test for endogeneity, the discreteness in flood damages indicates that a test based on the generalized residuals is more powerful (Wooldridge, 2014). Therefore, endogeneity tests were conducted with the generalized residuals from a first stage Tobit model, calculated following the notation of Vella (1993) and Wooldridge (2014). If flood damages equal zero, the generalized residual is given in Equation 1.5 such that the generalized residual $\hat{g}_{i,t}$ is the result of the estimated standard deviation from the Tobit model, which is denoted by σ, multiplied by -1 and the inverse mills ratio, denoted λ, of the linear prediction using all exogenous variables, which is denoted as *XB*.

$$\hat{g}_{i,t} = -\sigma\lambda(-XB) \tag{1.5}$$

When flood damages exceed 0, the generalized residual is simply the given flood damages, denoted *y*, minus the linear prediction, as shown in Equation 1.6.

$$\hat{g}_{i,t} = (y - XB) \tag{1.6}$$

A test for endogeneity was performed, using the generalized residuals from a Tobit model as regressors alongside the endogenous variables and exogenous variables in the two-part model, because it has the most asymptotic power (Wooldridge, 2014). The two-part model is composed of a probit model and Poisson model that are assumed independent. The Poisson model has 44 clusters, since only 44 of the 67 counties invested in flood control infrastructure. Therefore, separate first-stage regressions were performed to calculate generalized residuals for the probit model, using the full set of 67 counties, and the Poisson model, using the set of 44 counties with infrastructure. The results from the first-stage Tobit models are shown in Tables 2 and 3 at the end of this chapter, which include separate regressions for IHS flood claims per capita, lagged IHS flood claims per capita, and the second lag of IHS flood claims per capita, which use the count of hurricanes, the lagged count of hurricanes, and the twice-lagged count of hurricanes as instruments, respectively. Hurricanes are strong instruments when used to test for endogeneity in the probit model. The first-stage F statistics for hurricane counts, lagged hurricane, and twice-lagged hurricane counts are 35.27, 24.09, and 22.74 when all 67 counties are included. Hurricanes are a weaker instrument when used to test for endogeneity in the Poisson model, as the first-stage F statistics do not all meet the common rule of thumb for instrument strength of 10. The first-stage F statistics for hurricane counts, lagged hurricane counties, and twice-lagged hurricane counts are 16, 9.46, and 6.38. Therefore, the test for the endogeneity of twice-lagged IHS flood damages in the second stage of the Poisson model may suffer from somewhat weak instruments.

Ultimately, correcting for endogeneity is not necessary. Table 4 below includes the generalized residuals from the Tobit first stage alongside the other predictors for the probit and Poisson models, respectively, and was calculated with cluster robust standard errors. No correction was made for the two-part nature of the estimation, because it is not required under the null hypothesis that IHS flood damages are exogenous (Wooldridge, 2014). As shown in Table 4, none of the included generalized residuals are significant in either regression. A chi squared test for the joint significance of the residuals in the probit model fails to reject the null hypothesis that IHS flood claims per capita or its lags are exogenous, with an associated p-value of .66, and a chi squared test for the joint significance of the generalized residuals in the Poisson model fails to reject the null hypothesis that IHS flood claims per capita and its lags are exogenous, with a p-value of .36. Since the correction for endogeneity is not necessary, the analysis proceeds without it from the pooled two-part model.

Hypothesis Testing

Different learning processes appear to drive counties' decision to initially invest in flood control infrastructure and the amount that they ultimately acquire. Results from the two-part model suggest that the median voter tends not to be myopic but may be biased by the representativeness heuristic when deciding whether to demand or not demand flood control infrastructure. However, once the median voter demands flood control infrastructure, new information on the extent of flooding from FISs tends to increase the amount of flood control infrastructure that they demand.

First, H1 and H3 proposed that counties with a greater amount of flood risk and more extensive flood histories should be more likely to have flood control infrastructure. The probit modeling counties' acquisition of flood control capital stock, shown in Table 5, reveals that H1 and H3 are not supported. Neither counties with 1) more property at risk per capita or 2) more floods per year were more likely to have flood control infrastructure. These results held even when the policy value at risk per capita was dropped from the regression. It is important to note that the probit model for 2019 featured one completely determined success. However, as shown in Table 6, the results from a logistic regression are similar, and did not suffer from overdetermination. These results suggest that voters in some counties may be myopic, because either they did not experience flooding or their measured risk of flooding increases their probability of having flood control infrastructure. However, a different learning process may be at play, in which the median voter responds to informational shocks.

Flood control infrastructure is more likely to be provided in counties which experienced recent, large damaging floods but not recent FISs. H2a and H4a posited that informational shocks in the form of FISs and damaging floods, respectively, should make counties more likely to develop flood control infrastructure. The results of the two-part model appear below in Table 7. As shown in the Probit results in column 1, new information from an FIS in the current period or near past is not likely to increase a county's probability of developing flood control capital stocks. Thus, H2a is rejected. However, H4a is not rejected. Counties which experienced a damaging flood two years ago were significantly more likely to have flood control infrastructure than those which did not. In fact, there is 95% confidence that a county which experienced a large flood causing $40.00 in per capita claims two years prior was 1-18% more likely to have flood control than a county which had experienced no damages.[7] While the median voter's initial decision to demand flood control infrastructure does not appear to be influenced by FISs, recent flood events may spark voters to update their beliefs about their exposure to disaster risk. This pattern of decision-making implies that the median voter learns from their experiences but may be biased by the representative heuristic.

While disastrous floods may prompt counties to increase their likelihood of developing flood control capital stocks, FISs act as an informational shock which increases counties' level of flood control capital stocks. H2b and H4b argued that FISs and damaging flood events should increase counties' capital stock accumulation by raising the median voter's perception of flooding risks. H2b is not rejected. As shown in Table 7, counties experiencing an FIS had significantly higher flood control capital stocks in the year the study took effect and the two

[7] This confidence interval was calculated by taking the mlincom command provided by Long and Freese (2014). Per capita county claims of $40.00 is roughly the 95th percentile of the claims distribution and corresponds to IHS transformed per capita claims of 4.382. The 95th percentile was chosen for interpretation because it corresponds to an unexpected, disastrous flooding event.

following years, at the .05 level. Because counties had vastly different levels of flood control infrastructure, this variable is best interpreted in percent terms. With 95% confidence, counties in which an FIS took effect had between 1.7% and 71% larger flood control capital stock, counties in which an FIS took effect in the prior year had between .86% and 101% larger flood control capital stocks, and counties in which an FIS had taken place two years prior had between 3.2% and 101% larger capital stocks.[8] While the effect of an FIS was estimated imprecisely, it has the potential to be quite large.

Contrary to expectations, H4b is not confirmed: the second lag of IHS flood claims per capita is significantly positive, with a p-value of .05. On the raw scale, the average county which experienced flood damages of $40.00 per capita had capital stocks that were approximately $776,700 to $13,342,300 lower than the average county which had not experienced any flood damages.[9] This relationship may reflect the two-stage nature of the estimation procedure. Counties which recently experienced large flood damages were also more likely to develop capital stocks; these may appear to be lower because they were making initial investments as a part of a long-term plan to improve their flood control infrastructure.

Of the 67 counties in Florida, 23 failed to invest in flood control infrastructure at all. The results in Table 7 indicate that these counties may be constrained by fiscal limitations. Counties with high levels of poverty and high tax prices were less likely to develop infrastructure. These results are intuitive. As the price of public services rises, the demand for public services should fall, and areas with higher levels of poverty have less resources and a greater need to direct resources elsewhere. Unexpectedly, counties with overall higher median incomes by the coast were less likely to develop infrastructure. While it seems counterintuitive that the median voter's

[8] Reported 95% confidence intervals are for the average marginal effect interpreted as a percent change.
[9] This confidence interval was calculated by taking the mlincom command provided by Long and Freese (2014).

demand for flood control infrastructure falls with their income, other explanations may exist. In areas with inequality, where both the median income and poverty are high, the median voter may prefer to purchase insurance. Some coastal counties may be less likely to develop flood control infrastructure due to geographic idiosyncrasies and/or may not be primarily responsible for coastal areas, which may be served by cities. Finally, counties which received a stormwater grant were more likely to develop flood control capital stocks, at the .071 significance level.

Once counties choose to invest in infrastructure, a different set of variables explain the level of flood protection demanded. Denser, growing counties on the coast invested significantly more in their capital stocks. This result is intuitive, because growing and dense coastal areas likely have a strong need for new flood control infrastructure. Interestingly, the main demographic variable predicting the extent of flood control developed is the percent of people who are college educated. It is possible that more educated populations are better able to consume information on their flood risks. Finally, counties increased their flood control capital stocks as the percent of revenue they received from intergovernmental sources grew.

Robustness Checks

Several robustness checks were conducted to certify the results. First, though many included control variables were found to be insignificant, dropping them does not change the tests for H1-H4b. As shown in Table 8, H1 and H3 are still rejected after dropping insignificant controls. Table 9 reveals that H2a and H4b are still rejected and H2b and H4a are still not rejected, at least the .05 level, after dropping insignificant controls other than year effects. Similarly, a simpler ordinary least squares regression on logged capital stocks produces the same results. Table 10 uses Cragg’s Lognormal Model to show that the tests for H2a, H2b, H4a, and

H4b are not affected by modeling log capital stocks using a linear regression rather than modeling the raw capital stocks with the Poisson model.

Additional endogeneity testing was conducted as well, as illustrated by Tables 11-13; a residual inclusion test for endogeneity used the raw residuals from a first-stage linear model rather than the generalized residuals from the Tobit. As with the latter result, the null hypothesis that IHS flood claims per capita is exogenous is not rejected. The chi squared test for the joint significance of the residuals in the second-stage Probit is not rejected, with an associated p-value of .59, and the joint significance of the residuals in the second-stage Poisson model is not rejected, with an associated p-value of .43. While correcting for endogeneity is not necessary, a cluster pairs bootstrap procedure was performed to test whether correcting for endogeneity changes the results of the hypothesis tests. Table 14 presents the results of a cluster pairs bootstrap, with 5,000 bootstrap replications in Stata, using code adapted from Terza (2016); these results suffer from a dramatic loss of efficiency. Only the percentage of people living in poverty explains the initial decision to acquire flood control infrastructure and only the second lag of Flood Insurance Studies significantly explains the amount of flood control demanded. This provides additional confirmation that FISs lead to infrastructure investments in counties which choose to supply flood control. However, IHS flood claims per capita no longer explain flood control infrastructure acquisition decisions.

Discussion

Conflicting interpretations of governments' disaster prevention efforts have portrayed disaster response decisions as myopic, cognitively-biased, and potentially rational (Gailmard & Patty, 2019; Healy & Malhotra, 2009). The balance of evidence in this study suggests that counties' flood control investment patterns are the result of a decision-making process that either results in a corner solution whereby flood control infrastructure projects are not undertaken, or an outcome in which flood control infrastructure projects are pursued based on changes in scientific information. Destructive flooding incidents may allow flood risks to be identified such that 1) local governments take the first step in investing in new flood control infrastructure and 2) those with existing stocks respond to Flood Insurance Studies with enhanced capital investment. It does not appear that local investment patterns are myopic. Rather, learning processes are driven by a combination of reactive investments based on experienced disaster and changes in the understood risk in a government's environment.

If voters were truly myopic or rationally failed to support preventative investments, then local governments would fail to mitigate flood damages (Gailmard & Patty, 2019; Healy & Malhotra, 2009). Yet, governments across Florida and Texas employ both structural and non-structural techniques to mitigate flooding (Brody et al., 2009). Such investments must be the result of the demand of local voters and imply that voters in some locations must perceive and respond to flood risks. Experienced flood damages may act as a shock, prompting the median voter to demand flood control infrastructure (Dumm et al., 2020; Grether, 1980; Volkman-Wise, 2015; Kahneman and Tversky, 1972). Similarly to this study, Brody and colleagues (2010) found that flood damages tend to prompt investments in structural mitigation, and Li and Landry (2012) found that histories of flooding prior to the creation of the CRS made participation in the CRS more likely. The net result of this study and the literature on flood mitigation indicate that voters are unlikely to be myopic and may rationally demand flood control infrastructure when they perceive the risk of flooding due to their experiences with flooding (Gailmard & Patty, 2019; Healy & Malhotra, 2009).

Future research should continue to assess how flood damages shocks differ from accumulated flood experiences. Importantly, Brody and colleagues' (2010) results differ from those of Landry and Li (2012): Li and Landry (2012) did not find that flood damages prompted counties to be more likely to participate in the CRS. The apparent discrepancy may occur because CRS participation is more akin to non-structural mitigation, which is triggered by histories of flood damage rather than shocks (Brody et al., 2010). This paper looks at the accumulation of flood control infrastructure, which may represent structural mitigation techniques, and finds that flood damages are shocks which prompt investments in flood control infrastructure. It would be interesting to examine how experienced histories of flooding might differently impact voters' risk perceptions, as compared to shocks, and how those risk perceptions connect to implemented policy. It is possible that non-structural techniques require more political capital and long-term support from voters who are cogent of their flood risks due to repeated instances of flooding. Li and Landry (2018) do not find that flood damages prompt meaningful increases in counties' acquisition of CRS points. However, this apparent discrepancy makes sense if flood damages prompt voters to demand flood protection in line with the scientifically available information on their risks.

Prior studies have demonstrated conflicting findings as to whether or not physical risk factors drive flood investments (Brody et al., 2010; Landry & Li, 2012; Li & Landry, 2018). By using FISs as a shock, this study does demonstrate that changes in the level of scientifically-revealed risk prompt investment, and imply that physical risk factors should increase governments' level of flood mitigation activities to the extent that they are incorporated into available measures of flood risk. However, the accumulation of flood control infrastructure in response to documented physical risk is more likely among voter who perceive their flood risks due to shocks or their accumulated experiences with flooding demand protection, as shown in the results of this study (Brody et al., 2010; Landry & Li, 2012; Li & Landry, 2018).

From a policy perspective, the results in this study have an encouraging takeaway for flood control management and policy. Information can matter to governments willing to put it to use. Normative frameworks for capital budgeting, sea level rise adaptation, and the combination of the two indicate that data generation and risk analysis practices are an essential foundation for infrastructure planning and response to a changing climate (Hines et al., 2022; Moser & Ekstrom, 2010; Srithongrung et al., 2019). This study shows that efforts to improve the information behind decision-making are not in vain; rather, they can lead to enhanced investment among counties which choose to invest in flood control infrastructure. From a policy perspective, FEMA has been criticized for not updating flood maps quickly enough (Highfield et al., 2013; Government Accountability Office, 2021). While having outdated information is inherently in-optimal for planning in many contexts, this study demonstrates that changes in publicly available risk information can lead to enhanced investments. More frequent updates may lead to more frequent local mitigation investment for governments which have decided to proactively invest in infrastructure.

In addition, reactive investment patterns imply that governments' investment decisions may be biased by the representativeness heuristic (Dumm et al., 2020; Grether, 1980; Volkman-Wise, 2015; Kahneman and Tversky, 1972). Given the fact that flood control infrastructure is efficient and potentially underprovided, and that flood risks may exist in unmapped areas, the fact that local governments invest in flood protection after a damaging flood is a good thing. In reality, flood risks shift and change over time, and strategic planning processes are driven by imperfect models. While it would be best if counties invested in flood control infrastructure once they received updated information on their flood risks through FISs, investments based on flood experience may indicate that governments are engaging in learning processes (Brody et al., 2009; Lee & Chen, 2021; Zhang et al., 2018; Zhang & Maroulis, 2021).

Still, some counties fail to invest. It is possible that the median voter in counties which fail to provide flood control infrastructure is myopic, is attempting to ferret out unnecessary, rent seeking investments in flood control infrastructure, or because they believe that their community will receive a federal bailout in the event of a disastrous flood (Gailmard & Patty, 2019; Healy & Malhotra, 2009). However, it is also possible that rural areas where the median voter has a higher tax share use strategies that do not require large up-front investments. Rural governments may make use of non-structural techniques which prevent floods by discouraging dangerous development in the floodplain (Highfield et al., 2013; Highfield & Brody, 2013). This may be especially important in financially constrained counties, which may lack the organizational capacity needed for adaptation (Brody et al., 2009, 2010). The results from this study suggest that counties with high levels of poverty, and for which the median voter has a high tax share, are less likely to have flood control infrastructure. A fuller picture of local governments' flood mitigation strategies would consider the full slate of structural and non-structural strategies that are possible for localities to employ to prevent flooding.

This study is subject to limitations. First, it does not attempt to estimate an optimal level of flood control capital stock for each community. It is very possible that flood control stocks are underprovided even if governments strategically plan for public risks. Second, this study only assesses counties' accumulation of capital stocks. While this simplification makes the analysis tractable, Florida's cities, counties, and special districts all provide flood control infrastructure in an intergovernmental context. Future studies should explore how flood control infrastructure is provided across a more diverse spectrum of local governments, and how intergovernmental networks respond to experienced disaster and acquire flood control infrastructure. Finally, this study only looks at local governments’ experiences in Florida, known for its extensive flooding. States with less salient flood risks may feature fewer rational patterns of planning. In states outside of Florida, other challenges such as tornadoes, wildfires, and mudslides may be prevalent. Similar investment dynamics may feature in those policy areas and would offer a way to test if flooding is a unique policy environment or if rare, but knowable, disasters offer similar dynamics. Interestingly, while novel wildfires were able to prompt communities to respond, historic wildfires did not prompt large changes (Mockrin et al., 2018).

Conclusion

Damaging floods can be prevented with cost effective infrastructure, but not all counties develop such systems (Congressional Budget Office, 2007). While changes in federal flood maps can inspire counties which have already decided to invest in flood control infrastructure to grow their infrastructure systems, they also appear to influence counties’ decision to take the initial step and begin investing in flood control systems. In a word, some counties appear to avoid investing in flood control infrastructure until a damaging flood shifts the median voter’s risk perceptions. From a policy perspective, the publication of official information on counties’ risk can influence local investment decisions. The remaining puzzle is to understand how that information can be utilized to convince voters, and, by extension, local governments, to initially take the plunge and decide to build flood control infrastructure systems.

Tables and Figures

Table 1: Descriptive Statistics

	Mean	Standard Deviation	25th Percentile	Median	75th Percentile
Capital Stock (1,000s)	14740.1	39207.0	0	19.4	4780.0
Property Value at Risk per Capita (1,000s)	61.5	68.3	26.4	37.2	63.8
Policy Value per Capita (1,000s)	19.4	23.8	2.9	7.7	31.2
FIS Occurred	0.1	0.3	0	0	0
Claims Per Capita	28.1	301.9	0	0.1	1.0
IHS Claims Per Capita	0.8	1.5	0	0.1	0.9
Floods per Year	0.9	0.8	0.3	0.6	1.3
Policy Value per Capita (1,000s)	19.4	23.8	2.9	7.7	31.2
Hazard Mitigation Programs	7.3	1.8	6	7	8
Intergovernmental Revenue %	19.6	11.7	11.5	15.9	23.6
Stormwater Grants (1,000s)	96.1	721.8	0	0	0
IHS Stormwater Grants	1.9	4.6	0	0	0
Debt Service % of Expenditures	4.4	4.2	1.8	3.3	5.4
Median Voter Tax Share (%)	0.003	0.003	0.0005	0.001	0.004
Median Income (1,000s)	49.2	9.0	41.7	48.4	55.0
% White Alone	69.0	15.0	61.2	73.2	79.0
% Over 65	19.2	7.3	14.0	17.4	22.5
% College Educated	20.3	9.5	11.5	18.8	27.3
% in Poverty	17.3	5.1	13.3	16.5	20.6
Population Density (1000s)	0.3	0.5	0.05	0.2	0.4
% Population Growth	0.8	2.0	0.10	0.7	1.7
Democratic Vote %	38.0	13.0	27.7	37.3	46.2

Table 2: First Stage Results - Tobit (Probit Variant)

	(1)		(2)		(3)	
	IHS Claims Per Capita		IHS Claims Per Capita Lag 1		IHS Claims Per Capita Lag 2	
	Coef.	Standard Error	Coef.	Standard Error	Coef.	Standard Error
FIS Occurred	-0.224	(0.222)	0.032	(0.236)	0.465*	(0.224)
Lag 1	-0.069	(0.193)	-0.503*	(0.213)	0.149	(0.269)
Lag 2	0.090	(0.231)	-0.345	(0.181)	-0.368	(0.196)
Policy Value per Capita (Ln)	0.286**	(0.108)	0.347**	(0.107)	0.385***	(0.087)
Hazard Mitigation Programs	0.025	(0.056)	-0.053	(0.049)	-0.060	(0.046)
Intergovernmental Revenue %	-0.005	(0.013)	0.007	(0.012)	0.009	(0.016)
IHS Stormwater Grants	0.022	(0.016)	0.031*	(0.014)	0.012	(0.011)
Debt Service % of Expenditures	-0.016	(0.014)	-0.025	(0.014)	-0.011	(0.014)
Median Voter Tax Share (%)	-108.843**	(40.202)	-65.131	(37.984)	-58.243	(39.280)
Median Income (1,000s)	-0.005	(0.019)	-0.012	(0.016)	-0.004	(0.016)
% in Poverty	0.002	(0.030)	-0.016	(0.026)	-0.014	(0.026)
% White Alone	0.013	(0.011)	0.007	(0.010)	0.009	(0.010)
% Over 65	-0.039***	(0.011)	-0.047***	(0.010)	-0.055***	(0.010)
% College Educated	0.003	(0.017)	0.009	(0.013)	0.004	(0.012)
Population Density (1000s)	0.302	(0.216)	0.084	(0.165)	-0.107	(0.176)
% Population Growth	-0.093	(0.069)	0.009	(0.040)	0.057	(0.037)
Democratic Vote %	-0.016	(0.014)	-0.008	(0.012)	-0.002	(0.011)
Coastal	0.317	(0.241)	0.233	(0.250)	0.229	(0.198)
Hurricane Count	2.766***	(0.466)				
Hurricane Count Lag 1			2.533***	(0.516)		
Hurricane Count Lag 2					2.504***	(0.525)
Constant	-2.477	(2.143)	-0.461	(2.021)	-1.568	(1.898)
N	666		666		666	
Clusters	67		67		67	
F(DF)	15(28, 638)		15(28, 638)		16(28, 638)	
Prob > F	0		0		0	

*Cluster robust standard errors, + p < 0.10, * p < 0.05, ** p < .01
*Year effects omitted.

Table 3: First Stage Results - Tobit (Poisson Variant)

	(1) IHS Claims Per Capita		(2) IHS Claims Per Capita Lag 1		(3) IHS Claims Per Capita Lag 2	
	Coef.	Standard Error	Coef.	Standard Error	Coef.	Standard Error
FIS Occurred	-0.174	(0.188)	-0.109	(0.295)	0.465	(0.262)
Lag 1	-0.076	(0.235)	-0.252	(0.203)	0.099	(0.329)
Lag 2	0.208	(0.283)	-0.149	(0.208)	-0.185	(0.183)
Policy Value per Capita (Ln)	0.055	(0.133)	-0.006	(0.146)	0.114	(0.128)
Hazard Mitigation Programs	0.014	(0.053)	0.021	(0.052)	0.033	(0.049)
Intergovernmental Revenue %	-0.001	(0.013)	0.008	(0.014)	0.025	(0.014)
IHS Stormwater Grants	0.018	(0.014)	0.030	(0.017)	0.024	(0.015)
Debt Service % of Expenditures	-0.044^{**}	(0.015)	-0.050^{**}	(0.019)	-0.019	(0.021)
*Median Voter Tax Share (%)	-65.239	(99.641)	-23.048	(89.003)	-92.618	(93.443)
Median Income (1,000s)	0.024	(0.022)	0.052	(0.027)	0.049	(0.026)
% in Poverty	-0.002	(0.047)	0.047	(0.049)	0.082	(0.047)
% White Alone	0.019	(0.010)	0.025^{*}	(0.011)	0.033^{**}	(0.011)
% Over 65	-0.037^{**}	(0.011)	-0.041^{***}	(0.012)	-0.058^{***}	(0.011)
% College Educated	-0.023	(0.018)	-0.036^{*}	(0.016)	-0.033^{*}	(0.017)
Population Density (1000s)	0.066	(0.132)	0.031	(0.128)	-0.052	(0.140)
% Population Growth	-0.115	(0.062)	-0.063	(0.063)	0.105	(0.061)
Democratic Vote %	0.013	(0.013)	0.026^{*}	(0.013)	0.021	(0.014)
Coastal	0.616^{*}	(0.281)	0.774^{*}	(0.318)	0.722^{**}	(0.234)
Hurricane Count	2.237^{***}	(0.557)				
Hurricane Count Lag 1			2.181^{**}	(0.709)		
Hurricane Count Lag 2					1.720^{*}	(0.681)
Constant	-2.828	(1.971)	-4.624^{*}	(2.212)	-5.906^{*}	(2.511)
N	376		376		376	
Clusters	44		44		44	
F(DF)	21(28, 348)		18(28, 348)		14(28, 348)	
Prob > F	0		0		0	

*Cluster robust standard errors, + p < 0.10, * p < 0.05, ** p < .01
*Year effects omitted.

Table 4: Two-Part Model - Endogeneity Check with Tobit First Stage

	(1) Probit Coef.	Standard Error	(2) Poisson QMLE Coef.	Standard Error
IHS Claims Per Capita	-0.044	(0.069)	-0.116	(0.109)
Lag 1	0.001	(0.089)	-0.133	(0.105)
Lag 2	0.101	(0.101)	-0.128	(0.112)
FIS Occurred	-0.179	(0.149)	0.261+	(0.139)
Lag 1	-0.140	(0.131)	0.316+	(0.170)
Lag 2	0.050	(0.141)	0.344*	(0.168)
Policy Value per Capita (Ln)	0.431+	(0.241)	-0.259	(0.380)
Hazard Mitigation Programs	-0.072	(0.111)	-0.042	(0.108)
Intergovernmental Revenue %	-0.001	(0.026)	0.098**	(0.029)
IHS Stormwater Grants	0.037+	(0.020)	0.016	(0.026)
Debt Service % of Expenditures	-0.036	(0.022)	-0.011	(0.034)
Median Voter Tax Share (%)	-185.180*	(80.469)	-149.867	(280.020)
Median Income (1,000s)	-0.085*	(0.039)	0.058	(0.067)
% in Poverty	-0.244**	(0.051)	0.014	(0.098)
% White Alone	0.012	(0.024)	-0.033	(0.023)
% Over 65	-0.053+	(0.032)	0.037	(0.041)
% College Educated	0.003	(0.033)	0.119*	(0.047)
Population Density (1000s)	0.353	(0.558)	0.612**	(0.211)
% Population Growth	-0.104+	(0.055)	0.068	(0.046)
Democratic Vote %	0.020	(0.028)	0.012	(0.030)
Coastal	-1.191*	(0.524)	1.706*	(0.785)
2011	0.301**	(0.107)	-0.157	(0.197)
2012	0.635**	(0.196)	0.222	(0.245)
2013	0.644*	(0.255)	0.267	(0.282)
2014	0.513+	(0.304)	0.286	(0.323)
2015	0.445	(0.328)	-0.006	(0.350)
2016	0.491	(0.417)	-0.119	(0.427)
2017	0.636	(0.534)	0.060	(0.556)
2018	0.424	(0.605)	-0.191	(0.562)
2019	0.205	(0.596)	-0.587	(0.557)
Residual 1	0.049	(0.073)	0.089	(0.121)
Residual 2	0.039	(0.086)	0.119	(0.103)
Residual 3	-0.011	(0.092)	0.061	(0.103)
Constant	5.308	(3.925)	4.373	(5.596)
N	666		376	
Clusters	67		44	
Chi-squared(DF)	160(33)		2898(33)	
Prob > Chi-squared	0		0	

*Cluster robust standard errors, + p < 0.10, * p < 0.05, ** p < .01

Table 5: Probit Results (2019)

	(1) Coef./Standard Error	(2) Coef./Standard Error	(3) Coef./Standard Error
Floods per Year	0.047	0.051	0.088
	(0.299)	(0.309)	(0.307)
Property Risk per Capita (Ln)	-0.192		0.301
	(0.455)		(0.377)
Policy Value per Capita (Ln)	0.925*	0.834*	
	(0.391)	(0.337)	
Hazard Mitigation Programs	-0.048	-0.040	0.014
	(0.162)	(0.165)	(0.163)
Intergovernmental Revenue %	0.045	0.043	0.029
	(0.037)	(0.035)	(0.032)
IHS Stormwater Grants	0.140**	0.143**	0.114**
	(0.045)	(0.045)	(0.042)
Debt Service % of Expenditures	-0.045	-0.039	0.005
	(0.113)	(0.117)	(0.114)
Median Voter Tax Share (%)	-287.729*	-311.139*	-380.248*
	(129.067)	(126.327)	(152.070)
Median Income (1,000s)	-0.034	-0.033	0.001
	(0.061)	(0.062)	(0.060)
% in Poverty	-0.194+	-0.202+	-0.177
	(0.115)	(0.113)	(0.116)
% White Alone	0.030	0.039	0.035
	(0.040)	(0.038)	(0.039)
% Over 65	-0.030	-0.038	-0.032
	(0.045)	(0.043)	(0.036)
% College Educated	-0.076	-0.085	-0.085
	(0.055)	(0.056)	(0.057)
Population Density (1000s)	2.965**	3.195**	2.862*
	(1.101)	(1.220)	(1.183)
% Population Growth	0.018	0.019	0.013
	(0.054)	(0.053)	(0.051)
Democratic Vote %	0.030	0.035	0.026
	(0.048)	(0.047)	(0.045)
Coastal	-2.271*	-2.351**	-1.326+
	(0.915)	(0.888)	(0.739)
Constant	-1.699	-3.313	-1.288
	(7.212)	(6.686)	(7.697)
N	67	67	67
Chi-squared(DF)	66(17)	61(16)	43(16)
Prob > Chi-squared	0	0	0

*Robust standard errors, + p < 0.10, * p < 0.05, ** p < .01

*One success is completely determined in models (1) and (3). Two successes completely determined in model (2).

Table 6: Logit Results (2019)

	(1) Coef./Standard Error	(2) Coef./Standard Error	(3) Coef./Standard Error
Floods per Year	0.079	0.091	0.161
	(0.583)	(0.598)	(0.566)
Property Risk per Capita (Ln)	-0.333		0.508
	(0.827)		(0.657)
Policy Value per Capita (Ln)	1.528*	1.358*	
	(0.749)	(0.619)	
Hazard Mitigation Programs	-0.081	-0.066	0.031
	(0.286)	(0.289)	(0.287)
Intergovernmental Revenue %	0.076	0.073	0.050
	(0.065)	(0.061)	(0.054)
IHS Stormwater Grants	0.229**	0.234**	0.189*
	(0.078)	(0.076)	(0.075)
Debt Service % of Expenditures	-0.084	-0.073	0.014
	(0.210)	(0.220)	(0.228)
Median Voter Tax Share (%)	-471.584+	-513.658*	-653.472*
	(243.267)	(235.813)	(291.817)
Median Income (1,000s)	-0.054	-0.052	-0.008
	(0.111)	(0.114)	(0.117)
% in Poverty	-0.321	-0.333	-0.312
	(0.214)	(0.212)	(0.241)
% White Alone	0.049	0.063	0.056
	(0.074)	(0.072)	(0.071)
% Over 65	-0.047	-0.061	-0.055
	(0.082)	(0.080)	(0.060)
% College Educated	-0.130	-0.143	-0.136
	(0.099)	(0.104)	(0.102)
Population Density (1000s)	4.963*	5.342*	4.632*
	(2.135)	(2.444)	(2.332)
% Population Growth	0.026	0.028	0.022
	(0.090)	(0.087)	(0.084)
Democratic Vote %	0.054	0.062	0.043
	(0.086)	(0.084)	(0.080)
Coastal	-3.660*	-3.788*	-2.140
	(1.712)	(1.664)	(1.312)
Constant	-2.933	-5.609	-1.526
	(13.343)	(12.818)	(14.663)
N	67	67	67
Chi-squared(DF)	53(17)	50(16)	34(16)
Prob > Chi-squared	0	0	0

*Robust standard errors, + p < 0.10, * p < 0.05, ** p < .01

Table 7: Two-Part Model

	(1) Probit Coef.	Standard Error	(2) Poisson QMLE Coef.	Standard Error
IHS Claims Per Capita	0.006	(0.048)	-0.024	(0.039)
Lag 1	0.046	(0.044)	-0.012	(0.033)
Lag 2	0.093*	(0.044)	-0.067+	(0.034)
FIS Occurred	-0.165	(0.144)	0.277*	(0.133)
Lag 1	-0.123	(0.133)	0.353*	(0.176)
Lag 2	0.053	(0.131)	0.365*	(0.170)
Policy Value per Capita (Ln)	0.413+	(0.227)	-0.290	(0.373)
Hazard Mitigation Programs	-0.072	(0.110)	-0.040	(0.107)
Intergovernmental Revenue %	-0.001	(0.026)	0.097**	(0.029)
IHS Stormwater Grants	0.035+	(0.020)	0.009	(0.023)
Debt Service % of Expenditures	-0.034	(0.021)	-0.001	(0.027)
Median Voter Tax Share (%)	-184.093*	(80.533)	-157.824	(275.349)
Median Income (1,000s)	-0.085*	(0.039)	0.048	(0.068)
% in Poverty	-0.244**	(0.051)	-0.004	(0.099)
% White Alone	0.012	(0.024)	-0.036	(0.023)
% Over 65	-0.051+	(0.031)	0.042	(0.041)
% College Educated	0.003	(0.033)	0.124**	(0.047)
Population Density (1000s)	0.370	(0.583)	0.611**	(0.213)
% Population Growth	-0.097+	(0.055)	0.083+	(0.043)
Democratic Vote %	0.021	(0.029)	0.010	(0.031)
Coastal	-1.222*	(0.528)	1.551*	(0.763)
2011	0.347**	(0.121)	-0.045	(0.134)
2012	0.616**	(0.211)	0.247	(0.233)
2013	0.599*	(0.266)	0.179	(0.264)
2014	0.503	(0.306)	0.181	(0.319)
2015	0.442	(0.344)	-0.036	(0.344)
2016	0.482	(0.433)	-0.158	(0.430)
2017	0.504	(0.530)	-0.254	(0.556)
2018	0.339	(0.558)	-0.579	(0.553)
2019	0.211	(0.548)	-0.768	(0.592)
Constant	5.330	(3.910)	5.501	(5.531)
N	666		376	
Clusters	67		44	
Chi-squared (DF)	129(30)		1794(30)	
Prob > Chi-squared	0		0	

*Cluster robust standard errors, + p < 0.10, * p < 0.05, ** p < .01

Table 8: Reduced Probit Results (2019)

	(1) Coef./Standard Error	(2) Coef./Standard Error	(3) Coef./Standard Error
Floods per Year	-0.210	-0.213	-0.131
	(0.228)	(0.235)	(0.227)
Property Risk per Capita (Ln)	-0.321		-0.000
	(0.380)		(0.290)
Policy Value per Capita (Ln)	0.645+	0.451+	
	(0.359)	(0.263)	
IHS Stormwater Grants	0.094*	0.097**	0.065+
	(0.037)	(0.037)	(0.038)
Median Voter Tax Share (%)	-71.230	-91.837	-171.141
	(89.875)	(88.072)	(105.576)
% in Poverty	-0.058	-0.076	
	(0.057)	(0.049)	
Population Density (1000s)	2.081*	2.232*	2.005*
	(0.819)	(0.901)	(0.948)
Coastal	-1.466*	-1.397*	-0.154
	(0.665)	(0.642)	(0.432)
Constant	-0.915	-2.345	0.079
	(3.172)	(2.755)	(3.118)
N	67	67	67
Chi-squared(DF)	43(8)	41(7)	21(6)
Prob > Chi-squared	0	0	0

*Robust standard errors, + p < 0.10, * p < 0.05, ** p < .01
*1 success completely determined

Table 9: Two-Part Model Reduced

	(1) Probit Coef.	Standard Error	(2) Poisson QMLE Coef.	Standard Error
IHS Claims Per Capita	0.006	(0.048)	-0.005	(0.053)
Lag 1	0.052	(0.047)	0.018	(0.048)
Lag 2	0.094*	(0.042)	-0.042	(0.041)
FIS Occurred	-0.135	(0.148)	0.438**	(0.153)
Lag 1	-0.096	(0.131)	0.462**	(0.126)
Lag 2	0.020	(0.131)	0.421**	(0.131)
Policy Value per Capita (Ln)	0.305	(0.232)		
IHS Stormwater Grants	0.041+	(0.022)		
Median Voter Tax Share (%)	-250.021**	(68.488)		
Median Income (1,000s)	-0.078*	(0.033)		
% in Poverty	-0.241**	(0.047)		
% Over 65	-0.051*	(0.024)		
% Population Growth	-0.084	(0.054)	0.235**	(0.086)
Coastal	-1.118*	(0.536)	1.164*	(0.566)
Intergovernmental Revenue %			0.061**	(0.024)
% College Educated			0.154**	(0.035)
Population Density			0.682**	(0.139)
2011	0.333**	(0.109)	-0.108	(0.146)
2012	0.530**	(0.154)	0.053	(0.174)
2013	0.476**	(0.178)	-0.060	(0.164)
2014	0.438*	(0.211)	-0.133	(0.162)
2015	0.317	(0.232)	-0.319+	(0.168)
2016	0.300	(0.226)	-0.331+	(0.182)
2017	0.234	(0.268)	-0.231	(0.243)
2018	0.045	(0.289)	-0.519+	(0.266)
2019	-0.023	(0.268)	-0.708**	(0.242)
Constant	7.244**	(2.565)	3.471*	(1.636)
N	666		376	
Clusters	67		44	
Chi-squared(DF)	102(23)		142(20)	
Prob > Chi-squared	0		0	

*Cluster robust standard errors, + p < 0.10, * p < 0.05, ** p < .01

Table 10: Cragg's Lognormal Model

	(1) Probit Coef.	Standard Error	(2) OLS Coef.	Standard Error
IHS Claims Per Capita	0.006	(0.048)	-0.081	(0.068)
Lag 1	0.046	(0.044)	-0.072	(0.080)
Lag 2	0.093*	(0.044)	-0.091	(0.099)
FIS Occurred	-0.165	(0.144)	0.618*	(0.283)
Lag 1	-0.123	(0.133)	0.806**	(0.254)
Lag 2	0.053	(0.131)	0.694**	(0.229)
Policy Value per Capita (Ln)	0.413+	(0.227)	-0.139	(0.500)
Hazard Mitigation Programs	-0.072	(0.110)	0.152	(0.199)
Intergovernmental Revenue %	-0.001	(0.026)	0.166**	(0.034)
IHS Stormwater Grants	0.035+	(0.020)	0.083*	(0.039)
Debt Service % of Expenditures	-0.034	(0.021)	0.035	(0.043)
Median Voter Tax Share (%)	-184.093*	(80.533)	-755.201**	(216.138)
Median Income (1,000s)	-0.085*	(0.039)	-0.089	(0.100)
% in Poverty	-0.244**	(0.051)	-0.035	(0.121)
% White Alone	0.012	(0.024)	-0.101*	(0.047)
% Over 65	-0.051+	(0.031)	0.038	(0.058)
% College Educated	0.003	(0.033)	0.194*	(0.077)
Population Density (1000s)	0.370	(0.583)	1.589**	(0.450)
% Population Growth	-0.097+	(0.055)	-0.049	(0.107)
Democratic Vote %	0.021	(0.029)	-0.077	(0.058)
Coastal	-1.222*	(0.528)	0.655	(1.297)
2011	0.347**	(0.121)	-0.104	(0.281)
2012	0.616**	(0.211)	-0.215	(0.505)
2013	0.599*	(0.266)	-0.221	(0.587)
2014	0.503	(0.306)	-0.425	(0.714)
2015	0.442	(0.344)	-0.484	(0.794)
2016	0.482	(0.433)	-0.826	(0.981)
2017	0.504	(0.530)	-0.579	(1.069)
2018	0.339	(0.558)	-0.552	(1.100)
2019	0.211	(0.548)	-0.557	(1.163)
Constant	5.330	(3.910)	22.043*	(9.157)
N	666		376	
Clusters	67		44	
Chi-squared(DF) / F(DF)	129(30)		23(30,43)	
Prob > Chi-squared / Prob > F	0		0	

*Cluster robust standard errors, + p < 0.10, * p < 0.05, ** p < .01

Table 11: First Stage Results - OLS (Probit Variant)

	(2)		(2)		(3)	
	IHS Claims Per Capita		IHS Claims Per Capita Lag 1		IHS Claims Per Capita Lag 2	
	Coef.	Standard Error	Coef.	Standard Error	Coef.	Standard Error
FIS Occurred	-0.171	(0.143)	0.035	(0.165)	0.354*	(0.164)
Lag 1	-0.063	(0.117)	-0.340**	(0.127)	0.119	(0.192)
Lag 2	0.053	(0.161)	-0.196+	(0.106)	-0.264*	(0.128)
Policy Value per Capita (Ln)	0.170**	(0.060)	0.187**	(0.059)	0.231**	(0.056)
Hazard Mitigation Programs	0.003	(0.038)	-0.041	(0.033)	-0.053	(0.034)
Intergovernmental Revenue %	-0.004	(0.007)	0.003	(0.007)	0.006	(0.009)
IHS Stormwater Grants	0.011	(0.010)	0.022*	(0.011)	0.011	(0.008)
Debt Service % of Expenditures	-0.019*	(0.009)	-0.023*	(0.011)	-0.015	(0.009)
Median Voter Tax Share (%)	-27.141	(18.668)	-4.631	(16.459)	-4.886	(19.556)
Median Income (1,000s)	0.010	(0.011)	0.004	(0.012)	0.009	(0.010)
% in Poverty	0.016	(0.017)	0.002	(0.016)	0.005	(0.016)
% White Alone	0.006	(0.007)	0.003	(0.008)	0.004	(0.008)
% Over 65	-0.022**	(0.008)	-0.025**	(0.007)	-0.032**	(0.008)
% College Educated	-0.011	(0.010)	-0.004	(0.008)	-0.006	(0.008)
Population Density (1000s)	0.116	(0.113)	-0.038	(0.098)	-0.206+	(0.105)
% Population Growth	-0.065	(0.055)	-0.007	(0.028)	0.036	(0.028)
Democratic Vote %	-0.011	(0.008)	-0.006	(0.009)	-0.002	(0.008)
Coastal	0.271+	(0.152)	0.228	(0.166)	0.240	(0.153)
Hurricane Count	2.593**	(0.431)				
Hurricane Count Lag 1			2.374**	(0.477)		
Hurricane Count Lag 2					2.380**	(0.474)
Constant	-1.353	(1.268)	-0.034	(1.450)	-0.850	(1.329)
N	666		666		666	
Clusters	67		67		67	
F(DF)	21(28, 66)		23(28, 66)		21(28, 66)	
Prob > F	0		0		0	

*Cluster robust standard errors, + p < 0.10, * p < 0.05, ** p < .01
*Year effects omitted.

Table 12: First Stage Results - OLS (Poisson Variant)

	(3)		(2)		(3)	
	IHS Claims Per Capita		IHS Claims Per Capita Lag 1		IHS Claims Per Capita Lag 2	
	Coef.	Standard Error	Coef.	Standard Error	Coef.	Standard Error
FIS Occurred	-0.215	(0.158)	-0.033	(0.242)	0.456*	(0.203)
Lag 1	-0.060	(0.174)	-0.245	(0.171)	0.128	(0.265)
Lag 2	0.126	(0.230)	-0.088	(0.146)	-0.208	(0.161)
Policy Value per Capita (Ln)	0.041	(0.109)	-0.014	(0.114)	0.040	(0.101)
Hazard Mitigation Programs	-0.007	(0.041)	0.003	(0.044)	0.022	(0.045)
Intergovernmental Revenue %	-0.002	(0.010)	0.003	(0.009)	0.016	(0.011)
IHS Stormwater Grants	0.009	(0.011)	0.025+	(0.015)	0.015	(0.012)
Debt Service % of Expenditures	-0.048**	(0.012)	-0.039*	(0.015)	-0.023	(0.018)
Median Voter Tax Share (%)	-18.497	(66.012)	24.731	(56.751)	-29.776	(65.915)
Median Income (1,000s)	0.027	(0.019)	0.047*	(0.021)	0.046*	(0.022)
% in Poverty	0.013	(0.034)	0.043	(0.035)	0.077*	(0.035)
% White Alone	0.010	(0.008)	0.015+	(0.008)	0.022*	(0.010)
% Over 65	-0.021*	(0.009)	-0.022*	(0.010)	-0.033**	(0.011)
% College Educated	-0.025+	(0.014)	-0.034**	(0.012)	-0.030*	(0.014)
Population Density (1000s)	-0.011	(0.102)	-0.038	(0.108)	-0.121	(0.118)
% Population Growth	-0.092+	(0.052)	-0.081	(0.051)	0.073	(0.050)
Democratic Vote %	0.005	(0.011)	0.016	(0.010)	0.011	(0.013)
Coastal	0.480+	(0.240)	0.555*	(0.262)	0.596**	(0.207)
Hurricane Count	2.234**	(0.572)				
Hurricane Count Lag 1			2.181**	(0.695)		
Hurricane Count Lag 2					1.759*	(0.672)
Constant	-1.708	(1.637)	-3.146+	(1.711)	-3.947+	(2.140)
N	376		376		376	
Clusters	44		44		44	
F(DF)	28(28, 43)		22(28, 43)		29(28, 43)	
Prob > F	0		0		0	

*Cluster robust standard errors, + p < 0.10, * p < 0.05, ** p < .01
*Year effects omitted.

Table 13: Two-Part Model - Endogeneity Check with Linear First Stage

	(1) Probit Coef.	Standard Error	(2) Poisson QMLE Coef.	Standard Error
IHS Claims Per Capita	0.062	(0.102)	-0.149	(0.180)
Lag 1	0.222	(0.137)	-0.197	(0.188)
Lag 2	0.283+	(0.165)	-0.181	(0.229)
FIS Occurred	-0.203	(0.151)	0.270+	(0.158)
Lag 1	-0.073	(0.138)	0.309+	(0.165)
Lag 2	0.119	(0.139)	0.330*	(0.152)
Policy Value per Capita (Ln)	0.331	(0.254)	-0.248	(0.381)
Hazard Mitigation Programs	-0.056	(0.115)	-0.048	(0.106)
Intergovernmental Revenue %	-0.002	(0.026)	0.101**	(0.030)
IHS Stormwater Grants	0.031	(0.021)	0.017	(0.028)
Debt Service % of Expenditures	-0.026	(0.024)	-0.017	(0.041)
Median Voter Tax Share (%)	-183.768*	(81.224)	-171.796	(283.871)
Median Income (1,000s)	-0.089*	(0.039)	0.063	(0.067)
% in Poverty	-0.249**	(0.051)	0.021	(0.098)
% White Alone	0.011	(0.024)	-0.033	(0.024)
% Over 65	-0.042	(0.033)	0.036	(0.042)
% College Educated	0.005	(0.034)	0.116*	(0.047)
Population Density (1000s)	0.401	(0.584)	0.587**	(0.215)
% Population Growth	-0.097+	(0.056)	0.065	(0.047)
Democratic Vote %	0.023	(0.028)	0.010	(0.029)
Coastal	-1.370*	(0.533)	1.771*	(0.781)
2011	0.496**	(0.148)	-0.186	(0.272)
2012	0.875**	(0.269)	0.194	(0.265)
2013	0.712**	(0.273)	0.256	(0.293)
2014	0.502	(0.320)	0.296	(0.340)
2015	0.547	(0.340)	-0.013	(0.360)
2016	0.610	(0.430)	-0.125	(0.431)
2017	0.496	(0.568)	0.134	(0.642)
2018	0.035	(0.628)	-0.042	(0.674)
2019	-0.020	(0.645)	-0.488	(0.683)
Residual 1	-0.053	(0.116)	0.128	(0.202)
Residual 2	-0.188	(0.154)	0.193	(0.204)
Residual 3	-0.203	(0.179)	0.119	(0.232)
Constant	5.665	(3.896)	4.276	(5.639)
N	666		376	
Clusters	67		44	
Chi-squared(DF)	133(33)		2782(33)	
Prob > Chi-squared	0		0	

*Cluster robust standard errors, + p < 0.10, * p < 0.05, ** p < .01

Table 14: Two-Part Model - Bootstrap with Tobit First Stage

	(1) Probit Coef.	Standard Error	(2) Poisson QMLE Coef.	Standard Error
IHS Claims Per Capita	-0.044	(0.110)	-0.116	(0.133)
Lag 1	0.001	(0.123)	-0.133	(0.143)
Lag 2	0.101	(0.142)	-0.128	(0.141)
FIS Occurred	-0.179	(0.213)	0.261	(0.194)
Lag 1	-0.140	(0.194)	0.316	(0.204)
Lag 2	0.050	(0.205)	0.344*	(0.174)
Policy Value per Capita (Ln)	0.431	(0.402)	-0.259	(0.676)
Hazard Mitigation Programs	-0.072	(0.178)	-0.042	(0.225)
Intergovernmental Revenue %	-0.001	(0.048)	0.098+	(0.055)
IHS Stormwater Grants	0.037	(0.031)	0.016	(0.035)
Debt Service % of Expenditures	-0.036	(0.033)	-0.011	(0.043)
Median Voter Tax Share (%)	-185.180	(160.854)	-149.867	(1113.414)
Median Income (1,000s)	-0.085	(0.069)	0.058	(0.120)
% in Poverty	-0.244*	(0.096)	0.014	(0.162)
% White Alone	0.012	(0.048)	-0.033	(0.062)
% Over 65	-0.053	(0.060)	0.037	(0.085)
% College Educated	0.003	(0.072)	0.119	(0.098)
Population Density (1000s)	0.353	(2.040)	0.612	(0.969)
% Population Growth	-0.104	(0.093)	0.068	(0.071)
Democratic Vote %	0.020	(0.051)	0.012	(0.068)
Coastal	-1.191	(0.921)	1.706	(1.506)
2011	0.301	(0.192)	-0.157	(0.234)
2012	0.635+	(0.338)	0.222	(0.499)
2013	0.644	(0.422)	0.267	(0.618)
2014	0.513	(0.492)	0.286	(0.698)
2015	0.445	(0.535)	-0.006	(0.761)
2016	0.491	(0.715)	-0.119	(0.910)
2017	0.636	(0.891)	0.060	(1.141)
2018	0.424	(0.971)	-0.191	(1.150)
2019	0.205	(0.972)	-0.587	(1.121)
Residual 1	0.049	(0.110)	0.089	(0.134)
Residual 2	0.039	(0.121)	0.119	(0.133)
Residual 3	-0.011	(0.129)	0.061	(0.130)
Constant	5.308	(6.946)	4.373	(11.132)
N	666		376	
Clusters	67		44	

*Cluster robust standard errors from cluster pairs bootstrap with 5,000 replications
*+ p < 0.10, * p < 0.05, ** p < .01

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CHAPTER 3: PUBLIC WORKS OVER TROUBLED WATERS: HOW PUBLIC WORKS DIRECTORS NAVIGATE THE UNCERTAINTY AND AMBIGUITY OF SEA LEVEL RISE[10]

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Abstract

Local government public works directors are fighting to protect their locality's key infrastructure systems from rising seas. While local public works departments provide clean water, flood protection, and public transportation, investing in resilience is challenging given the uncertainty of future sea level rise. As leaders in their departments, public works directors must make key project prioritization decisions as seas rise. So, how do they navigate the risk and uncertainty of sea level rise? This study tests if public works directors' prioritization decisions align with the predictions of cumulative prospect theory, by inviting those working in local governments on the United States coast to participate in a decision-making experiment and interview. Results indicate that public works directors' risk preferences differ from cumulative prospect theory because directors tend to be decreasingly sensitive to increases in assets' criticality and probability of failure. As a result, most public works directors are characterized as risk averse when prioritizing projects. Participating directors are shown to have heterogenous preferences across other important prioritization criteria.

Introduction

Coastal municipalities' public infrastructure systems are threatened by the enhanced flood risks created by rising seas and climate change (Maxwell et al., 2018). Under a high emissions scenario, discounted damage to U.S. coastal properties could rise to a cumulative $3.5 trillion by 2100 if we fail to adapt to sea level rise (Fleming et al., 2018). However, adaptive investments can be extremely expensive (Fleming et al., 2018). Coastal local governments have begun to recognize and plan for the impact of rising tides (Fleming et al., 2018; Hines et al., 2022). As managers of key infrastructure systems, public works directors (hereafter PWDs) already make critical decisions on behalf of local governments to adapt to sea level rise.

This research project aims to understand how public works directors prioritize public funds when investing in resiliency projects, via an online experiment. Assets threatened by rising seas have different levels of criticality and probabilities of failure should seas rise. This study seeks to test if public works directors' prioritization decisions exhibit the non-linear preference patterns implied by prospect theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). However, project prioritization decisions are not made on the basis of asset criticality and likelihood of failure alone. Assets differ in their adaptability to sea level rise in later periods, and planned repairs may be more or less cost-efficient. Projects may also have differing levels of political support and fit with localities' overarching strategic goals.

This chapter first reviews the literature on local government adaptive budgetary decision-making in the United States, then consults that research to develop a theory to explain how PWDs prioritize different investments when adapting to climate change. Prioritization is based on projects' exposure to sea level rise risk, potential for adaptability, cost-efficiency, managerial importance, and level of political support. The theory was tested using an experiment designed to elicit public works directors' prioritization decisions. Results from 16 participating PWDs indicate that they are generally risk-averse, with diminishing sensitivity to increases in asset criticality and likelihood of failure. Because they are risk averse, public works directors are likely to prioritize more critical, less likely-to-fail projects over less critical, more likely-to-fail systems. The observed risk aversion differs from the prediction of cumulative prospect theory, which indicates that PWDs should be risk seeking when the probability of failure is high, but agrees with prior findings on public financial managers' decision-making (Fennimore & McCue, 2021; McCue, 2000).

Literature Review

Coastal municipal governments in the United States are already forced to adapt to sea level rise. As waters rise, coastal flooding will become more intense and frequent, saltwater intrusion will threaten groundwater supplies, mean high tide events and king tides will increase disruptive sunny day flooding, and, eventually, lands may become inundated (Glavovic et al., 2022; Magnan et al., 2022; Oppenheimer et al., 2019; Sweet et al., 2022). Globally, wealthy, developed cities along the coast experience pressing threats from sea level rise and can substantially reduce their risk by investing in adaptive infrastructure (Glavovic et al., 2022; Magnan et al., 2022). Still, within the United States, sea level rise has often struggled to surface to the top of the policy agenda in the minds of the public, local officials, or state legislators (Akerlof et al., 2019; John & Yusuf, 2019; Yusuf et al., 2016). However, there are hotspots of adaptation, where governments are coming together to understand the issue of sea level rise and develop plans of response (Ekstrom & Moser, 2013; Hines et al., 2022; Lubell & Robbins, 2021; Vella et al., 2016). Responding to sea level rise will require coastal governments to invest in hard and soft infrastructure systems to make lived in areas more resilient. However, the risk of sea level rise damages calls for more than investing in new infrastructure systems (Glavovic et al., 2022). Current assets must also be maintained.

Local governments in the United States develop and own long-lived infrastructure systems for transportation, stormwater management, and water supply, all of which could be at risk of damage from rising seas (Allen et al., 2019; Fisk, 2019; Price, 2019). Eventually, governments will have to move from planning for sea level rise to budgeting for it, by sequencing and prioritizing adaptive investments into their capital improvement plans and budgets (Hines et al., 2022). Given the immediacy and tangibility of threatened capital assets, it is possible that protecting current assets from failure may be a critical first step for localities, helping them advance from understanding and planning for sea level rise to prioritizing and making adaptive investments. Specifically, how might local officials responsible for threatened capital assets approach making adaptive investments in their budgetary processes?

Public budgetary decisions result from a complex and collaborative interplay between elected and public officials (Rubin, 2016; Thurmaier & Willoughby, 2001; Wildavsky, 1964; Willoughby, 1991; Willoughby & Finn, 1996). At the state level, budget analysts are understood to use multiple rationalities to weigh political and economic factors when making recommendations to the governor or legislature (Thurmaier & Willoughby, 2001; Willoughby, 1991; Willoughby & Finn, 1996). At the local level, public works departments are responsible for transportation infrastructure, stormwater drainage, and water supply systems that may be threatened by rising seas. A natural starting point for understanding public works departments' approach to adaptive decision-making is to understand the weight their directors assign to the different factors of resiliency investments.

There is a rich literature on both the local government capital budgeting process and the budgetary decision-making of public officials, providing a starting point for understanding the dimensions of adaptive investment decision-making by public works directors. Ideally, local government capital budgeting begins with strategic and comprehensive plans; such plans set goals allowing for the prioritization and sequencing of capital projects within capital improvement plans (CIP) and their funding through annual budget processes (Srithongrung et al., 2019). Project prioritization, a key element of investment sequencing, is essential; this role may fall to public works directors as they participate in the budget process. As leaders of their department, PWDs are professionally responsible for managing departmental initiatives and their budgets (Felbinger, 1989). Departmental leaders, distinct from state budget analysts in their ongoing responsibility for project proposal, implementation, funding, and budget outcomes, facilitate capital budgeting processes such that they propose, defend, and administer their budgetary requests (Rubin, 2006). A clear example of this process is described in the City of Sault Ste. Marie's CIP (pg. 3, n.d.):

> In December, Department Heads began reviewing their capital improvement projects and began working on new proposed projects. Correspondingly, various Boards & Commissions are asked to review their priority projects. Department Heads complete the CIP forms and turn them into Engineering. The booklet is then put together in draft form for review at department head meetings to later be presented to the Planning Commission and City Commission for final approval.

The handbook goes on to describe the ranking process, whereby department heads and the city manager score projects, out of 200, for prioritization. In this example, department heads play a facilitative role in which they develop and prioritize projects. However, capital budgeting processes vary over governments, so individual PWDs' roles feature different mixes of facilitation and determinative decisions.

Understanding PWDs' decision-making related to sea level rise provides essential micro-foundations for a broader theory of local government adaptive decision-making. However, adaptive decision-making presents unique challenges. Mainly, protecting threatened infrastructure from rising seas requires decision-makers to deal with the uncertainty of future climate change-related damages (Keenan, 2019; Price, 2019; Sweet et al., 2022). Public works directors' decisions may depend on their preferences across a range of likely outcomes. In the future, the probability of failure of local infrastructure assets will depend on their risk of failing across a range of probable scenarios. Sea level risk forecasts contain considerable uncertainty, because they depend on assumptions about future emissions levels and imperfect estimates of Earth's responsiveness to emissions levels (Sweet et al., 2022).

When evaluating and sequencing resiliency initiatives, decision-makers must consider the uncertainty in their forecast, each assets' risk of failure given the forecast, and the potential consequences that may occur from asset failure (Buurman & Babovic, 2016; Haasnoot et al., 2019; Keenan, 2019; Price, 2019). Normatively, it is possible to measure the expected value of future sea level rise damages and base adaptive investments on such formal cost-benefit analysis, but, realistically, the considerable uncertainty behind sea level rise forecasts makes this task challenging in its application (Price, 2019). However, people do not tend to make decisions based on straightforward expectations; instead, they show non-linear preferences across the outcomes and probabilities of occurrences for risky events (Altman, 2010; Barberis, 2013; Tversky & Kahneman, 1992; Tversky & Wakker, 1995; Wakker, 2010; Walker et al., 2003).

Prospect theory is the leading framework of decision-making under conditions of risk and uncertainty (Barberis, 2013; Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). Combining the insights of their original theory from 1979 and Quiggin's (1982) cumulative representation of uncertainty, Tversky and Kahneman (1992) proposed that decision-makers are decreasingly sensitive to gains, decreasingly sensitive to losses, overweight low probability events, underweight high probability events, and are more sensitive to losses than gains. The result explains the commonly observed four-fold pattern of risk preferences, in which decision-makers are risk-averse for gains and low probability losses and risk-seeking for high probability losses and high probability gains (Tversky & Kahneman, 1992). Prospect theory has been replicated numerous times in experimental studies and broadly applied to questions in behavioral finance (Barberis, 2013; Bellé et al., 2018). While scholars initially considered prospect theory to be less applicable to professional financial decision-makers, it has generally been successful in explaining the decisions of private financial managers (Abdellaoui et al., 2013). Of course, cumulative prospect theory argues that the non-linear transformation of probabilistic decision-weights are not the result of decision-makers' misperception of probabilistic events, but rather reflect their preferences (Barberis, 2013), which may differ in the context of protecting public infrastructure systems.

There is some reason to believe that PWDs may not be risk-seeking over moderate-probability losses. Prior experimental evidence shows that while public finance directors, as individuals, may be risk-seeking when evaluating losses, they are risk-averse when making decisions for their government (McCue, 2000). Further, organizational and professional cultures that prioritize prudence and risk avoidance may change individual-level risk preferences, resulting in risk averse public financial decision-makers (Fennimore & McCue, 2021). This is likely to be true for PWDs whose infrastructure systems quietly form the foundation for city life while protecting life and property. A case of serious infrastructure failure would be a catastrophe, which would incentivize risk aversion on the behalf of public works directors. Professional standards may similarly reinforce risk aversion. Felbinger (1989), though somewhat outdated, indicates that most PWDs are trained engineers who emphasize the managerial nature of their work. In the context of climate change-induced damages, the uncertainty behind climate models may make risk aversion more attractive to PWDs who are attuned to preventing infrastructure failures through high design standards. As argued by Price (2019, pg. 14):

> If the data on the frequency of the larger storms indicates that rainfall and stream flows are rising, is a probability distribution (risk) known? Yet too often a probability

distribution is unknown (uncertainty), so it is desirable to set design parameters beyond the estimated range of such events to avoid any risk of disaster.

As public sector decision-makers are facing considerable uncertainty over future levels of sea rise, public works directors may be quite likely to be highly risk averse, a tendency likely compounded by their responsibility, as departmental leaders, to both build and maintain infrastructure and answer to elected officials and the public.

Local governments will be challenged to prioritize needed investments under conditions of risk and uncertainty. This paper aims to develop a micro-foundation for understanding local government prioritization of capital assets by better understanding the budgetary decision-making strategies of PWDs. This research extends prospect theory insights to the public budget process and contributes to the growing number of experimental studies seeking to contribute to behavioral approaches in public finance (Espinosa et al., 2021; Mohr & Kearney, 2021).

Theory

Sea level rise poses an uncertain risk to local government capital assets. Sea level rise forecasts, based on models projecting future sea level rise, depend on assumptions about future warming scenarios and model structuring decisions (Walker et al., 2003). Therefore, sea level rise forecasts feature distinct sources of uncertainty about socioeconomic factors, like future emissions pathways, and physical factors, like potential ice loss scenarios (Jevrejeva et al., 2019; Sweet et al., 2017). Risky outcomes are governed by knowable probabilities, whereas ambiguous outcomes are defined by unknowable probabilities (Tversky & Wakker, 1995; Wakker, 2010). Therefore, decision-makers treat risk and uncertainty differently. In this context, while an asset's probability of failure may be calculable under a particular sea level rise scenario, that scenario's probability of occurrence itself is incalculable, though it may be intuited. Credible, national-level scenarios of global mean sea level rise, produced by the National Oceanic and Atmospheric Administration (NOAA), can serve as a reference point for decision-makers across the country (Sweet et al., 2017; Sweet et al., 2022). The following theory is based on decision making under a specific sea level rise scenario. This scenario allows the source of uncertainty facing decision-makers to remain constant, because probabilistic risk estimates of damage are drawn from the same family of modeling assumptions (Tversky & Wakker, 1995; Wakker, 2010). Therefore, and in this case, the theory describes how public works directors navigate risks drawn from a similar family of uncertain events defined by a particular sea level rise scenario.

Roads, bridges, stormwater/sewer infrastructure, and other key assets may all be vulnerable to damage or failure under different sea level rise scenarios (Fleming et al., 2018; Hines et al., 2022). Public works directors are responsible for infrastructure portfolios which feature assets with different levels of criticality and exposure to climate change risks. Criticality refers to an asset's expense and ability to protect life and property. Critical pieces of infrastructure may last for decades, protect lives and/or property, and play an important role in interconnected systems, causing severe consequences upon failure. Assets with greater exposure to sea level rise are more likely to fail under a wider range of sea level rise scenarios.

To operationalize this relationship, an asset's probability of failure is defined as its percent chance of failing if seas were to rise. An asset's overall level of vulnerability can be considered its criticality multiplied by its probability of failure. When prioritizing different projects aimed at adapting to climate change, public works directors should seek to protect vulnerable pieces of infrastructure which are more critical and likely to fail.

H1a**:** Public works directors prioritize more critical assets.

H1b: Public works directors prioritize assets that are more likely to fail.

In this context, an asset's level of vulnerability is analogous to the expected consequences of its failure in a future sea level rise scenario. Thus, PWDs' decisions to prioritize or not prioritize certain assets for adaptive investments depends on their perceptions of the asset's importance and risk of failure. However, decision-makers do not tend to have linear preferences when making decisions under conditions of risk and uncertainty. Specifically, decision-makers tend to overweight small probabilities and underweight large probabilities, and are decreasingly sensitive to losses or gains as they increase in size (Altman, 2010; Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). Prospect theory, as a theory of decision-making under risk and uncertainty, has found significant empirical support and been successfully applied to explain the decisions of public managers (Bellé et al., 2018; Ruggeri et al., 2020).

Public works directors are expected to increase their prioritization of an asset at a decreasing rate as its criticality increases. Because assets threatened by rising seas are "safe" in the status quo but may fail if seas rise, asset failure is likely to be perceived as a loss by PWDs. In the context of this study, the failure of a critical asset should be perceived as a loss, because it comes with consequences and PWDs are likely attuned to loss prevention. Decision-makers tend to become decreasingly sensitive to the absolute size of losses as they increase (Barberis, 2013; Tversky & Kahneman, 1992). If public works directors become less sensitive to losses as they grow, the perceived criticality of an asset would fall below its numerical value (see Figure 1 at the end of this chapter), creating a concave relationship between assets' criticality and their level of prioritization.

H2: Project prioritization is concave with respect to the value protected by a planned acquisition or the consequences of a current asset's failure.

Public works directors are expected to increase their prioritization of a threatened asset at a decreasing rate as it moves from being very unlikely to moderately unlikely to be damaged by sea level rise, and at an increasing rate as it moves from being moderately likely to very likely to be damaged by sea level rise. When evaluating risky decisions, decision-makers tend to perceive changes in low probability events as more significant than changes in high probability events and display a preference for certainty (Allais, 1953; Bleichrodt & Pinto, 2000; Tversky & Kahneman, 1992; Wu & Gonzalez, 1996). Prospect theory captures decision-makers' weighting of probabilistic events through an inverse S-shaped weighting curve, which overweights low probability events and underweights high probability events (Tversky & Kahneman, 1992). Figure 2 shows a typical representation of the inverse S-shaped curve as weighting failure probabilities, following Tversky and Kahneman's (1992) functional form.

If PWDs are decreasingly sensitive to probabilistic changes as they move away from impossibility or certainty, then their prioritization decisions should be inverse S-shaped with respect to the probability at risk. While decision-makers' tendency to make decisions based on inverse S-shaped probability weighting curves has been confirmed in multiple laboratory studies, substantial individual heterogeneity exists (Bleichrodt & Pinto, 2000; Tversky & Kahneman, 1992; Wu & Gonzalez, 1996). Indeed, strictly concave, convex, linear, and inverse S-shaped curves have been proposed, estimated, and empirically supported throughout the literature (Abdellaoui, 2000; Bruhin et al., 2010; Harrison & Swarthout, 2020; Quiggin, 1993; van de Kuilen & Wakker, 2011). The inverse S-shaped curve theorized in cumulative prospect theory is concave when the probability is low and convex when the probability of failure is high (Tversky & Kahneman, 1992). Hypotheses 3a and 3b test the concavity and convexity of public works directors' prioritization decisions when the probability of failure is low or high, as implied by the inverse S-shaped probability weighting function. However, due to the plethora of functional forms estimated in the literature, separate tests were performed in order to observe either concavity or convexity alone.

H3a: Asset prioritization is concave with respect to the probability of failure when the probability of failure is low.

H3b: Asset prioritization is convex with respect to the probability of failure when the probability of failure is high.

Risk Preferences and the Decision-making Context

Public works directors' risk preferences influence, but do not solely determine, their prioritization of threatened assets. Public budgeting decisions are inherently political, and budgetary decision-makers likely use a blend of social, legal, political, and technical rationalities to complement their decisions on how best to invest in protective infrastructure (Rubin, 2016; Thurmaier & Willoughby, 2001; Willoughby, 1991; Willoughby & Finn, 1996). In a realistic decision-making scenario, PWDs will consider assets' criticality and probability of failure alongside other factors, which must be considered to truly capture PWDs' risk preferences.

Public budgetary decisions about public infrastructure threatened by sea level rise are made for public works departments pursuing managerial objectives in political environments subject to budgetary constraints. Because PWDs are limited by their budgets, they likely seek to prioritize cost-effective projects, and, as departmental leaders, they must also pursue their strategic objectives. Therefore, cost-effective projects that align with departmental goals are likely to be more highly prioritized than those that do not. PWDs who prioritize managerial objectives and cost-efficiency may be considered more economic in their budgetary orientation (Willoughby, 1991; Willoughby & Finn, 1996). Naturally, public works departments are organizations whose budgets are subject to review and approval by local elected leaders. Recognizing the political nature of their tasks, public works directors should prioritize projects with popular political support; those more oriented towards partisan factors may be considered as more political in their decision-making orientation (Willoughby, 1991; Willoughby & Finn, 1996). However, asset adaptability is uniquely important to making decisions about assets threatened by sea level rise.

Capital projects may differ in their ability to be modified once sea level rise damages begin to accumulate. For instance, responding to a greater degree of sea level rise by investing in additional greenspace or public park drainage may be significantly easier than re-engineering a threatened bridge built to an insufficient standard. Given the uncertainty of climate change, flexible and no-regrets funding strategies have been advocated as potential solutions to the consequences of planning for uncertain events (Buurman & Babovic, 2016; Keenan, 2019). As governments learn more about their risk to sea level rise and the likeliest scenarios, they will be able to invest more accurately in climate change adaptations. Acquiring new adaptive infrastructure that can be flexibly re-worked in higher sea level rise scenarios and investing in adaptive fixes to current assets that are modifiable based on additional data may be preferred strategies. Projects' adaptability, cost-efficiency, alignment with departmental strategic goals, and alignment with elected officials' objectives are all criteria that should theoretically impact PWDs' decision-making; these factors should be evaluated alongside their treatment of asset criticality and probability of failure to paint a complete picture of their risk preferences.

Empirical Strategy

This study examines the risk preferences and decision-making orientations of public works directors using an experiment asking them to prioritize 40 different capital assets threatened by sea level rise in order to increase sea level rise resiliency, based on their levels of criticality, probability of failure, and other key criteria. To test if PWDs' prioritization of an asset is concave with respect to criticality, concave with respect to the probability of failure when it is low, and convex with respect to the probability of failure when the probability of failure is high, non-linear least squares was used to impose flexible parametric criticality and probability weighting functions (Luce, 2001; Prelec, 1998; Stott, 2006; Tversky & Kahneman, 1992). The next section describes the framework used to design the experiment, the contents of the project profiles, the randomization procedure, and the study's implementation.

Representativeness Design Framework

To maximize the ability of the decision-making experiment to speak to the true risk preferences of public works directors, social judgement theory was used as a framework to design the experiment. Social judgment theory stresses that decision-making experiments should be representative of the decision-making environment that the decision-makers experience in their professional life to ensure their external validity (Cooksey, 1996a, 1996b; Dhami et al., 2004; Dhami & Mumpower, 2018; Willoughby, 1991). Following prior work using a social judgment theory framework, this experiment uses a single-lens experimental design to elicit PWDs' asset prioritization decisions, asking them to make a judgement based on a set of cues drawn from their decision-making ecology (Willoughby, 1991; Willoughby & Finn, 1996).[11] Prior research has defined state budget analysts as judges who consider the agency workload, efficiency, political support, and other factors as cues when making budget recommendations in their decision-making ecology (Willoughby, 1991). In this case, PWDs are judges called upon to

[11] The terms are defined as follows: judges are decision-makers, cues represent the most important decision-making criteria relevant to some decision tasks, and the ecology represents the decision-making setting and defines what relevant cues exist (Cooksey, 1996b).

prioritize adaptive investments protecting threatened capital assets in the context of their local governments' budgetary processes. To maximize the external validity of the findings, this experiment proceeded in two phases, including an initial pilot and a refined design based on the feedback of working public works directors.

The decision-making simulation itself involved two steps undertaken to maximize its validity. First, the initial draft project profiles were generated based on theory. Second, a pilot study was conducted, consisting of 1) interviews with PWDs who described their role in the capital budgeting process and 2) a session in which these interviewees completed a draft simulation and provided feedback. Four PWDs participated in the pilot study, representing a blend of rural and urban county and city governments of varying sizes. Public works directors participating in the pilot study confirmed that they play an active role in their government's capital budgeting process (Felbinger, 1989). While capital budgeting processes and procedures vary across governments, each PWD took an active role in developing their department's capital budget and shepherding it through the budgetary process. Typically, PWDs act as requestors, by proposing projects that are subject to approval by elected officials. In this context, they work to prioritize projects that align with the desires of elected officials and get projects with a good degree of political support approved. PWDs described working as advocates for certain projects which they felt to be important, even when those projects received political pushback.

Local governments are beginning to plan for sea level rise resiliency by generating data on their sea level rise risk and conducting risk assessment processes designed to evaluate the value of assets at risk to inform future adaptive plans (Hines et al., 2022). Pilot study participants differed in their ability to systematically analyze their level of risk scaled with departmental resources. Simulating the impact of forecasted future sea level rise is a complex task. Public works departments from the largest governments generally have access to well-developed and supported simulation techniques for projecting sea level rise, whereas PWDs from smaller governments must intuit threats to assets already showing signs of stress from rising tides. Regardless of resources, public works directors from across the sample recognized the current impact of rising seas on their assets' susceptibility to flooding, and were taking steps to begin adapting their most threatened assets to mitigate flooding risks.

Description of Judgement Task

In the simulation, public works directors were asked to prioritize assets on a 1 to 10 scale based on six criteria: level of criticality, probability of failure (under the International Panel on Climate Change's Representative Concentration Pathway (RCP) 4.5 scenario), adaptability, cost-efficiency, strategic goal alignment, and alignment with current elected officials' agendas (Sweet et al., 2017). Appendices A and B at the end of the document present the instructions for completing the survey and an example project profile, respectively. Prioritizing capital projects is a complex decision task; therefore the number of cues was kept to a minimum of six, following prior studies (Cooksey, 1996; Willoughby, 1991; Willoughby & Finn, 1996).

The project-ranking protocol was based on the common practice of localities, which rank projects for prioritization for inclusion in capital improvement plans. Across state and local governments, ranking capital projects based on their criteria is a critical part of sequencing investments into capital improvement plans and funding projects in annual capital budgets (Bland, 2013; Srithongrung et al., 2019; Vogt, 2004). Interviewed PWDs confirmed that capital improvement project prioritization decisions typically occurred at their level and were used to navigate risky decisions when evaluating capital projects. One director remarked that they, "make these types of decisions every day."

Assets' criticality and probability of failure under a specific sea level rise scenario determine expected consequences of asset failure. These types of criteria are already being considered by local governments, which are beginning to plan for sea level rise resiliency by generating risk data and conducting risk assessment processes designed to evaluate the value of assets at risk to inform future adaptive plans (Hines et al., 2022). For instance, in Florida, Sarasota's Climate Adaptation Plan features an assessment of the vulnerability of their capital assets, defined by its adaptive capacity and sensitivity to risk, the consequences of the asset failure, and the likelihood of asset damages (City of Sarasota, 2017).

As a cue, asset criticality was designed to capture the myriad criteria that would generate negative consequences for an asset failure, while leaving open the actual consequences of failure. Critical pieces of public infrastructure may be expensive and long-lived, protect human life and property, and be integrated into larger critical systems. Sarasota's Climate Adaptation Plan defines critical assets as those:

> Public assets, systems, and networks vital to the City of Sarasota such that their disengagement or destruction would result in debilitating impacts to public health and safety, functionality of critical public utilities, safe evacuation, or the environment (City of Sarasota, 2017 pg. vii).

Assets' probability of failure was given in terms of a specific sea level rise scenario, to allow for comparability across directors who may be referencing different scenarios. Climate change is based on future emissions pathways, which are uncertain. However, under assumptions about future emissions, probabilistic assessments of future sea level rise are possible. While scenario analysis under different emissions assumptions is good practice, an underlying linear scale is required to prevent non-linear differences in forecasted sea level rise scenarios from contaminating the non-linear patterns implied by theory (Jevrejeva et al., 2019; Sweet et al., 2017). Therefore, the prompt states that the percent chance of damages for each asset is calculated under a constant, reasonable sea level rise scenario derived from NOAA's set of sea level scenarios (Sweet et al., 2017).

Adaptability represents the ability to flexibly invest in resiliency as more is learned about sea level rise. Theoretically, adaptable assets may be prioritized because they may be flexibly re-worked in later periods (Keenan, 2019). Originally, the study referred to adaptability as “flexibility,” but participating PWDs were confused by the meaning of the term. Since participants noted the importance of future adaptability, the cue was re-written to explicitly reference the ability of assets to be flexibly remodeled as seas continue to rise.

Though the initial set of project profiles lacked a cost variable for each project, each of the interviewed PWDs mentioned the difficulty of making their decision without a cost variable. Operationalizing cost is difficult in this context: it is unclear what costs would be reasonable for projects with differing abstract levels of political support, goal alignment, and levels of probabilistic risk. Including a cost variable could introduce scaling problems between probabilistic risk estimates and cost estimates when displaying the project profiles. To resolve these difficulties, cost-efficiency was included as a variable capturing the efficiency of the planned repair. Therefore, the cost variable renders the project profiles more realistic, and prompts the participant to imagine a certain project cost that results in the given degree of cost-efficiency, based on the other criteria. Project profiles with unrealistic cost-profiles were not displayed to participants, since cost-efficiency implies a certain level of absolute cost relative to the other characteristics of the project.

Asset alignment with departmental strategic goals and level of current political support reflects asset integration into overall departmental plans and the local political environment. CIPs are often long-term plans that aim to push communities' politically selected goals, as given in their strategic plans (Srithongrung et al., 2019). Therefore, asset alignment with strategic goals reflects the managerial direction of the department based on long-term plans. However, current elected officials may support or oppose individual projects for failing to align with their or their constituents' particular needs. During the pilot study, PWDs extensively discussed the importance of project alignment with strategic goals and political support, noting that instances in which a project's level of political support and strategic goal alignment were wildly different were unrealistic, as strategic goals are determined politically. Therefore, inter-cue correlations were added between a project's level of political support and strategic goal alignment.

Implementation

Using the above criteria, decision-making project profiles were randomly generated using the EnvStats package (Millard, 2013), which employs Iman and Conover's (1982) algorithm to randomly sample from potentially correlated random variables following different distributions. The percent chance of damages was randomly sampled from a beta distribution, which has two useful properties. First, it is bounded between 0 and 1 and naturally can be used to randomly generate proportions. Prospect theory implies tail effects around conditions of almost certainty and great improbability. Therefore, it is important for project profiles to contain projects that are very unlikely and almost certain to be affected by sea level rise. The shape of the beta distribution was controlled by shape parameters, which allow for oversampling at the extremes of the distribution. Probabilities were sampled from a beta distribution with shape parameters both set to 0.8 to oversample from the tails, rounded to two digits, and presented as percentages for interpretability. Randomly generated probabilities that rounded down to 0 or up to 1 were rounded to 1% and 99% before profile inclusion, in order to exclude impossible or certain events. Each remaining cue was sampled on a uniform distribution from 1 to 10 and rounded for display. A correlation of 0.6 was introduced between strategic goal alignment and alignment with current elected officials' agenda for realism.

The experiment was implemented in Qualtrics for distribution. First, participants were asked to review the instructions in Appendix A. Second, participants filled out three practice profiles, excluded from statistical analysis, as shown in Appendix C. Third, participants were asked to prioritize 40 projects on a 1 to 10 scale, with 1 indicating that the project should be prioritized less than competing projects and 10 indicating that the project should be prioritized above competing projects. Participants were allowed to move backwards and forwards as they completed the survey, and buttons were inserted allowing participants to review the prompt and definitions at any time.[12] Surveys were subject to order effects, whereby participants' responses change due to the ordering of questions (Dillman, 2014). During the pilot study, PWDs mentioned that they were gaining an understanding of the task and changing their perceptions of the profiles as they proceeded through the experiment. However, it is unclear exactly how participants were updating their responses. Therefore, the order of the profiles was randomized in each experiment to correct for any potential learning effects which could bias the results.

The experiment was distributed in two waves. In the first wave, letters were sent to 406 PWDs, as identified in the American Public Works Association's list of United States public works directors in coastal zip codes.[13] The first wave contained follow-up questions on public

[12] The button was inserted using script from the Qualtrics XM Community (TomG, 2020).
[13] ZipcodR, readxl, the Geographic Names Information System, and the United State Census Bureau's list of coastal counties were used to identify coastal governments with public works directors on the list (Rozzi, 2021; United States Census Bureau, Population Division, 2018; United States Geological Survey, n.d.; Wickham & Bryan, 2022).

works directors' opinions on sea level rise and their government's response to the issue, as shown in Appendix D, and basic demographic questions, as shown in Appendix E. This wave of solicitation yielded just five participants, so a second wave of contacts were made, using a modified study procedure. In the second wave, 225 public works directors in coastal municipal governments were identified through manual review of government websites. To gain more insight into PWDs' decision-making, an interview procedure was added to the invitation, structured as an online experiment administered over Zoom.[14] Following review of a consent document, the instrument asked career-related questions, posed the simulation in Qualtrics, and then asked follow-up questions regarding their government's sea level rise policies (see Appendix F for the full interview procedure). Participants were able to ask clarification questions when given the simulation.

While this survey had a low response rate and cannot be considered representative of all public works directors, there is no reason to suspect that the sample biases the hypotheses tests for PWDs' risk preferences. The experiment and interview process were long. Participating public works directors were likely motivated to contribute to science; non-participants may have opted out simply because they are busy leaders of their departments. There is no reason to suspect that a public works director's decision to respond or not respond to the survey would be correlated with any potential non-linearities in their risk preferences. Further, individual PWDs' observed non-linear risk preferences cannot be the result of sample bias because the experimental design randomizes the treatment within subjects. No issue with sample bias would bias individual-level estimates of risky weighting parameters, because the treatment is within

[14] The United State Census Bureau's list of coastal counties, Geographic Names Information System, readxl, and the Office of Coastal Management's Sea Level Rise viewer were used to help identify coastal governments not initially contacted for the second implementation of the experiment (Office for Coastal Management, n.d.; United States Census Bureau, Population Division, 2018; United States Geological Survey, n.d.; Wickham & Bryan, 2022).

participants. Instead, it would imply the wrong distribution of risk parameters across the population of public works directors.

Because the sample was dominated by white men over 40, it does not exhibit gender or racial diversity. However, it does reflect the demographics of public works directors. As of 2012, the American Public Works Association itself indicated that 64% of its members were between the ages of 40 and 60, 85% were male, and 83% were Caucasian (2013). Thus, the sample may be more demographically representative of PWDs than it appears at first glance. While the sample is small, it captures coastlines across the United States, governments of large and small size, and governments with different governing structures.

Data Analysis

Sixteen public works directors participated in the study. In the first wave, five directors responded to the initial survey experiment and participated independently. In the second wave, 11 directors participated in the interview/online experiment format. The study represents a wide swath of the United States' coast, with directors hailing from Hawaii (1), Washington (1), California (4), Texas (2), Florida (1), South Carolina (1), North Carolina (1), Maryland (2), and Massachusetts (1). Similarly, the sample represents a wide range of populations served, including two very large governments (serving > 900,000 residents), five large governments (serving >100,000-300,000), two medium size governments (serving >20,000-60,000), and finally four small governments (serving 25,000 people or less) (United States Census Bureau, n.d.). Participating governments are nested in democratic-leaning counties. Using MIT's election data, only three represented counties failed to provide a majority of votes for President Biden in the 2016 election (MIT Election Data and Science Lab, 2018). Most represented governments take either a council-administrator or council-manager form. Only three cities had mayor-council forms. Two public works directors participated anonymously; their government form could not be determined.

Most participants were white males with considerable experience in local government service. Demographically, 13 of 15 directors providing their race were white, 2 of 15 who indicated their gender were woman, and the average age of the 14 participants who gave their age was 53. From the sample, 11 of the 16 participating directors served as PWD for a municipality, two as chief engineer and director of the engineering and environmental services division for a large water utility, and two chose to remain anonymous. Participating directors had been in their role for a long time, one for less than a year, four serving 1-5 years, five for 5-10 years, and three for more than 10 years. The following sections present the analysis of this data, by first pooling the 16 participating directors' decisions to create a summative statistical model. Second, individual-level data were analyzed, alongside interview responses, to explore the heterogeneity in participating PWDs' risk attitudes and decision-making strategies.

Results for Representative Public Works Director

Response data were first pooled to characterize the decision-making strategies deployed by the participating directors. While the pooled results do not necessarily reflect any individual's treatment of risk and decision-making, they provide a summative way to assess the dominant treatment of risk and uncertainty across the dataset. The representative PWDs' decisions were fit using pooled non-linear least squares with the functional form shown in equation 1.1, in which i indexes each director, n indexes each project profile, B_o is a constant, x represents asset criticality, p represents the probability of failure, d represents adaptability, c represents cost efficiency, s represents political support, g represents strategic goal alignment, and e is the random error inherent in the decision.

$$y_{i,n} = \left(B_o + B_1 \left(x_{i,n}{}^{\alpha} e^{-r\left(-\ln\left(p_{i,n}\right)\right)^s} \right) + B_2 \left(d_{i,n} \right) + B_3 \left(c_{i,n} \right) + B_4 \left(s_{i,n} \right) + B_5 \left(g_{i,n} \right) + e_{i,n} \right) \qquad (1.1)$$

The criticality of the asset and its probability of failure enter nonlinearly as a simple risky prospect scaled by the vulnerability weight B_1. Asset criticality was weighted using power function with parameter a and probabilities were weighted using the two parameter Prelec-2 probability function with *s* and *r* parameters (Luce, 2001; Prelec, 1998; Stott, 2006). The power criticality weighting function is linear when *a* is equal to one, and the Prelec-2 probability weighting function is linear when *s* and *r* both equal one. Usefully, the Prelec-2 takes an inverse S-shape when *s* is less than one and collapses to a power function when *s* is equal to one. By allowing the curve to take either a strictly concave, convex, or S-shaped functional form, the Prelec-2 functional form allows for hypotheses 3a, which hypothesizes that prioritization is convex with respect to the probability of failure for low probability events, and 3b, which hypothesizes that prioritization is convex with respect to the probability of failure for high probability events, to be tested separately. If Tversky and Kahneman's (1992) functional form was fit to the data instead of the Prelec-2 function, the resultant test would jointly test hypotheses 3a and 3b against linear probability weighting, because the degree of concavity in the lower portion of the curve and convexity in its upper portion are controlled by the same parameter.

The pooled results are shown in Table 15 at the end of this chapter. Estimates are presented with cluster robust standard errors. In this experiment, with just 16 participants, the number of clusters is low. Traditional cluster robust standard errors are known to be undersized when the number of clusters is small (Cameron et al., 2008; Colin Cameron & Miller, 2015).

Therefore, cluster jackknife standard errors were used for inference instead, because they are less undersized (Cameron et al., 2008; Colin Cameron & Miller, 2015).

Participating public works directors increased assets' prioritization at a decreasing rate with regards to level of criticality. The effect of asset criticality on a PWD's decision enters non-linearly based on the vulnerability weight and *a*. Thus, no one parameter is able to summarize the effect of a change in criticality. Hypothesis 1a was tested by estimating the average marginal effect of a one unit increase in criticality. Unsurprisingly, the representative PWD increased the prioritization afforded to an asset based on its level of criticality. On average, PWDs increased their prioritization of a threatened asset by .46 for a one unit increase in asset criticality, with the associated 95% confidence interval for the effect ranging from 0.38 to 0.54 (Long & Freese, 2014). Second, hypothesis 2 predicts that the project prioritization is concave with respect to asset criticality. As shown in Table 15, hypothesis 2 is not rejected because *a* is significantly less than 1 at the 0.01 level. Figure 3 visualizes this effect, showing that increases in an asset's criticality substantially increases asset prioritization at a slightly decreasing rate.

Contrary to cumulative prospect theory, public works directors increasingly prioritized threatened assets at a decreasing rate for both high and low probability events. Hypothesis 1b indicates that increases in assets' probability of failure if seas rise should increase their prioritization. In this case, the probability of failure enters non-linearly based on the vulnerability weight, *s*, and *r*. Therefore, it was tested by taking the average marginal effect of a 10% change in an asset's probability of failure. As predicted by hypothesis 1b, PWDs significantly increased asset prioritization when the probability of asset failure increased. On average, PWDs increased an asset's prioritization by 0.25 for a 10% increase in the asset's probability of failure, with the 95% confidence interval for this effect lying between 0.19 and 0.31 (Long & Freese, 2014).

Public works directors' estimated probability weighting function did not take on the inverse S-shape predicted by cumulative prospect theory. The Prelec-2 functional form collapses to a power function when *s* equals 1. As shown in Table 15, the linear restriction that *s* equals 1 is not rejected, with an associated p-value of .18. However, *r* is significantly less than 1 at the 0.01 level. Therefore, hypothesis 3b is rejected. Figure 4 displays this relationship between asset probability of failure and prioritization. Prioritization increases at a sharply decreasing rate for low probability events but takes on a roughly linear pattern as the probability of failure rises above 0.2. Therefore, hypothesis 3a is not rejected. Asset prioritization is concave with respect to the probability of failure for low probability events. However, prioritization is not convex with respect to the probability of damage for high probability events. These results are stable when the linear restriction that *s* is equal to one is imposed. As shown on Table 15, imposing the linear restriction that *s* is equal to one results in nearly identical estimates for *a* and *r*, with a notably smaller confidence interval for *a*.

Public works directors' non-linear preferences generate risk aversion such that critical assets with low failure probabilities tend to be prioritized over non-critical assets with high failure probabilities at all failure probability levels. An asset's level of vulnerability is given by its criticality multiplied by its probability of failure. If PWDs engaged linear probability and criticality weighting functions, assets with the same level of vulnerability would be given the same level of prioritization. To characterize PWDs' risk preferences over assets' criticality and failure probabilities, prioritization levels were predicted for the average asset at asset criticality and at failure probability levels, which appeared in the randomly generated project profiles. Figure 5 shows the average predicted prioritization for selected pairs of assets that have different levels of criticality and failure probabilities, but similar vulnerability scores, of 0.35 and 0.36, 0.9

and 1.58, 1.95 and 2.1, 3.84 and 3.88, and 6.79 and 7.74 respectively. As shown in Figure 5, assets that were more critical and less likely to fail tended to receive slightly higher levels of prioritization than assets that were more likely to fail and less critical. Because PWDs prefer preventing a low chance of losing a highly critical asset to preventing the higher chance of losing a non-critical asset, they can be considered risk averse.

The pooled results indicate that public works directors decreased easily adaptable assets' level of prioritization and increased that of assets which 1) could be cost-effectively adapted to sea level rise and 2) were aligned with their government's strategic goals and current elected officials' objectives. The pooled results indicate that PWDs tended to de-prioritize more adaptable assets at the 0.05 significance level. It is possible that assets' adaptability in future periods makes a wait-and-see approach more viable, and allows the investment to be prioritized after more pressing concerns are addressed. The cost-efficiency of the planned repair, strategic goal alignment of the asset, and the alignment of the asset with current elected officials' agendas all increased the prioritization of the asset at the 0.01 significance level. Of course, the above results summarize decision-making across the sample. It is more interesting to assess the heterogeneity of individual public works directors' preferences.

Individual-Level Analysis of Risk Preferences

Individual-level non-linear least squares regressions were fit to characterize each public works director's decision-making orientation. While the considerable flexibility of the Prelec-2 functional form is preferable for analyzing the pooled data, it is too complex to fit at the individual level and would often fail to converge. Instead, a model selection process was used to select the best fitting one parameter probability weighting function for each director. Two different inverse S-shaped curves were fit to each director. These include the Prelec-1 form, as shown in equation 1.2, and the functional form suggested by Tversky and Kahneman (1992) in equation 1.3 (Luce, 2001; Prelec, 1998; Stott, 2006)

$$y_n = \left(B_o + B_1 \left(x_n{}^{\alpha} e^{-1\left(-\ln\left(p_n\right)\right)^s} \right) + B_2 \left(d_n \right) + B_3 \left(c_n \right) + B_4 \left(s_n \right) + B_5 \left(g_n \right) + e_n \right) \tag{1.2}$$

$$y_n = \left(B_o + B_1 \left(x_n{}^{\alpha} \frac{p_n^s}{(p_n^s + (1 - p_n)^s)^{1/s}} \right) + B_2 \left(d_n \right) + B_3 \left(c_n \right) + B_4 \left(s_n \right) + B_5 \left(g_n \right) + e_n \right) \tag{1.3}$$

Second, the power probability function was used as it is nested in the Prelec-2 functional form, as is shown in equation 1.4 (Luce, 2001; Prelec, 1998; Stott, 2006).

$$y_n = \left(B_o + B_1 \left(x_n{}^{\alpha} p_n^r \right) + B_2 \left(d_n \right) + B_3 \left(c_n \right) + B_4 \left(s_n \right) + B_5 \left(g_n \right) + e_n \right) \tag{1.4}$$

Finally, a model with no probability weighting was fit, as in equation 1.5, to characterize public works directors who did not exhibit probability weighting.

$$y_n = \left(B_o + B_1 \left(x_n{}^{\alpha} p_n \right) + B_2 \left(d_n \right) + B_3 \left(c_n \right) + B_4 \left(s_n \right) + B_5 \left(g_n \right) + e_n \right) \tag{1.5}$$

Equations 1.1 through 1.5 were fit using non-linear least squares for each director. The Akaike Information Criterion (AIC), a measure of model fit that can be used for non-nested model selection, represents log-likelihood of the fit model penalized by its number of parameters (Akaike, 1973; Long & Freese, 2014). To compare the non-nested models in equations 1.1-1.5, the AIC was calculated for each model and each director was assigned the probability weighting function which minimized the AIC (Akaike, 1974; Stott, 2006). This procedure allows for an objective and clear decision criterion for assigning the best fitting probability weighting function to each director.

Individual-Level Risk Preferences

As with the results of the pooled analysis, most public work directors weighed asset criticality and probability of failure by a concave power function. The results of the individual-level analysis are summarized in Table 16.[15] Table 16 contains the probability weighting parameters from the functions which achieved the lowest AIC for each director, the point estimate for the weighing parameters *a*, and *r* or *s*, and the p-value from the F-test for the linear restriction that the weighting parameter is equal to 1. Of the 16 directors, seven displayed significantly concave criticality weighting functions at the 0.05 level, three displayed significantly inverse S-shaped probability weighting functions at the 0.05 level, and 12 displayed significantly concave power probability weighting functions at the 0.05 level. As with the summative results, most PWDs in the sample decreasingly increased project prioritization for increases in asset criticality and assets' probabilities of failure. However, a small minority of directors did exhibit the concave-convex probability weighting pattern described by cumulative prospect theory.

Findings indicate that most PWDs tend to demonstrate risk averse project selection. Table 17 shows the predicted prioritization for assets with vulnerability scores of 0.35 and 0.36, 0.9 and 1.58, 1.95 and 2.1, and 6.79 and 7.74, but differing levels of criticality and probabilities of failure. As shown on the table, directors 1, 3, 4, 5, 6, 10, 11, 13, 14, 15, and 16 could be considered mildly-to-moderately risk averse, because they tended to prioritize assets that were more critical and less likely to fail over those that were less critical but more likely to fail. Directors 2, 7, and 8 tended towards risk neutrality. While only director 8 was classified as having linear criticality and probability weighting functions, directors 2 and 7 had power criticality and probability weighting functions which tended to offset one, another leading to risk neutral project selection patterns. Only directors 9 and 12, both of whom displayed inverse S-shaped probability weighting curves, tended to be risk averse when considering projects with a

[15] The Prelec-1 function did not converge for two directors and the power probability function did not converge for one director.

low likelihood of failure but risk-seeking when considering projects with a high likelihood of failure.

Individual Approaches to Resiliency Decision-making

Almost all participating PWDs placed heavy weight on an asset's probability of failure and criticality. Table 18 contains the average marginal effect of a one unit increase in criticality, a 10% increase in an asset's probability of failure, and a one unit increase in an asset's adaptability, cost-efficiency, strategic goal alignment, and alignment with current elected officials' agendas on each PWD's prioritization of an asset. As shown in Table 18, directors tended to change the prioritization of an asset dramatically based on its criticality and likelihood of failure. In fact, director 4 only significantly considered assets' criticality and probability of failure when evaluating threatened assets. This result is intuitive: the failure of a critical asset is a worst-case scenario that could result in service outages, large repairs in later periods, or, in the worst case, a loss of life.

Participating directors had significantly different decision-making strategies regarding assets' other criteria. Past literature on state executive and legislative budget analysts found budgetary decision-makers tend to use a mix of cognitive styles, including economic and political factors, when prioritizing agency budget requests (Willoughby, 1991; Willoughby & Finn, 1996). For instance, director 11 evenly weighted cost-efficiency, strategic goal alignment, and the support of current elected officials. Director 16 took a balanced approach as well but tended to de-prioritize adaptable assets. In contrast, director 7 heavily prioritized adaptable assets. His focus on easy-to-adapt projects may reflect his need to maximize his staff capacity. Other participating PWDs functioned on a continuum, with some more heavily weighing economic factors and others being more attuned to political factors. Three tended to prioritize economic efficiency. Directors 8, 9, and 13 prioritized cost-efficient investments that furthered their department's strategic goals. Explaining his prioritization decision, director 8 emphasized that funding was a perpetual challenge for his government, which faced substantial exposure to sea level rise. He chose to focus on cost-efficiency to maximize his departments' scarce resources in tackling the huge problem created by sea level rise.

Other PWDs heavily prioritized their departments' strategic goals and their current elected officials' agendas. Directors 2, 3, 6, and 12 heavily prioritized their department's strategic goals, and director 1 balanced strategic goal alignment and asset alignment with current elected officials' agendas. A minority of directors were more sensitive to political concerns. Directors 5, 10, 14, and 15 heavily prioritized the agendas of current elected officials. When describing their relationships with their councils, politically-oriented PWDs indicated that they had a professional responsibility to uphold their democratically-elected leaders' vision for the city. Participating directors who did not weight current elected officials' opinions as heavily indicated that they were delegated more authority by their commissioners or councils. Perhaps these directors are more confident in relegating political factors as less important when making decisions about the infrastructure over which they are responsible. In some instances, PWDs believed they had a professional obligation to educate elected officials on the technical reasons for prioritizing certain projects.

Individual-level analysis permits characterization of the heterogeneity in individual-level decision-making, as clarified in the following example. Directors 9 and 14 provide an interesting comparison: they feature quite different risk attitudes and decision-making preferences that capture some of the observed heterogeneity in the dataset. Table 19 contains their estimated weighting functions.

Director 9's risk preferences aligned with cumulative prospect theory, and he prioritized economic criteria over political criteria. Director 9 prioritized assets that were more critical and likely to fail. As shown on Table 19, a one-unit increase in asset criticality increased his level of prioritization of the average asset by .42, and a 10% increase in the average asset's probability of failure resulted in a .27 increase in his level of prioritization. Because the average marginal effect was taken over all the estimated profiles, it averages out the non-linearity in director 9's risk preferences. As shown in Table 19, director 9 weighted asset criticality through an insignificantly concave power curve, because *a* is not significantly less than zero, and probability of failure through a significantly inverse-S shaped probability weighting curve, because *s* is significantly less than one. Director 9's preferences appear in Figures 6 and 7 below: because he decreasingly prioritized unlikely-to-fail assets as they became more likely to fail and increasingly prioritized likely-to-fail assets risk as they became certain to fail, he is risk averse for assets with low probabilities of failure and risk seeking for assets with high probabilities of failure. Figure 8 shows that while an asset with a criticality rating of 7 and a probability of failure of .05 was prioritized over an asset with a criticality rating of 3 and a probability of failure of .12, an asset with a criticality rating of 4 and a probability of failure of .97 was prioritized over an asset with a criticality rating of 6 and a probability of failure of .64. Director 9 cared about economic objectives. He increased an asset's prioritization for increases in their cost-efficiency by .16 for a one-unit increase in cost-efficiency, and increased an asset's prioritization by .23 for a one-unit increase in its strategic goal alignment.

In contrast, director 14's risk preferences were more typical of the PWDs in the sample. As shown in Table 19, director 14 had significantly concave power weighting functions for both criticality and an asset's probability of failure, because both *a* and *r* are significantly less than 1.

As shown in Figures 9 and 10, increases in both an asset’s criticality and probability of failure increase prioritization at a decreasing rate. However, the curve weighting the asset’s probability of failure is sharply concave as compared to the curve weighting asset criticality. Resultantly, director 14 is risk averse across the entire range of failure probabilities, as shown in Figure 11. Director 14 always prioritized assets with higher criticalities and lower probabilities of failure over assets with lower criticalities and higher probabilities of failure, and was primarily concerned with asset criticality, probability of failure, and the support of current elected officials. For director 14, a one-unit increase in asset criticality increased his prioritization of the average asset by .65, a 10% increase in an asset’s probability of failure increased his prioritization of an average asset by .52, and a one-unit increase in the average asset’s level of support from current elected officials increased his prioritization of the asset by .21.

Interview Results

Public works directors are beginning to adapt to sea level rise by using options ranging from managed retreat to a variety of hard, soft, and adaptive resiliency choices. Different resiliency options come with tradeoffs. While soft options or managed retreat may preserve natural environmental functions or permanently remove sea level rise induced risks, such choices may not be cost effective. For instance, soft options may require replacement after a damaging disaster, and managed retreat may cost more. In some instances, creative adaptive options are possible. For example, one director described working to make a riverwalk more resilient by improving the accessibility of its underlying electrical systems, to ease repairs during short circuits and after weather-induced failures.

Further, PWDs indicated that planning for sea level rise will require intergovernmental collaboration between federal, state, and local partner organizations. In Hawaii and California, public works directors' adaptive decisions were heavily influenced by state regulatory bodies. They considered it essential to maintain a relationship with the California Coastal Commission, a powerful regulator, when prioritizing threatened coastal assets. Other directors mentioned working with partner governments in their region. In one southern state, a director described collaboratively funding and building backflow prevention devices to manage regional drainage problems created by king tide events. After all, water knows no political boundaries.

Directors agreed that the uncertainty inherent in sea level rise forecasts is challenging. Beliefs about future sea level rise ranged across the sample, with five directors anticipating less than a foot of sea level rise, two anticipating between 1-2 feet, three anticipating 2-3 feet, and two anticipating above three feet of sea level rise. These are largely in line with NOAA's latest forecast of sea level rise, which ranges from approximately 9.5 inches on the low end to 26 inches on the high end for the contiguous United States (Sweet et al., 2022). In interviews, directors described basing their sea level rise beliefs on forecasts from higher governmental layers. Hawaii and California have state-level projections that directors referenced; those in southern states without state-level forecasts mentioned referencing federal data. However, the uncertainty inherent in future sea level forecasts makes planning difficult. A few directors mentioned that they planned to iteratively develop resiliency projects by starting with current drainage challenges and building out into the future. As one director put it, "we're eating the elephant one bite at a time."

Most directors agreed that the project profiles were valid, if somewhat oversimplified, the profile criteria fundamentally matched that used to evaluate projects, and profiles themselves were familiar and easy to complete. However, one director mentioned that their government conducts a citizen survey each year, which does influence project selection. The reported primary limitation of the profiles is their simplicity. Project prioritization decisions are often the result of complex budgetary processes. As one director mentioned in their survey response:

> Granted this is for research, but this is somewhat over simplified. A low ranked project with a cost of $100,000 or less would most likely get completed to round out a budget year between the larger projects. Similarly, a $100m project ranked 7 very likely would get moved below a $1m project that only ranked 5.

One director mentioned that precise probabilities of failure were difficult to come by and that they would only trust an extremely robust engineering analysis to produce comparable and consistent failure probabilities. Another director indicated that criticality and adaptability can be complex terms. Criticality, especially, can sometimes refer to life or death situations, which are difficult to quantify.

Discussion

Public works directors and other local officials will have to protect their governments' assets from rising seas (Allen et al., 2019; Fleming et al., 2018; Price, 2019). This study establishes a micro-foundation that can be used to characterize the heterogeneity in PWDs' decision-making when approaching resiliency investments. There is substantial heterogeneity in PWDs' prioritization of projects in terms of their level of adaptability, cost-efficiency, strategic goal alignment, and alignment with elected officials' current agendas. Mirroring prior studies of state-level budget analysts, this study finds that many public works directors use a blend of economic and political cues to help inform their project prioritization decisions (Willoughby, 1991; Willoughby & Finn, 1996). Health and human safety are often major concerns in local capital project prioritization schemes, and, in this case, the criticality and probability of asset failure was found to be most important to most participating directors (Bland, 2013; Vogt, 2004).

However, PWDs did display non-linear preferences over assets' criticality and probability of failure in a sea level rise scenario.

Public works directors tend to be decreasingly sensitive to increases in both asset criticality and the probability of asset failure. A PWD's decreasing sensitivity to criticality and failure probabilities results in mildly risk averse project prioritization decisions for assets with both low and high probabilities of failure. Generally, critical assets with a low probability of failure were prioritized over non-critical assets with a high probability of failure across the full range of failure probabilities. This differs from the risk preference pattern described by Tversky and Kahneman's (1992) inverse S-shaped probability weighting function, which predicted that decision-makers should be risk-averse for low probability losses and risk-seeking for moderate to high probability losses. Instead, PWDs' probability weighting function is best described by a concave power function. Interestingly, findings from this study agree with Fennimore and McCue (2021) and McCue (2000), which indicate that public financial managers tend to be globally risk averse regardless of their personal risk preferences. Future studies should continue to explore the risk preferences of government budgetary decision-makers, with an eye to the drivers of risk aversion.

Public works directors' observed risk aversion may arise from the underlying uncertainty behind sea level rise induced damages. As displayed in the profiles, the risk of asset failure is conditional on the uncertain likelihood that seas will rise in line with the ICCP's forecast levels. This uncertainty may prevent inverse S-shaped probability curves from being observed. Even if an asset is very likely to fail if seas rise, its failure rate, conditional on seas rising, is far from being a sure event. This may be a reason that public works directors did not tend to increasingly prioritize assets more likely to fail as their failure became certain in a sea level rise scenario. This preference pattern would fit with Price's (2019) argument that risk aversion is to be preferred when investing in resilient public infrastructure systems, as the public may prefer project prioritization decisions to be relatively risk averse. Intuitively, one may suspect that the public would be dissatisfied to hear that their particular city's entire system of threatened culverts was 100% functional and protected upon receiving the news that a de-prioritized local bridge failed. Future studies should attempt to elicit the public's risk preferences, to test if the risk averse project selection displayed by public works directors matches the desires of the public.

Follow-up work should more deeply explore the heterogeneity in PWDs' risk attitudes and project prioritization decisions, as this study is limited by its low response rate. While public works directors' risk preferences are unlikely to bias the tests of the risky weighting parameters, and the study features diversity in the geographies represented, government types sampled, and governments sizes, it is not possible to quantitatively draw conclusions about how PWDs' decisions change under different operating environments. Future large-n studies may consider exploring how different environments drive risk preferences and project weighting across wider areas. A larger-n study could assess how public works directors' risk preferences vary over different institutional arrangements, budgetary conditions, and levels of risk exposure. For instance, it is possible that PWDs whose budgetary processes leave them more open to accountability from elected officials and the public are more likely to be risk averse, since they could be unfairly blamed for project failures.

Conclusion

Local government resiliency investments will be led by their public works officials. Public works directors displayed substantial heterogeneity in their weighting of assets' criticality, probability of failure, adaptability, cost-efficiency, and alignment with their governments' strategic goals and elected officials' agendas. Experimental results indicate that public works directors are decreasingly sensitive to increases in both assets' criticality and probability of failure. Results here indicate that they are mildly risk averse when prioritizing threatened assets across the full spectrum of asset failure probabilities.

Tables and Figures

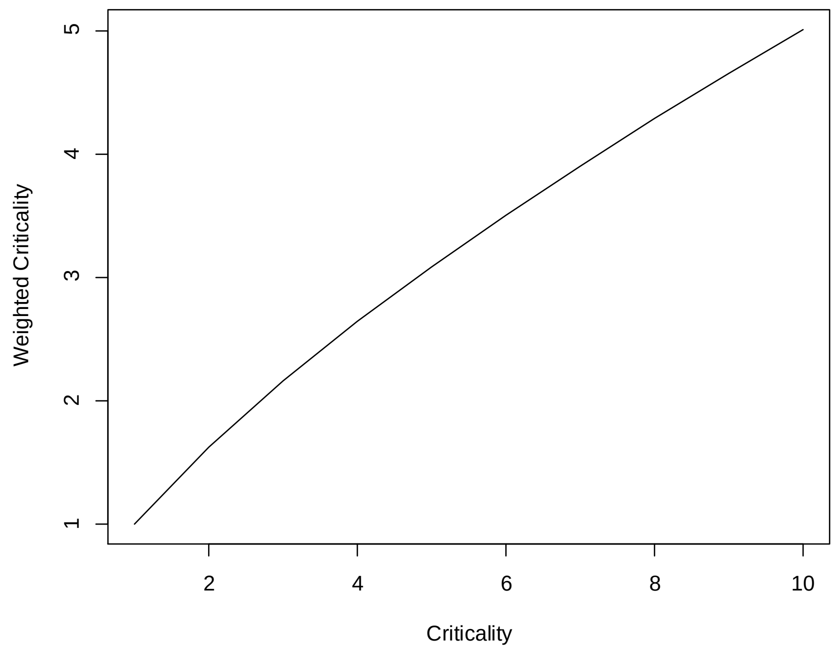

Figure 1: Criticality Weighting Curve

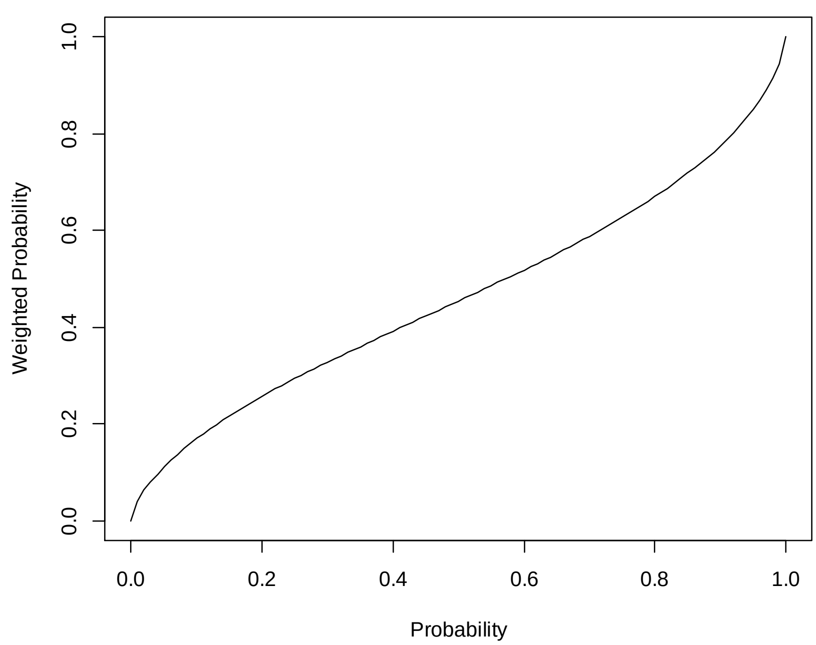

Figure 2: Probability Weighting Curve

Table 15: Results for Representative Public Works Director

	Prelec-2 Weighting Function with Cluster Jackknife Standard Errors		Prelec-2 Weighting Function with Cluster Jackknife Standard Errors with *s* Restricted to 1	
	Coef./Standard Error	95% CI	Coef./Standard Error	95% CI
Constant	-1.266 (0.958)	[-3.308,0.776]	-0.568 (0.611)	[-1.871,0.735]
Asset Vulnerability Weight	2.385* (0.896)	[0.476,4.294]	1.792** (0.434)	[0.866,2.718]
a	0.554** (0.129)	[0.280,0.829]	0.636** (0.098)	[0.428,0.844]
r	0.330** (0.063)	[0.196,0.464]	0.311** (0.057)	[0.190,0.432]
s	0.805 (0.138)	[0.510,1.100]	1	
Adaptability	-0.055* (0.025)	[-0.107,-0.002]	-0.056* (0.025)	[-0.109,-0.004]
Cost-efficiency	0.123** (0.037)	[0.045,0.201]	0.106** (0.032)	[0.038,0.174]
Strategic Goal Alignment	0.120** (0.019)	[0.079,0.162]	0.121** (0.020)	[0.079,0.164]
Elected Officials Alignment	0.177** (0.039)	[0.094,0.260]	0.174** (0.041)	[0.088,0.261]
N	631		631	
AIC	2313.6		2297.1	

*Note: Significance starts are assigned for the *a, r,* and *s*, parameters based on an F test for the linear restriction that the parameter is equal to one. Significance stars are assigned as follows: p < 0.10, * p < 0.05, ** p < .01

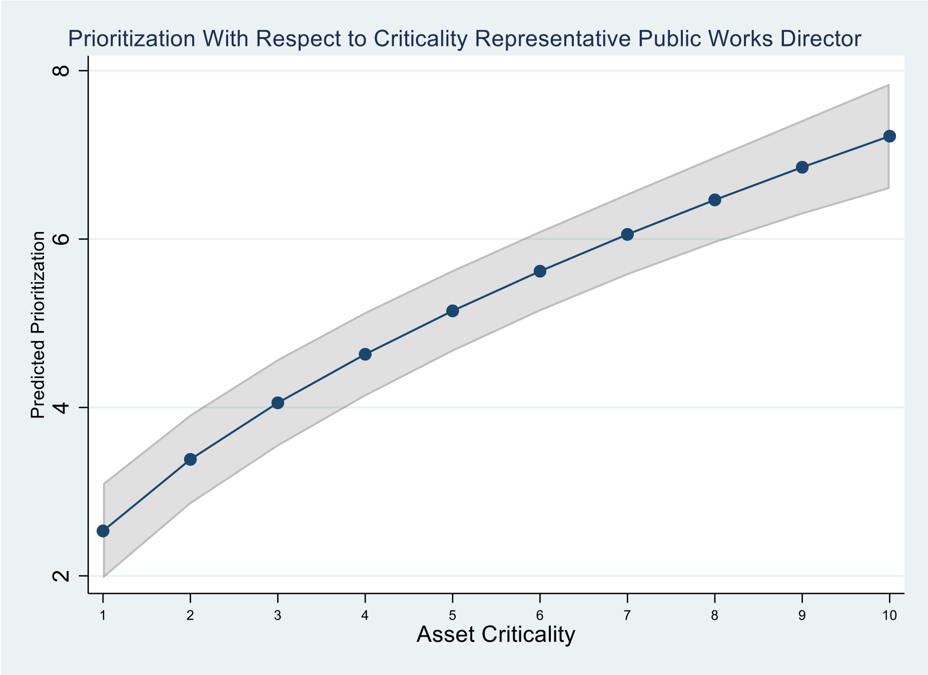

Figure 3: Project Prioritization Given Asset Criticality

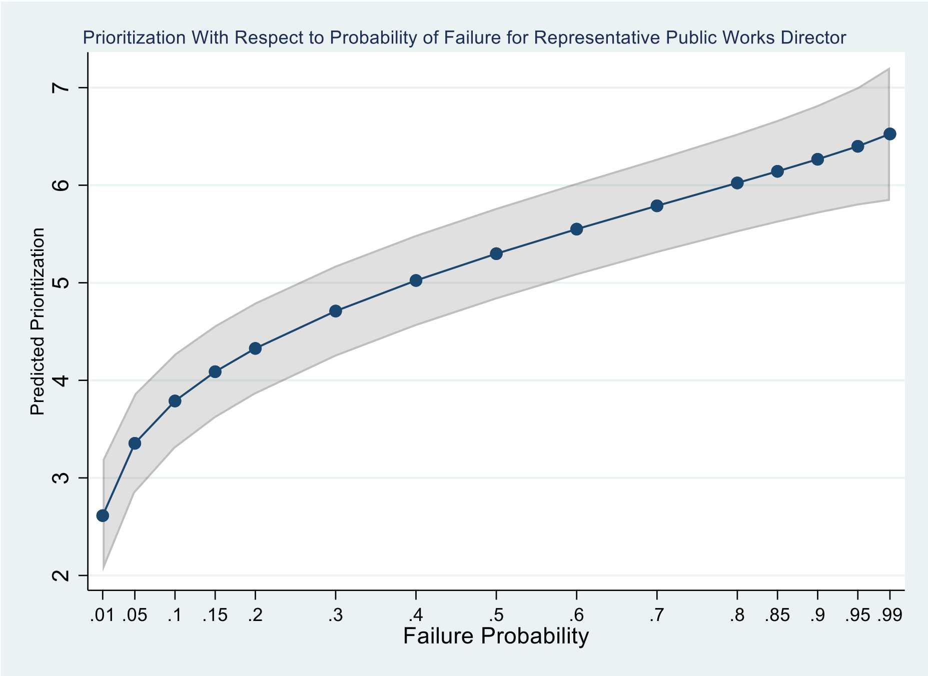

Figure 4: Project Prioritization Given Probability of Failure

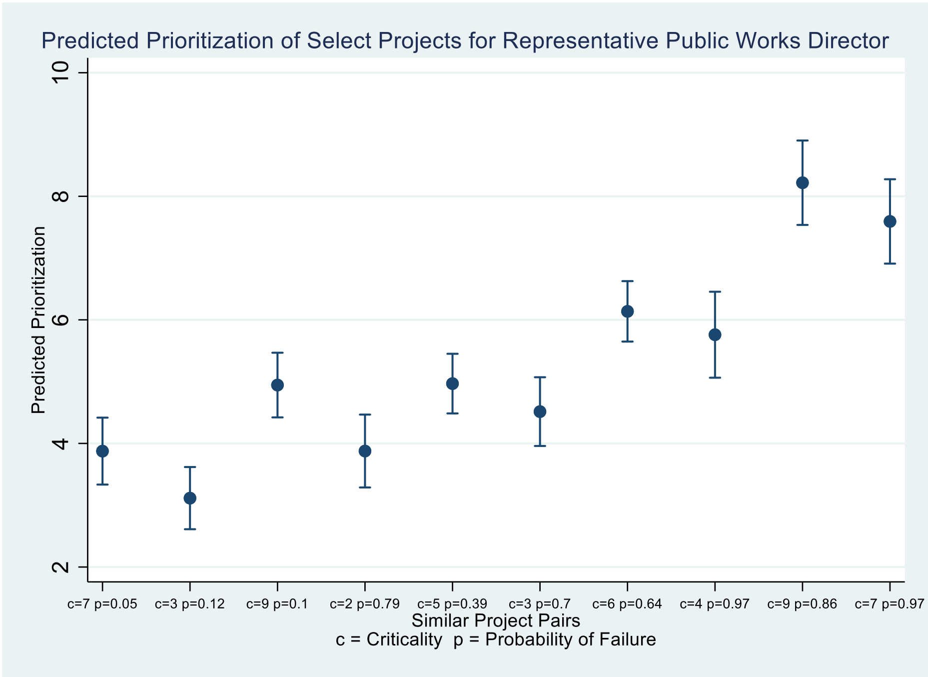

Figure 5: Vulnerability Equivalents

Note: Each pair of assets has similar levels of vulnerability with the high criticality, low probability of failure asset on the left and the low criticality, high probability of failure asset on the right. Vulnerability increases in asset pairs when moving left to right.

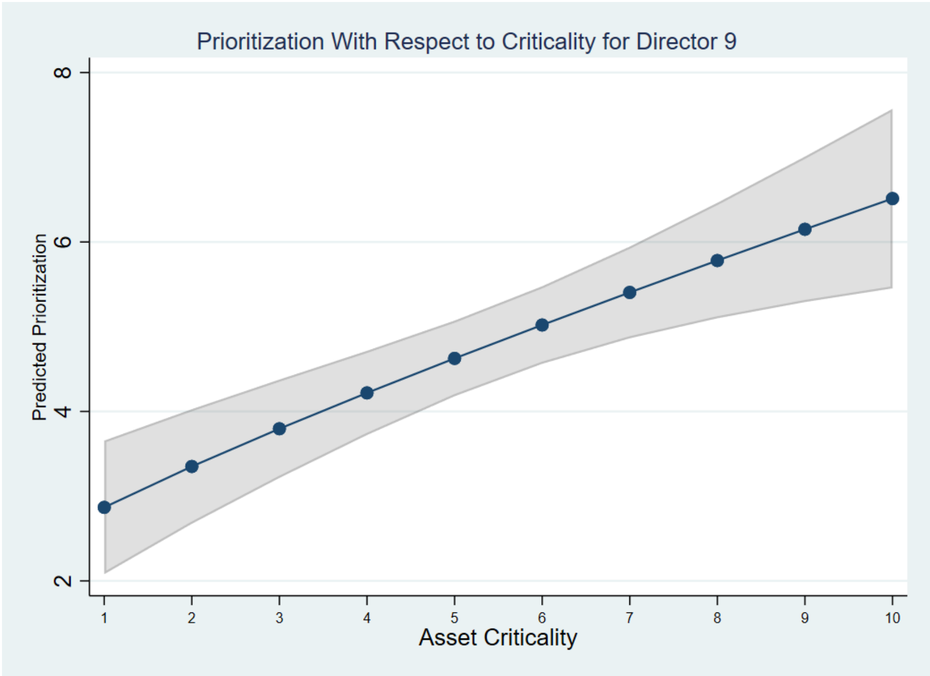

Figure 6: Project Prioritization Given Asset Criticality for Director 9

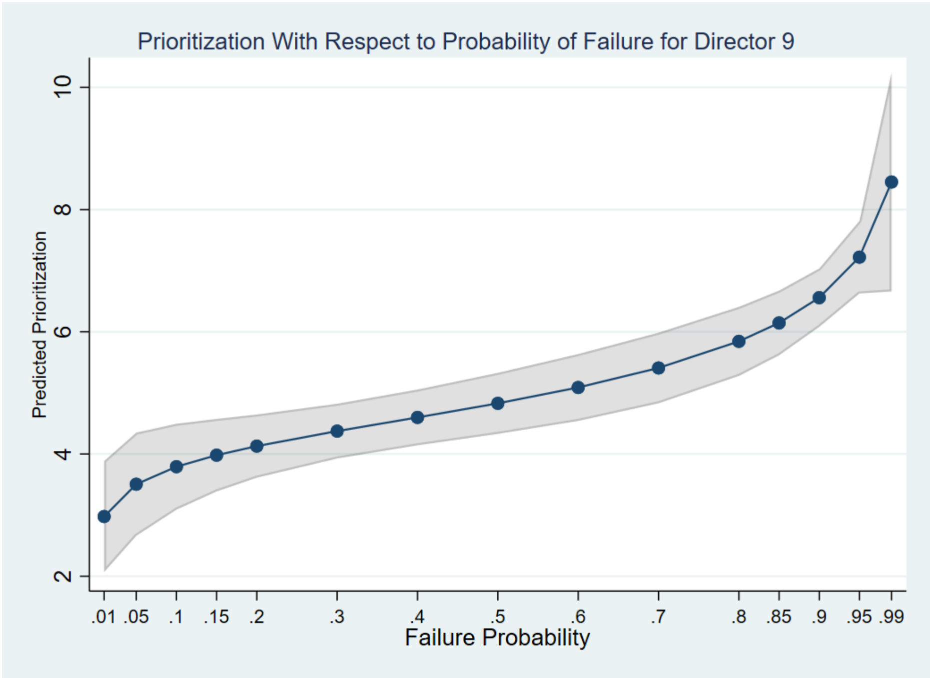

Figure 7: Project Prioritization Given Probability of Failure for Director 9

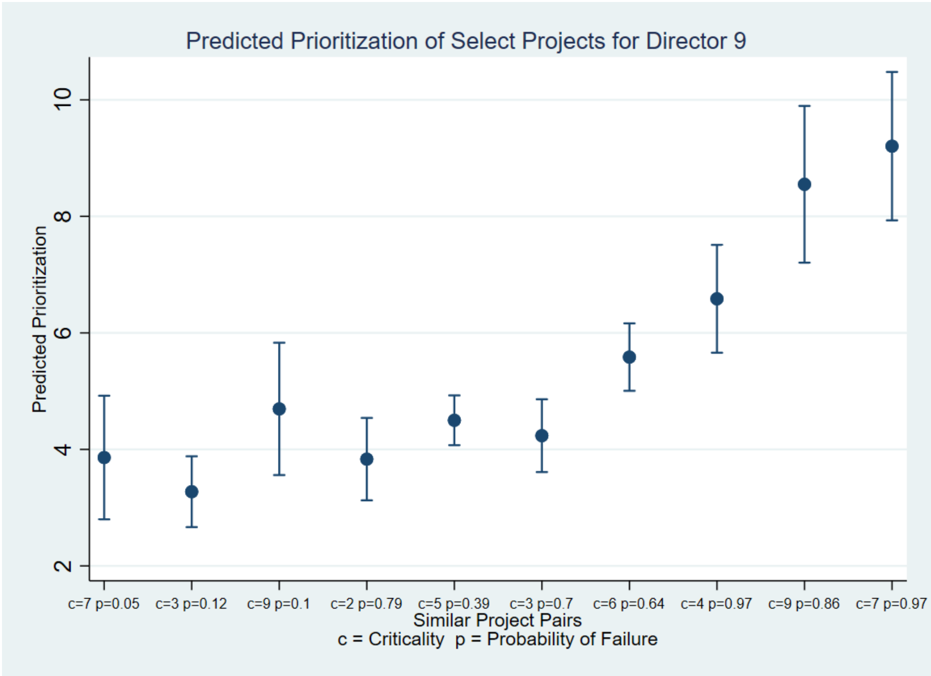

Figure 8: Vulnerability Equivalents for Director 9

Note: Each pair of assets has similar levels of vulnerability, with the high criticality, low probability of failure asset on the left and the low criticality, high probability of failure asset on the right. Vulnerability increases in asset pairs when moving left to right.

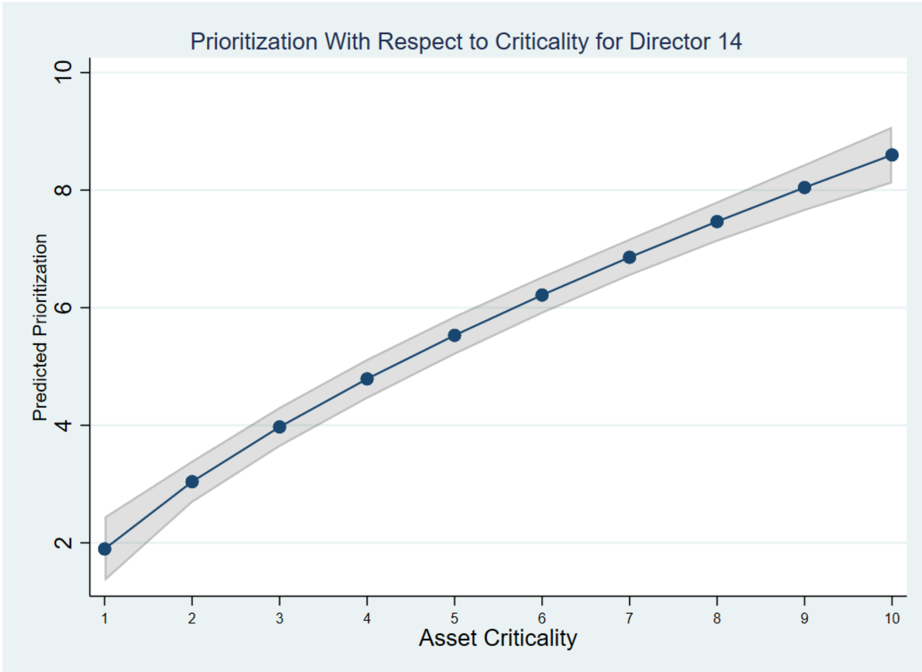

Figure 9: Project Prioritization Given Asset Criticality for Director 14

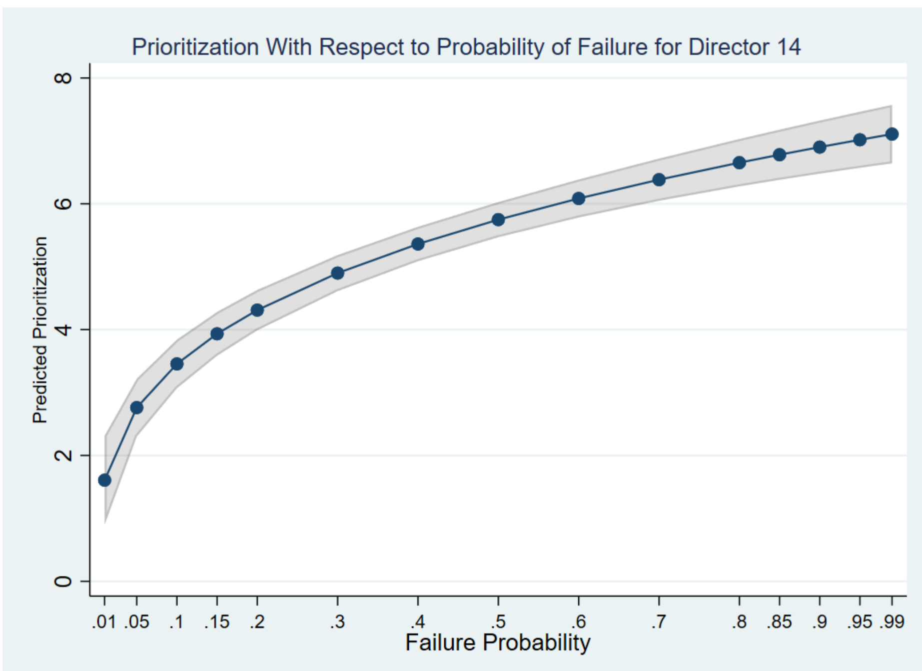

Figure 10: Project Prioritization Given Probability of Failure for Director 14

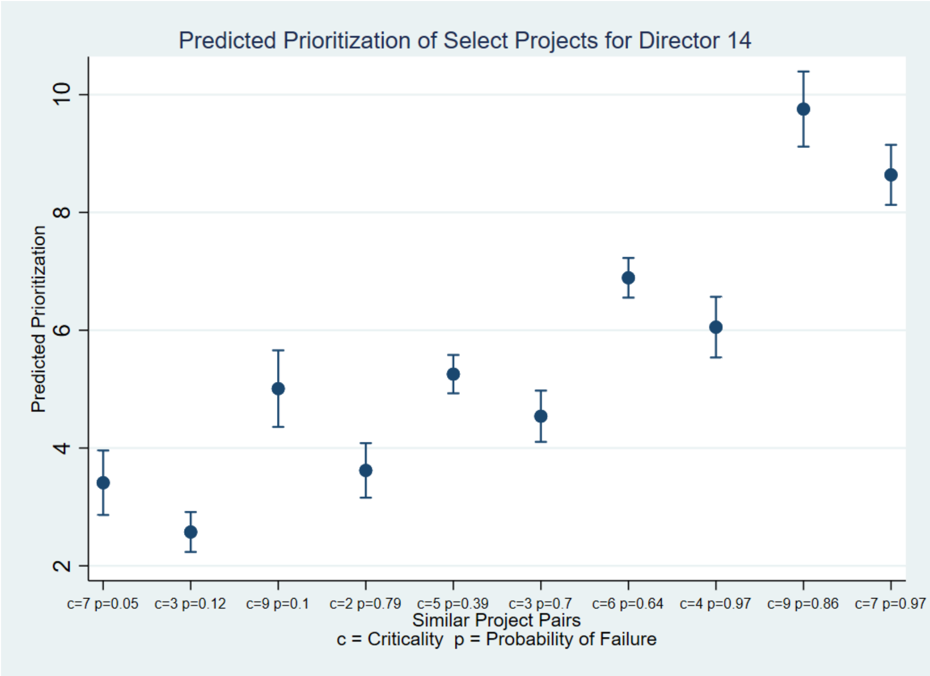

Figure 11: Vulnerability Equivalents for Director 14

Note: Each pair of assets has similar levels of vulnerability, with the high criticality, low probability of failure asset on the left and the low criticality, high probability of failure asset on the right. Vulnerability increases in asset pairs when moving left to right.

Table 16: Individual Public Works Directors' Risky Weighting Parameters

	Probability Weighting Function	a	r	s
Director 1	Power	0.89	0.51	
p-value		0.50	0.00	
Director 2	Power	0.15	0.30	
p-value		0.00	0.02	
Director 3	Prelec	0.53		0.11
p-value		0.62		0.00
Director 4	Power	0.55	0.40	
p-value		0.00	0.00	
Director 5	Power	0.05	0.01	
p-value		0.22	0.00	
Director 6	Power	0.66	0.23	
p-value		0.20	0.00	
Director 7	Power	0.27	0.32	
p-value		0.00	0.00	
Director 8	EUT	0.68		
p-value		0.22		
Director 9	Tversky and Kahneman	0.85		0.47
p-value		0.47		0.00
Director 10	Power	2.03	0.18	
p-value		0.15	0.00	
Director 11	Power	0.13	0.08	
p-value		0.02	0.00	
Director 12	Prelec	0.47		0.21
p-value		0.03		0.00
Director 13	Power	1.02	0.57	
p-value		0.91	0.00	
Director 14	Power	0.61	0.30	
p-value		0.01	0.00	
Director 15	Power	0.37	0.28	
p-value		0.07	0.03	
Director 16	Power	.80	.21	
p-value		.68	0.00	

Note: P-values were calculated using robust F test on the linear restriction that a, r, or s are equal to 1.

Table 17: Individual-Level Vulnerability Equivalents

	1		2		4		5	
	c=7 p=0.05	c=3 p=0.12	c=9 p=0.1	c=2 p=0.79	c=6 p=0.64	c=4 p=0.97	c=9 p=0.86	c=7 p=0.97
Director 1	1.97	1.5	3.33	2.54	5.78	5	9.49	8.09
95% C.I.	(1.4, 2.5)	(1, 2)	(2.3, 4.4)	(1.9, 3.2)	(5.3, 6.3)	(4.3, 5.7)	(8.8, 10.2)	(7.4, 8.8)
Director 2	4.42	4.79	5.11	6.66	7.14	7.49	7.97	7.97
95% C.I.	(3.6, 5.3)	(4, 5.5)	(4, 6.2)	(5.4, 7.9)	(6.8, 7.5)	(6.6, 8.3)	(7.1, 8.9)	(7.1, 8.8)
Director 3	5.62	4.82	6.04	4.84	5.93	5.97	6.93	6.91
95% C.I.	(4.8, 6.4)	(4.4, 5.3)	(5.1, 6.9)	(4.1, 5.5)	(5.5, 6.4)	(4.9, 7.1)	(6, 7.8)	(5.8, 8)
Director 4	3.26	3.06	4.19	4.21	6.09	5.84	7.98	7.42
95% C.I.	(2.9, 3.6)	(2.8, 3.3)	(3.7, 4.7)	(3.7, 4.7)	(5.8, 6.4)	(5.4, 6.3)	(7.5, 8.4)	(7.1, 7.8)
Director 5	5.39	3.77	6.37	3.73	6.32	5.52	7.5	6.92
95% C.I.	(4.7, 6.1)	(2.9, 4.6)	(5.6, 7.1)	(2.6, 4.9)	(5.7, 6.9)	(4.8, 6.2)	(6, 9)	(6, 7.9)
Director 6	4.44	3.3	5.89	3.77	6.78	5.81	9.21	8.11
95% C.I.	(3.6, 5.2)	(2.7, 3.9)	(4.9, 6.8)	(3.1, 4.4)	(6.4, 7.2)	(5.3, 6.4)	(8.3, 10.1)	(7.5, 8.7)
Director 7	3.77	3.86	4.4	5.09	5.94	6.02	6.85	6.7
95% C.I.	(3.3, 4.2)	(3.5, 4.2)	(3.8, 5)	(4.5, 5.6)	(5.6, 6.3)	(5.6, 6.4)	(6.3, 7.4)	(6.2, 7.2)
Director 8	1.63	1.71	1.93	2.88	3.93	4.31	5.87	5.65
95% C.I.	(1, 2.2)	(1.2, 2.2)	(1.4, 2.5)	(2, 3.8)	(3.4, 4.4)	(3.3, 5.3)	(5, 6.7)	(4.8, 6.5)
Director 9	3.86	3.27	4.7	3.83	5.58	6.58	8.55	9.21
95% C.I.	(2.8, 4.9)	(2.7, 3.9)	(3.6, 5.8)	(3.1, 4.5)	(5, 6.2)	(5.7, 7.5)	(7.2, 9.9)	(7.9, 10.5)
Director 10	4.65	2.8	6.72	2.6	4.98	3.57	8.73	6.24
95% C.I.	(3.5, 5.9)	(2, 3.6)	(4.9, 8.6)	(1.6, 3.6)	(4.2, 5.7)	(2.9, 4.2)	(7.7, 9.7)	(5.3, 7.2)
Director 11	4.1	3.75	4.99	4.71	6.06	5.85	6.98	6.7
95% C.I.	(3.1, 5.1)	(3.2, 4.3)	(3.9, 6.1)	(3.9, 5.5)	(5.5, 6.6)	(5.2, 6.5)	(5.9, 8.1)	(5.8, 7.6)
Director 12	4.2	2.78	5.3	3.9	6.45	7.93	9.78	10.65
95% C.I.	(3.6, 4.8)	(2.2, 3.4)	(4.6, 6.1)	(3.1, 4.7)	(6.1, 6.8)	(6.6, 9.3)	(8.9, 10.6)	(9.8, 11.5)
Director 13	2.69	2.31	3.8	3.09	5.88	5.16	9.34	7.99
95% C.I.	(2.1, 3.3)	(1.9, 2.8)	(3, 4.6)	(2.6, 3.6)	(5.5, 6.2)	(4.6, 5.7)	(8.7, 10)	(7.4, 8.6)
Director 14	3.41	2.57	5.01	3.62	6.89	6.05	9.75	8.64
95% C.I.	(2.9, 4)	(2.2, 2.9)	(4.4, 5.7)	(3.2, 4.1)	(6.6, 7.2)	(5.5, 6.6)	(9.1, 10.4)	(8.1, 9.1)
Director 15	2.65	2.38	4.16	4.36	6.91	6.64	9.21	8.58
95% C.I.	(1.4, 3.9)	(1.2, 3.5)	(2.6, 5.8)	(3.4, 5.4)	(6.3, 7.5)	(5.8, 7.5)	(7.9, 10.5)	(7.5, 9.6)
Director 16	4.80	3.56	6.12	3.72	6.45	5.44	8.74	7.59
95% C.I.	(3.4, 6.2)	(2.8, 4.4)	(4.5, 7.8)	(2.8, 4.6)	(5.8, 7.1)	(4.6, 6.3)	(7.4, 10.0)	(6.8, 8.4)

Note: Average prediction intervals given with 95% confidence intervals in parentheses. Confidence intervals calculated with robust standard errors using normal distribution.

Table 18: Individual Prioritization

	Criticality	Probability of Failure	Adaptability	Cost Efficiency	Strategic Goal Alignment	Support of Current Elected Officials
Director 1	0.66	0.55	0.02	-0.02	0.16	0.17
95% C.I.	(0.5, 0.81)	(0.45,0.64)	(-0.11,0.15)	(-0.16,0.12)	(0.03,0.3)	(0.01,0.32)
Director 2	0.12	0.43	0.07	0.04	0.14	0.06
95% C.I.	(-0.06, 0.31)	(0.3,0.55)	(-0.07,0.22)	(-0.16,0.24)	(-0.01,0.28)	(-0.11,0.23)
Director 3	0.24	0.08	-0.1	0.16	0.19	0.09
95% C.I.	(0.1, 0.39)	(-0.02,0.18)	(-0.22,0.03)	(0.05,0.28)	(0.07,0.3)	(-0.1,0.27)
Director 4	0.37	0.4	-0.05	0.07	0.03	0.07
95% C.I.	(0.29, 0.45)	(0.34,0.46)	(-0.13,0.02)	(-0.01,0.16)	(-0.08,0.14)	(-0.04,0.19)
Director 5	0.51	0.22	-0.19	0.23	-0.01	0.36
95% C.I.	(0.27, 0.75)	(0.1,0.33)	(-0.4,0.02)	(0.05,0.41)	(-0.22,0.2)	(0.08,0.63)
Director 6	0.61	0.4	-0.1	0.11	0.14	0.05
95% C.I.	(0.46, 0.75)	(0.28,0.51)	(-0.22,0.03)	(-0.03,0.25)	(0,0.28)	(-0.09,0.19)
Director 7	0.17	0.34	0.15	0.04	0.06	0.07
95% C.I.	(0.07, 0.28)	(0.26,0.42)	(0.06,0.23)	(-0.05,0.14)	(-0.07,0.18)	(-0.04,0.18)
Director 8	0.21	0.35	-0.14	0.41	0.09	0.1
95% C.I.	(0.1, 0.31)	(0.22,0.49)	(-0.32,0.04)	(0.18,0.65)	(-0.09,0.27)	(-0.11,0.3)
Director 9	0.42	0.27	0	0.16	0.23	0.14
95% C.I.	(0.25, 0.6)	(0.19,0.36)	(-0.13,0.14)	(0.01,0.31)	(0.08,0.38)	(-0.04,0.31)
Director 10	0.77	0.14	-0.12	-0.06	-0.01	0.59
95% C.I.	(0.56, 0.99)	(-0.01,0.3)	(-0.29,0.05)	(-0.21,0.09)	(-0.16,0.14)	(0.45,0.73)
Director 11	0.28	0.35	0.02	0.22	0.19	0.18
95% C.I.	(0.11, 0.44)	(0.2,0.5)	(-0.13,0.18)	(0.04,0.39)	(0.06,0.33)	(-0.03,0.39)
Director 12	0.6	0.32	0.03	0.05	0.12	0.06
95% C.I.	(0.46, 0.75)	(0.22,0.42)	(-0.11,0.16)	(-0.07,0.17)	(0.01,0.24)	(-0.09,0.2)
Director 13	0.56	0.47	-0.1	0.24	0.17	-0.06
95% C.I.	(0.46, 0.67)	(0.37,0.56)	(-0.21,0.01)	(0.09,0.39)	(0.08,0.27)	(-0.18,0.06)
Director 14	0.65	0.52	0	0.03	0.05	0.21
95% C.I.	(0.57, 0.74)	(0.43,0.61)	(-0.09,0.09)	(-0.08,0.13)	(-0.05,0.16)	(0.07,0.35)
Director 15	0.52	0.57	-0.13	0.29	0.26	0.4
95% C.I.	(0.31, 0.73)	(0.37,0.77)	(-0.33,0.06)	(0.06,0.51)	(0.06,0.47)	(0.12,0.68)
Director 16	0.57	0.29	-0.22	0.21	0.16	0.28
95% C.I.	(0.36, 0.79)	(0.12, 0.47)	(-0.44, -0.01)	(-0.01, 0.43)	(-0.04, 0.35)	(0.08, 0.49)

Note: Average marginal effects given with 95% confidence intervals in parentheses. Confidence intervals calculated with robust standard errors using normal distribution.

Table 19: Director Prioritization Comparison

	Director 9 – Tversky and Kahneman Weighting Function with Robust Standard Errors		Director 14 – Power Weighting Function with Robust Standard Errors	
	Coef./Standard Error	95% CI	Coef./Standard Error	95% CI
Constant	-0.646 (0.659)	[-1.989,0.697]	-1.874 (1.514)	[-4.961,1.214]
Asset Vulnerability Weight	1.921 (1.225)	[-0.574,4.415]	2.725* (1.038)	[0.608,4.841]
a	0.847 (0.208)	[0.424,1.270]	0.613** (0.137)	[0.334,0.892]
r			0.298** (0.072)	[0.151,0.446]
s	0.470** (0.134)	[0.197,0.743]		
Adaptability	0.004 (0.069)	[-0.137,0.145]	0.003 (0.046)	[-0.092,0.098]
Cost-efficiency	0.162* (0.076)	[0.007,0.317]	0.026 (0.055)	[-0.086,0.138]
Strategic Goal Alignment	0.228** (0.077)	[0.071,0.386]	0.052 (0.054)	[-0.057,0.162]
Elected Officials Alignment	0.135 (0.089)	[-0.046,0.317]	0.213** (0.071)	[0.067,0.358]
N	40		39	
AIC	134.9		96.72	

Note: Significance starts are assigned for the *a, r;* and or *s*, parameters based on an F test for the linear restriction that the parameter is equal to one.
Significance stars are assigned as follows: p < 0.10, * p < 0.05, ** p < .01

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CHAPTER 4: THE COST OF STORMWATER MANAGEMENT PROGRAMS: CAN SYSTEMATIC CAPITAL BUDGETING PRACTICES INCREASE COST-EFFICIENCY?[16]

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Abstract

Stormwater utilities provide critical drainage services that reduce flooding and prevent stormwater pollution. This study develops cost functions for stormwater utilities to show how performance, environmental factors, population, and labor and capital prices determine the minimum cost of providing stormwater services. Results from a panel of 114 stormwater utilities in Florida show that key environmental factors, like the percent of impervious surfaces in a region and the extent of development located in the floodplain, drive stormwater costs. Systematic capital budgeting practices were expected to improve stormwater utilities' cost efficiency by lowering their deviation from the minimum cost of providing stormwater services. However, stormwater utilities with better developed asset inventories or master plans do not appear to be more cost-efficient.

Introduction

Stormwater utilities collect and treat stormwater flows that are responsible for floods and pollution (Environmental Finance Center, 2020; Grigg, 2013; National Research Council et al., 2009). As populated areas continue to urbanize and national stormwater quality regulations push local governments to reduce stormwater pollution, local governments will need to continue investing in their stormwater management programs to protect both their residents and the environment. This study seeks to explain the costs of stormwater programs, and test if they can be more efficient by following recommended practices from the normative capital budgeting literature; it does so by analyzing a short panel of 114 stormwater utilities in Florida.

First, this study develops novel cost-functions for stormwater utilities. While a large and robust literature exists on the cost drivers of public services, the findings have yet to be applied to stormwater utilities (Duncombe, 1989, 1992; Duncombe & Yinger, 1993; Duncombe &

Yinger, 2007, 2011; Gronberg et al., 2011; Grosskopf et al., 2014). The public cost function literature emphasizes the importance of environmental factors in affecting the transformation of organizational outputs into high quality services for the public (Bradford et al., 1969; Duncombe, 1989, 1992; Duncombe & Yinger, 1993). In this case, stormwater utilities work to reduce flood damage and ensure that stormwater flows do not harm local waterbodies. This paper finds that key environmental factors, like regional impervious surfaces and floodplain development, increase costs.

Second, this study aims to test whether normative capital budgeting practices improve stormwater utilities' cost-efficiency. Stormwater management is a capital-intensive business. Among the 123 respondents of the Florida Stormwater Association's (2018) survey, the average utility estimated needed capital improvement investments at approximately $14 million, for a total of about $1.7 billion across the state. Given the large amount of capital spending required to develop stormwater infrastructure systems, stormwater utilities that coordinate their investments using master plans and maintain complete asset inventories may be more cost-efficient than those that do not. While the systematic capital budgeting literature recommends master planning and asset inventorying processes, the results to date do not show that the practices lead to efficiency gains for stormwater utilities (Ermasova, 2020; Srithongrung, 2008; Srithongrung et al., 2019).

This paper begins by demonstrating the need for, first, testing to determine test whether normative capital budgeting practices deliver promised efficiency gains, and, secondly, a more systematic explanation of the costs of stormwater management. Then, the paper introduces the theory on public sector costs functions, explaining how they provide a conceptual framework capable of predicting the minimum cost of providing stormwater services under full efficiency, and testing if organizations fall short of that ideal. Using data from the Florida Stormwater Associations' 2016 and 2018 surveys, the cost of providing stormwater services is estimated. Results from the cost function indicate that environmental factors drive stormwater costs, but recommended master planning and asset inventorying practices do not improve stormwater utilities' cost-efficiency. Master plans and asset inventories alone may not be able to improve systematic capital budgeting practices if they are not deeply integrated into year-to-year budgetary decision-making. Future studies should continue to test whether 1) recommendations from the systematic capital budgeting literature improve cost efficiency, and 2) governments committed to linking prepared master plans and asset inventories into capital project prioritization, finance, and maintenance decisions are more efficient.

Literature Review

The normative capital budgeting literature recommends a systematic capital budgeting process to improve the effectiveness and efficiency of public investments (Ermasova, 2020; Srithongrung, 2008; Srithongrung et al., 2019). A systematic capital budgeting process should begin with long-term comprehensive plans that establish community goals. These goals provide the foundation for needs assessments and future condition forecasts that identify capital projects that can be prioritized in capital improvement plans and selected into annual capital budgets (Srithongrung, 2008; Srithongrung et al., 2019). Once projects are selected, centralized project monitoring systems should be established to ensure that projects are delivered correctly, and asset management practices should be established to ensure that acquired assets remain in functional condition (Ammar et al., 2001; Ebdon, 2004; Ermasova, 2020; Kim & Ebdon, 2020; Srithongrung, 2008; Srithongrung et al., 2019). Ideally, governments will link comprehensive planning to project selection and financing with long-term commitments to project management and asset maintenance (Ammar et al., 2001; Ebdon, 2004; Srithongrung et al., 2019).

Much of the empirical work on capital budgeting has established how government practices align with normative recommendations. The Government Performance Project (GPP) was perhaps the largest examination of capital budgeting practices among the 50 states and selected large municipalities (Ammar et al., 2001; Ebdon, 2004; Jimenez & Pagano, 2012; Srithongrung, 2008). At a high level, states, counties, and cities tend to engage in long-term comprehensive planning and maintain project management systems, but struggle most with adequate infrastructure maintenance (Ammar et al., 2000; Ebdon, 2004; Jimenez & Pagano, 2012). While the GPP did look at some municipality capital budgeting practices, these are less understood than state practices and represent a need for additional research (Ermasova, 2020).

Less research has explicitly tested if recommended normative practices impact organizational efficiency and effectiveness. Generally, indirect empirical evidence has been used to support the systematic capital budgeting model's normative recommendations. Fiscally, governments which linked strategic plans to their capital budget showed stronger financial performance, and long-term capital planning was shown to reduce volatility in capital investments (Beckett-Camarata, 2003; Srithongrung, 2018). For example, in terms of infrastructure outcomes, state investments in highway maintenance led to better maintained roads (Chen, 2017). However, the most direct evidence of the importance of systematic capital budgeting practices comes from the GPP. At the macro scale, states with capital budgeting practices rated as highly systematic by the GPP experienced approximately a half a percent greater economic growth, with a 10% increase in their capital spending, than lower-rated states (Srithongrung, 2008). While the above studies provide insight into the ability of the systematic capital budgeting process to improve certain organizational and economic outcomes, they also argue that these processes directly impact organizational effectiveness and efficiency. This study tests the available literature by assessing if key recommended practices make a difference in the cost-efficiency of stormwater utilities.

Stormwater programs provide a bundle of inter-linked, complex services aimed primarily at improving stormwater quality and reducing stormwater quantity (Grigg, 2013). Modern stormwater management systems work to convey stormwater away from public areas, prevent flooding, reduce stormwater pollution, and beautify open spaces (Environmental Finance Center, 2020; Grigg, 2013; National Research Council et al., 2009). Stormwater programs accomplish these goals by implementing best management practices (BMPs) that may include green and structural infrastructure systems or activities designed to reduce the risk of stormwater pollution, like general water quality monitoring, public outreach, and other activities (Environmental Finance Center, 2020; Grigg, 2013; National Research Council et al., 2009). Stormwater programs must accomplish these objectives while staying within regulatory guidelines.

Stormwater programs are regulated under the U.S. federal Clean Water Act (1972), because stormwater flows contain pollutants and reduce the quality of regional waters (National Research Council et al., 2009). As established under the act, large, medium, and small Municipal Separate Storm Sewer Systems (MS4s) must work to reduce stormwater pollution to the maximum extent practical (Department of Environmental Protection, 2013; National Research Council et al., 2009), which is an ambiguous standard. Recent efforts have developed numeric total maximum daily loads (TMDLs) for waters; however, TMDLs, rolled out slowly, will take multiple permitting cycles to establish, as regulated entities work toward numeric targets at the maximum extent practical (National Research Council et al., 2009; Department of

Environmental Protection, 2013). While many have cited tightening stormwater regulations as a cost-driver, a study of stormwater utilities' costs in California did not find increases over time in line with rising regulatory pressure (Environmental Finance Center, 2020).

Stormwater programs may be funded by general taxation or by fees. Interest in stormwater fees has risen, as stormwater services have become more intense due to worsening flooding, regulatory pressure, and demand for such services. Fees, generally set to recover the cost of stormwater services, may track with individual fee payers' contribution to stormwater discharge via the imperviousness of their properties (Grigg, 2013; Kea et al., 2016; Zhao et al., 2019). As such, credits may also be provided to properties that work to reduce flows, as an incentive for property owners to reduce their stormwater contributions and as a way of increasing public support for stormwater fees (Grigg, 2013; Kea et al., 2016; Kertesz et al., 2014; Zhao et al., 2019). In an era where alternative financing mechanisms are being sought to provide enhanced stormwater services, understanding the cost drivers of stormwater management and the ways in which governments can more efficiently provide stormwater services is important. Though grey literature has sought common drivers of stormwater costs (Environmental Finance Center, 2020), these efforts, while descriptively useful, do not take the kind of theoretically-informed perspective on the production of public services that could produce an economic model forecasting the costs of stormwater service provision.

Public sector cost-functions are a rich and theoretically well-informed way to understand the costs of providing public services. The modern literature on cost functions as applied to the public sector is based in the pioneering work of William Duncan and John Yinger, who modeled the costs of firefighting services in local governments (Bradford et al., 1969; Duncombe, 1989, 1992; Duncombe & Yinger, 1993). Their model argues that governments' long-term costs are a function of their performance, population served, environmental factors that impact the delivery of public services, and the prices of labor and capital (Duncombe, 1989, 1992; Duncombe & Yinger, 1993). This framework has been most widely applied to understand the costs of providing public education (Duncombe & Yinger, 2007, 2011; Gronberg et al., 2011; Grosskopf et al., 2014). Cost functions can also be used to understand the factors that drive organizational efficiency. Donahue (2004) demonstrated that management practices were able to reduce the cost of firefighting services, and the impact of exogenous variables on the efficiency of educational provision has been widely studied (Gronberg et al., 2015; Grosskopf et al., 2014). Cost functions provide a way to rigorously understand the factors driving the cost of public service and the influence that management can have on efficiency (Donahue, 2004). Therefore, they provide an ideal foundation on which to understand the cost drivers of stormwater management and test the influence of normative practices from the capital budgeting literature on cost efficiency. This paper develops a theoretical model of stormwater utilities' costs and applies it to understand if systematic best practices improve cost-efficiency of stormwater utilities.

Theory and Hypotheses

The total cost (TC) of providing public services is determined by their quality (S), local environmental conditions (E), the population served (P), the price of labor (L), the price of capital (K), and the cost-efficiency (*e*) of the providing organization (Donahue, 2004; Duncombe, 1989, 1992; Duncombe & Yinger, 1993, 2011). As argued by Duncombe and Duncombe and Yinger (1992, 1993), public production is a result of a two-stage process. In the first stage, public organizations produce outputs (G), given labor (LI) and capital inputs (KI), as shown in equation 1.1. Equations 1.1-1.5 follow the notation of Duncombe (1992). In this context, the intermediate outputs of public organizations are their activities and actions.

$$G = p\left(LI, KI\right) \tag{1.1}$$

Assuming that governments minimize costs, the total cost of governments' intermediate outputs can be represented by a cost function, as shown in equation 1.2 (Bradford et al., 1969; Duncombe, 1992; Duncombe & Yinger, 1993).

$$TC = c(G, L, K) \tag{1.2}$$

However, citizens do not demand government activities for their own sake; instead, they are interested in the outcomes of public services (S) (Bradford et al., 1969; Duncombe, 1992; Duncombe & Yinger, 1993). The second stage of a public sector cost function models how governments transform intermediate outputs into quality public services. Governments' intermediate activities may not result in the same performance outcomes, for two reasons. First, governments provide services to populations of different sizes (Bradford et al., 1969; Duncombe, 1992; Duncombe & Yinger, 1993). Second, environmental factors may influence governments' ability to provide certain services. For instance, schools serving disadvantaged students may find it more difficult to achieve higher levels of test performance, firefighting organizations may struggle to protect older housing stocks, and police departments may find it more difficult to reduce crime in areas with high levels of poverty (Bradford et al., 1969; Duncombe, 1992; Duncombe & Yinger, 1993). As shown in equation 1.3, service outcomes are a function of government activities, the population served, and environmental conditions.

$$S = h(G, N, E) \tag{1.3}$$

Finally, the total cost of providing quality services can be calculated by first solving for G, as shown in equation 1.4, and substituting the function into the cost function from equation 1.2 (Duncombe, 1992; Duncombe & Yinger, 1993). The resulting equation, shown in equation

1.5, theoretically represents the cost of providing public services with perfect efficiency (Duncombe, 1992; Duncombe & Yinger, 1993). Generally, S is considered to be endogenous, because spending levels are simultaneously determined with desired performance during the budget process (Donahue, 2004; Duncombe, 1992; Duncombe & Yinger, 1993, 2011).

$$G = h^{-1}(S, N, E) \tag{1.4}$$

$$TC = c\left(h^{-1}(S, N, E), L, K\right) \tag{1.5}$$

Not all governments produce services efficiently. Less efficient governments may have to increase their total spending (TS) to provide the same public services at a certain quality level. Equation 1.6 modifies the cost function to include the inefficiency term *e* (Duncombe & Yinger, 2011; Greene, 2008).

$$TS = (TC)(e) = c\left(h^{-1}(S, N, E), L, K\right)(e) \tag{1.6}$$

If a government were operating perfectly efficiently, *e* would equal 1 and the observed level of spending would equal the minimum cost of providing stormwater services. Cost inefficiency can therefore be defined as increases in observed spending beyond the minimum required to achieve a level of performance, given environmental conditions, as captured in the cost function (Duncombe & Yinger, 2011; Greene, 2008).

Donahue (2004) considered the impact of managerial (M) and organizational (O) factors on fire departments' cost efficiency. Based on the definition in equation 1.7, managerial and organizational factors that influence efficiency should increase deviations from the minimum cost implied by the cost function, which represents fully efficient production (Greene, 2008; Gronberg et al., 2011, 2015). Modifying Donahue's (2004) notation, managerial and organizational factors were written to determine efficiency directly.

$$TS = \left(TC\right) f\left(O,M\right) = c\left(h^{-1}(S,N,E),L,K\right) f\left(O,M\right) \tag{1.7}$$

Inefficiency in equation 1.7 should be greater than or equal to 1, because it is defined as increases beyond the minimum costs as represented in the cost function (Greene, 2008).

Starting with the basic cost function in equation 1.2, the total cost of providing intermediate stormwater service outputs is modeled as a function of labor and capital prices. However, intermediate stormwater outputs must be translated into organizational outcomes. One major purpose of a stormwater utility is to provide drainage services (Grigg, 2013; National Research Council et al., 2009). In this case, stormwater utilities' performance will be measured by their ability to reduce flood damages. To better prevent flood damages, stormwater utilities must scale their level of activity by investing in better infrastructure systems and the human capital needed to design and maintain them. Therefore, decreasing flood damages should result in higher costs.

H1: Governments that experience less flood damages have higher costs.

Stormwater programs must work to reduce stormwater pollution (Environmental Finance Center, 2020; Grigg, 2013; National Research Council et al., 2009). Under the Clean Water Act, MS4 regulations were rolled out for large cities and urban areas in two phases, with phase one covering large and medium MS4s and phase two covering small MS4s. MS4 permits require activities across six elements, including education and outreach, public participation, illicit discharge management, construction runoff management, post-construction runoff management, and pollution prevention (National Research Council et al., 2009). Florida issues phase 2 permits under a generic permit that requires municipalities to prepare a stormwater management program with the six elements, whereas phase 1 permits require local monitoring and contain specific program elements within the six categories (Department of Environmental Protection, 2013;

National Research Council et al., 2009). To capture potential cost differences between phase 1 and phase 2 permit types, this study includes stormwater programs' MS4 status as a cost determinant.

The cost of implementing drainage services and treating stormwater pollution depends heavily on the environmental characteristics of the region. First, costs likely scale with population and area served, as more infrastructure must be built to cover larger areas and serve larger populations. Second, impervious surfaces prevent rainwater from draining naturally into the soil and have been recognized as a leading indicator of the impact of urbanization on stormwater runoff quality and quantity (Arnold & Gibbons, 1996; Chabaeva et al., 2009; National Research Council et al., 2009; Sohn et al., 2020). Stormwater programs that serve regions with more impervious surfaces should have higher costs: their drainage systems must handle increased flows from impervious surfaces and treat the stormwater pollutants that they produce (Arnold & Gibbons, 1996; Chabaeva et al., 2009; National Research Council et al., 2009; Sohn et al., 2020).

H2: Governments serving areas with more impervious surfaces have higher costs.

Third, drainage systems must handle flood level flows. Cities with larger, developed floodplains should have higher costs, because drainage services will have to handle the more frequent and intense flooding issues that exist in floodplains.

H3: Governments with more properties in the floodplain have higher costs.

Finally, cities may require property owners to retain and treat stormwater on their own property, and incentivize them to do so by providing credits that reduce their stormwater fees (Grigg, 2013; Kea et al., 2016; Zhao et al., 2019). These credits may reduce the cost of drainage services at the city level by encouraging property owners to handle flooding problems themselves (Kertesz et al., 2014; Zhao et al., 2019). Similarly, cities which require citizens to detain stormwater on site may have lower costs, because individual property owners are not contributing as much to stormwater flows.

H4: Governments which give credits for private detention facilities have lower costs.

H5: Governments which require private citizens to retain stormwater flows have lower costs.

Finally, the managerial and organizational factors of interest are governments' use of systematic capital budgeting practices, which are expected to reduced spending levels by improving efficiency. The systematic capital budgeting framework argues that governments should use comprehensive planning to appropriately plan their capital investments (Ammar et al., 2001; Ermasova, 2020; Srithongrung, 2008; Srithongrung et al., 2019). Stormwater utilities may establish master plans to understand the drainage and water quality problems in their area of service with accompanying capital projects to fix identified deficiencies. For instance, the City of Hialeah's Comprehensive Plan's Objective 1.2 states that, "The City shall maintain a Stormwater Master Plan which establishes high water elevations, addresses existing deficiencies, and coordinates the construction of new and replacement facilities" (Calvin, Giordano & Associates, Inc., 2017, Drainage Element, Page 3). In another example, the City of Naples Stormwater Master Plan identifies new water quality and quantity capital investments based on a comprehensive analysis of the city's existing stormwater program (Eason, 2018). Stormwater master plans are analogous to recommended comprehensive planning processes from the systematic capital budgeting model. If stormwater master plans comprehensively identify the areas where capital investments are needed most and identify efficacious investments, then stormwater utilities with stormwater master plans should be more cost efficient.

H6: Stormwater utilities with stormwater master plans are more cost efficient.

Complete asset inventories, important for both long-term capital planning and maintenance, should improve stormwater utilities' efficiency. Capital asset inventories are a key input into comprehensive capital planning, because they serve as a starting point for needs assessments (Hines et al., 2022; Srithongrung et al., 2019). At the end of the capital budgeting process, data on asset quality, which informs comprehensive maintenance decisions, is a critical input for asset management systems (Kim & Ebdon, 2020). A lack of adequate information systems for managing asset maintenance, a noted issue for large counties in the 2004 GPP, can frustrate staff working to maintain assets' quality (Ebdon, 2004; Kim & Ebdon, 2020). Given that complete asset inventories should inform needs assessment planning and are a fundamental component of asset maintenance, stormwater utilities with more complete asset inventories should be more cost efficient.

H7: Stormwater utilities with more complete asset inventories are more cost efficient.

Empirical Model

The impact of master plans and asset inventories on the cost-efficiency of stormwater utilities is conceptualized as deviations from the minimum cost of achieving a given level of flood protection, which is determined simultaneously with spending levels. This study observed 114 stormwater programs during 2016 and 2018 to form an unbalanced panel of 202 observations. The cost function, modeled using a semi-log functional form, was estimated by two-stage least squares to account for the endogeneity between flood damage and spending. Though cluster robust standard errors account for the threat of serial correlation in the panel, fixed effects were not used, because there is little to no time variation in the key variables of interest (see Table 20 for descriptive statistics). The following sections discuss the measurement of key concepts, describe the functional form, and explain the estimation technique.

Data and Measurement

This study is based on stormwater utilities, defined as stormwater programs with a fee-based revenue system, as identified in the Florida Stormwater Association's 2016 and 2018 Stormwater Utility Surveys. The Florida Stormwater Association conducts a bi-annual survey of stormwater utilities and shared the results for this study. Only city utilities strictly serving the incorporated area of their city were included in the sample, because impervious surfaces, flood zones, and other information that defines a stormwater utility's scope of service provision can be measured at the city level. There are 227 total observations in the 2016 and 2018 surveys that meet the criteria for this study.[17]

Stormwater utilities' total cost of providing stormwater services were gathered from utility annual comprehensive financial reports (ACFRs) and the Annual Financial Reports complied by the Florida Department of Financial Services (n.d.). Local governments' total costs are defined as the sum of their short-term operating and long-term capital spending (Donahue, 2004; Duncombe, 1992; Duncombe & Yinger, 1993). Cities in Florida may use either a governmental or enterprise fund to account for their stormwater utilities. Governmental funds were prepared using modified accrual accounting practices and report capital expenditures and debt service payments in the year they were made (Finkler et al., 2016). Stormwater utilities' total spending, as reported in governmental funds, was measured as their total expenditure and includes capital expenditures and debt service payments (Finkler et al., 2016). Enterprise funds

[17] Multiple datasets were combined in R for this study using the readxl, dplyr, and tidyr packages (Wickham, François, et al., 2023; Wickham, Vaughan, et al., 2023; Wickham & Bryan, 2022).

are prepared under full accrual accounting and do not report capital expenditures or debt service payments. Instead, capital assets' depreciation is amortized over time and reported as an annual expense, and interest expenses are recorded as non-operating expenses. Total spending for enterprise funds was calculated as total operating costs, which include depreciation and non-operating interest expenses. A similar approach has been used to calculate the total costs for airports (Martín & Voltes-Dorta, 2011). Specific stormwater spending was found for 202 out of the 227 city governments who responded to the Florida Stormwater Association's survey.

Flood damages were measured using the Federal Emergency Management Agency's National Flood Insurance Program V1 claims database (January 4th, 2021).[18] The NFIP claims database includes a searchable reported city column, but this column is afflicted by known spelling errors (Dombrowski et al., 2020). To ensure that claims were aggregated properly to the city level, the following procedure was used. First, all claims in a county were extracted for the relevant fiscal year, and a unique list of city names was generated that included all misspellings for that year. Second, fuzzy matching was used to match most city names to the correctly spelled names using R. Third, the results of the fuzzy matching procedure were checked such that each unique spelling of a city's name was correctly matched to the observation's city name with improper matches manually corrected. Flood damages were given as the aggregated total building and contents payouts. For comparability, flood damages were measured in per-capita terms and given the inverse hyperbolic sine transformation for skew (Bellemare & Wichman, 2020; Dombrowski et al., 2020).

[18] Flood claims were bulk downloaded from FEMA. Note that, "This product uses the Federal Emergency Management Agency's OpenFEMA API but is not endorsed by FEMA. The Federal Government or FEMA cannot vouch for the data or analyses derived from these data after the data have been retrieved from the Agency's website(s)" (FEMA, n.d.).

Cities that have more properties in the floodplain must deal with worse flood flows and likely spend more on stormwater management. The property at risk of flooding was calculated as the weighted average of the just value of property in the 100- and 500-year floodplains. FEMA's National Flood Hazard Layer specifies the extent of the 100-year floodplain, which has a 1% annual chance of flooding, and property in the 500-year floodplain, which has a .02% annual chance of flooding. The property at risk of flooding is given as the summed just value of property in the 100-year floodplain, multiplied by 1%, plus the summed just value of property in the 500-year floodplain, multiplied by .02%. To calculate the property at risk of flooding, the properties in each city that intersected the 100- or 500-year floodplains were extracted using QGIS and aggregated in R. For 2018, the 2018 version of the National Flood Hazard Layer, a map of city boundaries, and a map of all parcels in the state of Florida from the Department of Revenue were made available from the University of Florida GeoPlan Center (Department of Revenue, 2019; Federal Emergency Management Agency, 2018; University of Florida GeoPlan Center, 2019). For 2016, the 2017 version of the National Flood Hazard Layer, city boundaries map, and property card map were used, because the 2016 National Flood Hazard layer was incomplete for Florida and there is no 2016 city boundaries or property card layer available. Again, these maps were provided by the University of Florida GeoPlan Center (Department of Revenue, 2018; Federal Emergency Management Agency, 2017; University of Florida GeoPlan Center, 2018).

Cities that serve larger areas with more impervious surfaces likely have higher costs because they deal with worse quality stormwater in greater quantity. Total impervious area is typically expressed as the percent of impervious surfaces inside of a defined geographic area (Arnold & Gibbons, 1996; Chabaeva et al., 2009; National Research Council et al., 2009; Sohn et al., 2020). The U.S. Geological Survey's Percent Developed Impervious layer measures the percent of urban impervious surface in each 30m-by-30m square in the United States, and was used calculate the percent of impervious area in each city's boundaries, as shown in the University of Florida GeoPlan Center's 2017 and 2018 City Limits shapefiles (Dewitz & United States Geological Survey, 2021a, 2021b; University of Florida GeoPlan Center, 2018, 2019).[19] The percentage of impervious surface in each city was calculated as the average percent impervious in all the 30m-by-30m squares overlapped by the boundaries of each city using QGIS's Zonal Statistics plugin. The University of Florida GeoPlan Center's city limits shapefiles contain the acreage of each city and were used to measure the area of the city served by the stormwater utility (University of Florida GeoPlan Center, 2018, 2019). The population served, a critical determinant of costs, is available from the Florida Office of Economic and Demographic Research (University of Florida Bureau of Economic and Business Research, n.d.).

This study controlled for stormwater utilities' regulatory status and treatment of private stormwater retention infrastructure. Stormwater utilities reported whether they offered stormwater credits for private retention/detention facilities or if their local codes require private detention/retention facilities in their response to the Florida Stormwater Association's survey. Two dummy variables were used to capture stormwater credit provision and private retention requirements, coded 1 for the presence of a stormwater credit or private retention requirement and zero otherwise. Stormwater utilities' MS4 status was gathered from the Florida Department

[19] The USGS's Percent Developed Impervious Layer had to be reprojected to have the same coordinate reference system as the city boundaries layer for the zonal statistics calculations to be accurate. The original Percent Developed Impervious Layer was projected using the WGS 1984 geographic reference system and the Albers Conical Equal Area projection, while the city boundaries layer was projected using the NAD 1983 geographic reference system and the Albers HARN projection for Florida. Using ArcMap, the WGS 1984 (ITRF00) to NAD 1983 (WKID 108190) transformation was applied to convert from WGS 1984 to NAD 1983. Second, mirroring the transformation used by the University of Florida GeoPlan center to convert the National Flood Hazard Layer to the Albers HARN, the NAD 1983 to HARN Florida transformation (WKID 1480) was applied (Federal Emergency Management Agency, 2017, 2018). This transformation projected the Percent Developed Impervious Layer into the NAD 1983 geographic reference system and the Albers HARN projection for Florida using bilinear interpolation. These changes were applied prior to the zonal analysis, which was conducted using QGIS.

of Environmental Protection's 2007 and 2018 list of MS4 permits (Florida Department of Environmental Protection, 2007, 2018).[20] Utilities' MS4 status was recorded as a dummy variable, coded as 1 for utilities that are phase 1 MS4s and 0 for phase 2 and non-MS4s (only two governments in the sample were not regulated MS4s).

Labor and capital prices are critical determinants of costs. Since direct measures of stormwater professionals' salaries were not available, a proxy variable was used to control for systematic pay differences that impact the underlying wages each stormwater utility must pay. Similar to McCarthy (2014), wage information was drawn from the Quarterly Census of Earnings and Wages. Stormwater utilities in labor markets where local governments generally pay higher wages likely pay their stormwater professionals higher wages as well. In this case, the average annual salary of local government employees working in general executive, legislative, and other general government roles was used to capture inter-county differences in the pay for local governments.[21]

As compared to the theoretical model, capital prices were broken into separate measures for building materials and land. Pieces of stormwater infrastructure are site specific and vary in their use of land and input materials (King & Hagan, 2011). Stormwater best management practices can take diverse forms, including, but certainly not limited to, bioswales, constructed wetlands, stormwater ponds, and infiltration (Environmental Finance Center, 2020; King & Hagan, 2011). While prior studies have measured capital input prices by measuring the rental price of a standardized unit of capital, stormwater infrastructure is highly site-specific and may use different blends of capital and land inputs (Duncombe, 1989, 1992; Duncombe & Yinger,

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[20] Those cities which were MS4s in 2018 but not in 2008 were checked against the state's Nexus database to see if they were classified as MS4s in 2016.

[21] In 14 cases, county-level information was not available for NACIS code 921 because the Bureau of Labor Statistics anonymizes salary data in areas where they might inadvertently reveal someone's pay. In these cases, annual wages for all local government employees in NACIS code 92 was used instead of NACIS code 921.

1993; King & Hagan, 2011). Notably, it is reasonable that stormwater programs serving urban areas with high land prices may opt to build more engineered structures that require less space if land prices are too high, and areas with low land prices may opt to build fewer engineered structures, which require more space.

First, a proxy variable was used to capture systematic variation in building materials' prices. King and Hagan (2011) use the RS Means Materials Index, published quarterly and consisting of different commonly used construction materials, to adjust their stormwater best management practices cost estimates from county to county in Maryland. Intra-state differences in construction costs were proxied using the average RS Means Materials Index for the four quarters in the relevant fiscal year for the city closest to the stormwater utility (Gordian, 2018a, 2018b, 2018c, 2018d; RS Means, 2016a, 2016b, 2016c, 2016d).[22] Second, the rental price of an acre of the median-valued acre of land was calculated to capture systematic differences in regional land prices and projected differences in the cost of financing pieces of infrastructure. Similar to Duncombe (1989), the rental price of an acre of land was given as the purchase price times the real interest rate for the city.[23] The purchase price of an acre of land for each city was calculated as the median just value of an acre of land in each city, using the Department of Revenue's parcel layer for the state. Interest rates were calculated based on the best rate available to the utility. Florida's Clean Water State Revolving Fund offers low-cost loans for stormwater best management practices; its interest rates were given as the market rate for debt, as established in the Bond Buyer 20 Bond GO Index, adjusted downward for the population served and debt

[22] Using QGIS, the linear distance between the center of each city in the dataset and the center of each of the cities with an available RS Means data was calculated to permit the minimum distance city to be assessed.
[23] Depreciation was not included because land does not depreciate.

affordability index. Interest rates were calculated following the state's formula (Board of Governors of the Federal Reserve System, n.d.).[24]

Stormwater utilities' use of systematic capital budgeting practices were taken from the Florida Stormwater Association's survey data. Stormwater utilities' decision to have a master plan was represented by a dummy variable, coded 1 if the utility has a master plan and 0 otherwise. Most stormwater utilities have a master plan. In fact, only 16% of observations applied to stormwater utilities without a master plan. Utilities percent of assets inventoried was given in its natural scale; answers were limited to inventorying 0%, 25%, 50%, 75%, or 100% of their assets. Stormwater utilities generally do a good job of inventorying their assets; 56% had complete asset inventories, 31% had inventoried 75% of their assets, and only 13% had inventoried half of their assets or less.

Stormwater utilities' decision to inventory their assets or maintain a master plan were treated as exogenous determinants of inefficiency. At different spending levels, utilities may choose to develop asset inventories, master plans, or complete any number of other organizational objectives, including building additional infrastructure. Therefore, utilities' decision to develop asset inventories and master plans were treated as managerial choices that influence organizations' spending by giving them the ability to deploy their resources more effectively. While Donahue (2004) argued that fire departments' costs and managerial quality be determined simultaneously because they are both the result of managerial choices, master plans and asset inventories are endogenous only if spending levels influence a utility's decision to develop a master plan or complete an asset inventory.

[24] The Affordability Index for each city was calculated using the Division of Water Restoration Assistance's Excel Affordability Index calculator for census places. The Bond Buyer 20 Bond GO Index average for interest rate calculations was calculated based on the state's interest rate fact sheets for each quarter but had to be sourced from the St. Louis Federal Reserve's site for FY 2015-2016 (Board of Governors of the Federal Reserve System, n.d.).

Estimation

A semi-log functional form was used to estimate the cost of providing stormwater services. Typically, cost functions are estimated using a Cobbs-Douglas specification, where all variables are log transformed, or a transcendental logarithmic functional form, where all variables are logged and squared and interaction terms are included for all variables (Duncombe & Yinger, 2007, 2011; Gronberg et al., 2011, 2015; Grosskopf et al., 2014). While the transcendental logarithmic form is quite flexible, it is not practical given the sample size; further, it would require many instruments to identify flood damages, the interactions between flood damages and other variables in the model, and the squared flood damages term.

The semi-log form chosen is shown in equation 1.8 such that log total spending (TS) is explained by inverse hyperbolic sine transformed flood damages per capita (S), the percent of impervious surface (I), the log weighted value of property in the floodplain (F), log area in acres (A), log population (N), the log rental price of land (R), the log RS Means index of construction costs (C), the log price of labor (L), MS4 phase status dummy (P), stormwater credit provision (W), and private retention requirements (U). In equation 1.8, the percent of impervious surfaces (I) is not logged (because it is naturally expressed as a percent) and flood damages per capita (S) is not logged (because the log transformation is not defined at zero whereas the inverse hyperbolic sine is) (Bellemare & Wichman, 2020). Not logging variables naturally expressed as a percent or ratio is common in the literature on education costs, resulting in either modified Cobbs Douglas or modified translog specifications (Duncombe & Yinger, 2007, 2011; Gronberg et al., 2011, 2015; Grosskopf et al., 2014).

$$\begin{aligned}\ln\left(TS_{i,t}\right) = a &+ B_1 \mathrm{IHS}(S_{i,t}) + B_2 I_{i,t} + B_3 \ln\left(F_{i,t}\right) + B_4 \ln\left(A_{i,t}\right) \\ &+ B_5 \ln\left(N_{i,t}\right) + B_6 \ln\left(R_{i,t}\right) + B_7 \ln\left(C_{i,t}\right) + B_8 \ln\left(L_{i,t}\right) \\ &+ B_9 P_{i,t} + B_{10} W_{i,t} + B_{11} U_{i,t} + v_{i,t} + e_{i,t} + c_i\end{aligned} \qquad (1.8)$$

Deviations from the cost frontier can be caused by random error or by inefficiency. Equation 1.8 includes a multi-part error term containing an observation-specific random error $v_{i,t}$, an inefficiency error term $e_{i,t}$, and an observation specific effect c_i (Gronberg et al., 2011, 2015). In this case, inefficiency is given as the linear sum of unobserved, random inefficiency, the presence of a master plan (M), and the completeness of the asset inventory (AI), as shown in equation 1.9.

$$e_{i,t} = u_{i,t} + B_{12} M_{i,t} + B_{13} AI_{i,t} \tag{1.9}$$

Inefficiency was modeled as a linear function to avoid making distributional assumptions. It is debatable whether the functional form for efficiency, as shown in equation 1.9, is appropriate, because inefficiency is theoretically expected to be strictly positive (Greene, 2008). Stochastic frontier models can enforce this theoretical requirement by modeling inefficiency as a half normal or exponential distribution that is scaled by an exponential function of the determinants of inefficiency (Alvarez et al., 2006; Gronberg et al., 2011; Grosskopf et al., 2014; Kim & Schmidt, 2008; Wang & Schmidt, 2002).[25] Entering the determinants of inefficiency linearly alongside the other frontier variables may have power against these alternative functional forms. Kim and Schmidt (2008) show that for a cross-sectional stochastic frontier model, the F test for the joint significance of the inefficiency determinants in a linear regression alongside the other frontier variables is equivalent to a score test that the inefficiency determinants enter non-linearly by scaling the inefficiency distribution through a generic,

[25] A vast number of alternative functional forms have been suggested for stochastic frontier models (Greene, 2008). The scaled half normal and exponential forms are common and have been used in the educational cost function literature (Gronberg et al., 2015).

monotonic function.[26] In equation 1.10, the idiosyncratic inefficiency errors $u_{i,t}$ are independent and identically distributed draws from an unspecified distribution, and I is any function that is monotonic and differentiable at 0 (Kim and Schmidt, 2008).

$$e_{i,t} = u_{i,t} I(B_{11} M_{i,t} + B_{11} AI_{i,t}) \tag{1.10}$$

Equation 1.10 contains the scaled half-normal or exponential distributions among a plethora of other potential specifications. Thus, the testing for inefficiency determinants alongside the other frontier variables can test if the inefficiency determinants matter without imposing distributional assumptions.

Because organizations jointly determine their performance outputs and spending levels, performance levels are endogenous in cost function models (Donahue, 2004; Duncombe & Yinger, 2007, 2011; Gronberg et al., 2011, 2015; Grosskopf et al., 2014; Karakaplan & Kutlu, 2019). When inefficiency determinants enter linearly, simple two-stage least squares-based methods can be used to address endogeneity, whereas controlling for endogeneity is much more challenging in stochastic frontier models (Donahue, 2004; Duncombe & Yinger, 2007, 2011; Grosskopf et al., 2014).[27] Simple, pooled two-stage least squares was used to estimate the model. In this case, the limited amount of over-time variation in the panel limits the inference

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[26] Kim and Schmidt (2008) derive their OLS based test from stochastic production frontier such that $y = a + XB - ue^{Z\delta}$ where X is a matrix of inputs with the coefficient vector *B*, u is the expected value of $u_{i,t}$, and Z is a matrix of inefficiency determinants with the coefficients vector δ. Inefficiency in a stochastic production model is the result of output falling below the maximum that could be produced given the inputs used whereas inefficiency in a cost function is defined as spending above the minimum required to produce the expected outputs. Adapting Kim and Schmidt's (2008) result to a stochastic cost function simply requires that inefficiency enter positively such that $y = a + XB + ue^{Z\delta}$. This form would also result if the inefficiency determinants entered through a negative exponential function which is contained in the class of monotonic functions differentiable at zero that the OLS based test has power against.

[27] Control and pseudo control function approaches have been suggested to analyze panel stochastic frontier models with endogeneity, but control function approaches are generally inconsistent in models with non-continuous endogenous explanatory variables (Karakaplan & Kutlu, 2017, 2019; Wooldridge, 2014). In this case, inverse hyperbolic sine transformed flood damages per capita have a corner at 0 and a long right tail, making the control function approach likely inconsistent for the non-linear model (Wooldridge, 2014).

that can be made if fixed effects are included. While a random effects two-stage least squares estimation may be more efficient, pooled two-stage least-squares is simple and consistent under the assumption that the instruments are uncorrelated with the error term or individual effect (Wooldridge, 2010).

The count of tropical storms and thunderstorms experienced by a utility are used as instruments here. Tropical and thunderstorm counts were gathered from the National Weather Service to be used as instruments for flood damages per capita (National Oceanic and Atmospheric Administration National Weather Service, n.d.). Weather events are a valid instrument; storms cause flooding but do not independently impact stormwater utilities' spending levels, which are largely set through the prior fiscal year's budgeting process. While storms may cause damaging floods that lead a utility to potentially increase spending on repairs or cause citizens to demand better flood protection in later years, the mere presence of a storm should not have an independent impact on citizens' demand for flood protection. After all, a non-damaging storm is an unremarkable event that only becomes remarkable by causing damage.

Results

Estimation of the cost function reveals that environmental factors drive stormwater costs but fail to show that systematic capital budgeting best practices result in the more cost-efficient provision of stormwater services. Specification testing indicates that the correction for endogeneity is not necessary, and that the results from the pooled ordinary least squares model should be preferred to the two-stage least squares results because they are more efficient. The cost function estimates are shown in Tables 21 and 22.

While thunderstorms and tropical storms are decently strong instruments, the pooled ordinary least squares results are preferable to the two-stage least squares results, because the correction for endogeneity is not required. Two-stage least squares regression relies on instrument strength for consistency (Wooldridge, 2010). The F test for the significance of the instruments in the first stage regression provides an indication of their strength (Stock et al., 2002; Wooldridge, 2010). As a rule of thumb, selected instruments may be weak if the F test for their joint significance is less than 10 (Stock et al., 2002). The first stage regression results are reported in Table 22 with cluster robust standard errors. In this case, the F value for the count of tropical storms and thunderstorms is 10.28. Given a valid instrument, it is possible to test if the endogeneity correction is necessary. If no correction for endogeneity is necessary, then the results from the pooled ordinary least squares regression may be preferred because they are more efficient (Wooldridge, 2010). A control function can be used to test for endogeneity, in which the residuals from the first-stage regression are included alongside the other regressors in the second stage. If the first-stage residuals are insignificant, then no correction for endogeneity is required (Wooldridge, 2010). As shown in Table 22, the residuals from the first stage are an insignificant predictor of logged total spending, with a p-value of 0.26.[28] Therefore, the endogeneity correction is unnecessary, and the interpretation of results follows from the pooled ordinary least squares model; its results have strong predictive power because they explain 79.6% of the observed variance in total costs on the log scale.

Hypothesis 1 predicts that utilities with lower flood damages per capita should have higher spending, because they invest more to provide better flood protection. However, as shown in Table 21, governments which experienced higher flood damages per capita had higher spending levels, at the 0.05 significance level. Therefore, hypothesis 1 is rejected. Instead, it

[28] The results from the residual inclusion endogeneity test are not adjusted for the two-stage nature of the test because the correction is not required under the null hypothesis that the suspected endogenous variables and error term have a covariance of zero (Wooldridge, 2010).

appears that increases in stormwater utilities' ability to reduce flooding are associated with lower overall costs. There are two possible explanations for this observed relationship. First, flood events are relatively rare. In some cases, local governments may have experienced no flood damages due to a lack of exposure in that year rather than due to their quality storm infrastructure. As measured, flood damages per capita may capture underlying environmental factors related to cities' flood frequency that are not reflected in the other environmental variables. Stormwater utilities serving areas that flood more frequently may need to spend more on prevention. A second possibility is that governments with high levels of organizational capacity and recent flood experience may adaptively invest in preventing floods (Brody et al., 2010). In this case, high-capacity organizations may be investing responsibly in preventing future flooding disasters in the wake of a damaging flood (Zhang & Maroulis, 2021).

Environmental factors are critical drivers of stormwater utilities' spending. First, hypothesis 2 argues that impervious surfaces increase stormwater utilities' costs because they prevent stormwater from draining naturally into the soil (Arnold & Gibbons, 1996; Chabaeva et al., 2009; National Research Council et al., 2009; Sohn et al., 2020). As shown in the pooled ordinary least squares results in Table 21, the percentage of impervious surfaces in a city significantly increases their stormwater costs, at the 0.05 level. Increasing the proportion of impervious surface in a city by 1% is associated with an approximately 1.6% increase in costs. Second, hypothesis 3 argues that a city with more properties in the floodplain should experience higher costs, because they must deal with worse flood flows. As shown in the pooled ordinary least squares results, the weighted value of property in the floodplain has a borderline significant effect on costs, with a p-value of 0.06. A 1% increase in the weighted value of property in the floodplain is associated with a 0.17% increase in costs.

Hypotheses 4 and 5 argued that stormwater credits and private retention requirements reduce stormwater spending by incentivizing and forcing citizens to reduce their stormwater pollution. As shown in the pooled ordinary least squares results in Table 21, both hypotheses are rejected: stormwater credits or private retention requirements tend to increase costs at borderline significant levels. It is possible that private retention requirements and the provision of stormwater credits are reflective of underlying factors that increase the demand for stormwater programs. For instance, stormwater credits may cause taxpayers to demand additional spending on stormwater because consider their stormwater fees to be fair.

This study does not find greater efficiency among either stormwater utilities with master plans or those that have inventoried a higher percentage of their assets. As shown in Table 21, neither the coefficient on the percent of assets inventoried or the presence of a master plan is significant. Therefore, hypotheses 6 and 7 are rejected. Stormwater utilities which invest in master plans or more complete asset inventories do not have overall lower levels of spending when controlling for cost factors. Thus, master plans and complete asset inventories are not associated with enhanced cost-efficiency. While this analysis does demonstrate that simply having a master plan or complete asset inventory is not sufficient to improve efficiency, there may be unmeasured variation in stormwater utilities' implementation of systematic capital budgeting practices. Stormwater utilities' master plans and asset inventories may have differing levels of quality, and either be successfully or unsuccessfully integrated into governments' overall decision-making processes for their capital budgets.

Cost factors associated with the stormwater utilities' scale are significant, whereas others are not. Stormwater utilities' costs tend to increase with the size of the city they serve. Per the pooled ordinary least squares results, the land area and population served by a stormwater utility are significantly associated with higher costs, at the 0.05 and 0.1 levels, respectively. A 1% increase in the area served by a stormwater utility is associated with a 0.22% increase in costs, and a 1% increase in the population served by a stormwater utility is associated with a 0.63% increase in costs. Interestingly, the rental price of land, construction materials index, and average wage of a government employee are not significant predictors of costs. These variables are measured at the county or regional level. More precise measures would be more likely to achieve significance. Finally, phase 1 MS4s do not appear to have different costs than phase 2 MS4s, indicating that there is not a substantial difference in the costs of regulatory compliance between the programs despite their difference in statutory requirements.

How Can Master Planning Make a Difference?

Additional, qualitative context is necessary to interpret results showing that master planning processes and asset inventories fail to lead to improvements in stormwater utilities' cost-efficiency. Therefore, newspaper articles relating to the master planning processes of stormwater utilities in the sample were reviewed. Master plans may become outdated and fail to be implemented. As the City of St. Pete Beach indicated in their 2012 master plan update, the city had gone almost 20 years without an overall update to its master plan by the time of the 2012 update (Cribb Philbeck Weaver Group, 2012). Similarly, master planning processes can be expensive and defy implementation. The City of Sebastian spent $700,000.00 on updates to its stormwater master plan (Hodges, 2021). St. Petersburg spent $3 million on state-of-the-art updates to its master plan, which employs models that are precise to a hundredth of a foot in elevation. While such efforts are impressive, the city's original (1994) master plan called for $610 million in capital improvements, of which only $211 million were made (Parker, 2023).

Master plans, even if accurate, may not improve cost-efficiency if they do not return the value in their investment. Such expensive, top-down efforts may not be required to improve cost-efficiency if easily implemented and efficient projects are already available. For instance, in an article describing Brevard County's stormwater utility, the county forewent an expensive top-down study in order to focus resources on implementing cheap, easy, and in-demand stormwater projects they knew they needed (England, 2001). Brevard County was able to focus on implementing easy wins, which were less attractive to the large consulting companies that offered to implement their master plans (England, 2001). The above discussion is not to discredit master plans, which support the generation of capital projects and provide information. For instance, the City of Miami is updating its stormwater master plan in order to help manage stormwater and flood problems aggravated by rising seas (Staletovich, 2020). Data generation and risk assessment practices that can be part of master planning processes are likely critical to developing options to respond to rising seas (Hines et al., 2022). In a review of the 85 coastal counties in the southeast, Grandage and colleagues (2023) found that those counties which had invested in data generation and risk assessment practices were more likely to have more comprehensively addressed their sea level rise risks. After all, for a county to respond to the risk of sea level rise, they must project and understand its consequences.

Discussion

Local governments' stormwater programs beautify public spaces, prevent pollution, and provide flood protection (Environmental Finance Center, 2020; Grigg, 2013; National Research Council et al., 2009). Understanding stormwater utilities' cost drivers and the practices that allow them to be more efficient may allow these critical organizations to perform better while spending less. This paper develops a cost function for stormwater utilities that provides insight into the technology of providing stormwater services and shows that recommended systematic capital budgeting best practices fail to improve cost-efficiency.

The literature on the costs of public services does much to explain stormwater utilities' total costs. Stormwater utilities' basic costs are a function of their ability to prevent flooding given local environmental factors, population/area served, and labor and capital prices (Duncombe, 1989, 1992; Duncombe & Yinger, 1993, 2011). The primary contribution of this study is to establish the importance of environmental factors in explaining the cost of stormwater services. Both the extent of a city's development in the floodplain and the percent of impervious surface in a city increase the cost of providing stormwater services. The percent of impervious surface in a region has been frequently tied to worse water quality and quantity outcomes, so it is unsurprising that more urbanized cities must spend more (Arnold & Gibbons, 1996; Chabaeva et al., 2009; National Research Council et al., 2009; Sohn et al., 2020).

While reducing flood damages per capita was expected to increase costs due to the increased level of spending required to better prevent floods, it is possible that flood damages per capita instead measures underlying environmental factors that drive flood frequency. Because floods are rare events, observing stormwater utilities or aggregating flood damages over a longer period of time may better measure stormwater utilities' ability to reduce flood damages rather than flood frequency. Tropical storm and thunderstorm counts are available through the National Weather Service and can be used as instruments in future studies assessing the endogeneity between stormwater utilities' performance and spending.

The theoretical framework established in this paper can be used to better understand the technology of stormwater services. With additional data, translog functional forms may be employed to test if the modified Cobbs-Douglas functional form employed in this paper is correct, and if environmental factors impact substitution between land, capital inputs, and labor (Duncombe, 1992; Gronberg et al., 2011). For instance, it is possible that dense, urban areas with more impervious surfaces rely on more engineered structures. Economies of scale, scope, and quality may exist for stormwater utilities that serve more people, handle general floodplain management in addition to stormwater flows, and work to better prevent flood damage (Duncombe & Yinger, 1993). Testing for such economies may allow for insights to be gleaned on the optimal size of stormwater utilities, the cost-savings that could accrue from bundling inter-linked water management services, and to test if investing more in stormwater management services yields increasing gains in flood protection.

The second major contribution of this paper is to test whether recommended practices from the systematic capital budgeting framework improve stormwater utilities' cost-efficiency. Given that master-planning practices and asset inventories are critical parts of the systematic capital budgeting model, it is surprising that neither improved stormwater utilities' cost-efficiency (Ammar et al., 2001; Ebdon, 2004; Ermasova, 2020; Kim & Ebdon, 2020; Srithongrung, 2008; Srithongrung et al., 2019). However, there are reasons to doubt that strategic planning processes and asset inventories would lead to more efficient decision-making on their own. The systematic capital budgeting literature is based on the assumption that strategic planning processes will result in rational capital investment decisions (Ermasova, 2020; Srithongrung, 2008; Srithongrung et al., 2019). However, the empirical literature on public budgeting has long recognized that budgetary decision-makers are boundedly rational people who are subject to cognitive biases and work in complex political processes (Krause, 2006; Padgett, 1980; Thurmaier & Willoughby, 2001; Wildavsky, 1964). Simply having a plan or a complete asset inventory would not improve decision-making if the projects in the plan fail to find support in a boundedly rational, year-to-year budgeting process or for stormwater utilities in cities without the political will to fund identified projects.

Master plans may not matter if they are not linked to project prioritization and financing decisions, and the information produced by asset inventories may not matter if identified deficiencies are not addressed because maintenance is underfunded. This may be the case among Florida's stormwater utilities. While 84% of these have a master plan and 60% have a complete asset inventory, only 22% found stormwater fee revenue to be sufficient to meet all operations and maintenance needs, and only 10% found it sufficient to meet all the needs in their capital improvement plan (Florida Stormwater Association, 2018). The systematic capital budgeting literature argues that comprehensive and master planning processes should be linked to systematic project prioritization, implementation, and maintenance decisions (Ammar et al., 2001; Ebdon, 2004; Srithongrung et al., 2019). It is possible the linkages between the components of the systematic capital budgeting processes are, in fact, the key to ensuring that recommended normative processes result in efficiency gains. Future studies can test if variation in organizations' integration of master plans and the information produced in asset inventories with the other components of the systematic capital budgeting result in cost-efficiency gains.

The major limitation of this study is that government decisions to use systematic capital budgeting best practices depends on beliefs about the efficacy of those practices for the specific government. Governments which may benefit from complete asset inventories or master plans may have chosen to invest in those practices, while governments with no need for those practices did not. While this study can show that stormwater utilities with a master plan or complete asset inventory were no more cost efficient than those without, it is not possible to see if those governments with complete asset inventories or master plans would have been inefficient absent those practices. There is an opportunity for future research to better understand the contexts in which systematic capital budgeting best practices are more likely to be adopted, and work to causally tease out the impact of adoption through research designs capable of establishing stronger inference. Clearly, recommended best practices from the systematic capital budgeting literature are not one-size-fits-all. Future research should explore the nuanced question of why governments choose to adopt normative capital budgeting practices and follow up on them if those practices ultimately impact government efficiency once implemented.

Conclusion

Stormwater utilities are key to managing the flooding threats created by stormwater quantity and the environmental threats created by poor stormwater quality. As such, their spending is heavily driven by the environmental cost factors that drive stormwater flows. As cities grow in size, serve larger populations, expand into floodplains, and develop additional impervious surfaces, they must spend more on stormwater protection. Unfortunately, the mere presence of a master plan or complete asset inventory does not help stormwater utilities achieve their goals more cost-efficiently. Future research should work to understand the conditions in which systematic capital budgeting best practices can improve organizational cost-efficiency.

Tables and Figures

Table 20: Descriptive Statistics

	Mean	Overall Standard Deviation	Between Standard Deviation	Within Standard Deviation	25th Percentile	75th Percentile
Total Stormwater Spending (1,000s)	3479.2	5692.7	5434.3	666.3	550.2	3275.4
Flood Damages per Capita	3.9	23.8	21.0	14.3	0	0.4
Percent Urban Impervious Surface	33.9	15.4	15.7	.4	21.7	45.3
Weighted Value of Property in Floodplain (1,000s)	36383.0	63280.9	61712.2	1869.0	5093.1	35617.9
Area in Acres	19112.6	53698.1	50986.1	174.7	3912.6	15381.2
Population (1,000s)	60.0	104.8	100.0	2.0	14.2	63.5
Rental Price of Land	7.2	1.3	1.3	.2	6.4	8.0
Capital Cost	232.9	5.2	4.0	3.6	229.5	237.8
Local Employees' Average Annual Salary (1,000s)	56.5	9.3	9.2	.8	48.2	63.7
Percent of Assets Inventoried	0.8	0.2	.2	.03	0.8	1
Tropical Storm and Thunderstorm Count	4.3	3.1	2.6	1.8	1	6

Table 21: Cost Models

	Two-Stage Least Squares		Pooled OLS	
	Parameter	Standard Error	Parameter	Standard Error
Flood Damages per Capita (IHS)	0.28	(0.17)	0.083*	(0.039)
Percent Urban Impervious Surface	0.0098	(0.0086)	0.016*	(0.0069)
Weighted Value of Property in Floodplain (Ln)	0.17^{+}	(0.097)	0.17^{+}	(0.093)
Area in Acres (Ln)	0.54**	(0.16)	0.63**	(0.14)
Population (Ln)	0.32*	(0.15)	0.22^{+}	(0.13)
Rental Price of Land (Ln)	0.040	(0.084)	0.048	(0.078)
Capital Cost (Ln)	6.44	(4.59)	5.39	(4.46)
Local Employees' Average Annual Salary (Ln)	1.06^{+}	(0.60)	0.85	(0.54)
Phase 1 MS4	-0.083	(0.13)	-0.051	(0.13)
Stormwater Credits Provided	0.19	(0.14)	0.23^{+}	(0.14)
Private Retention Required	0.20	(0.16)	0.25	(0.15)
Percent of Assets Inventoried	0.38	(0.28)	0.33	(0.26)
Master Plan	0.0024	(0.17)	0.016	(0.17)
2016	0.22	(0.16)	0.17	(0.16)
Constant	-44.7^{+}	(26.7)	-36.7	(25.0)
Observations	202		202	
Clusters	114		114	

Note: Cluster robust standard errors in parentheses; $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < .01$

Table 22: Regression Diagnostics

	First-Stage Regression		Endogeneity Test	
	Parameter	Standard Error	Parameter	Standard Error
Percent Urban Impervious Surface	0.034*	(0.013)	0.0098	(0.0086)
Weighted Value of Property in Floodplain (Ln)	0.00017	(0.12)	0.17^{+}	(0.093)
Area in Acres (Ln)	0.43	(0.29)	0.54**	(0.16)
Population (Ln)	-0.53*	(0.25)	0.32*	(0.15)
Rental Price of Land (Ln)	-0.014	(0.13)	0.040	(0.079)
Capital Cost (Ln)	0.57	(5.05)	6.44	(4.71)
Local Employees' Average Annual Salary (Ln)	0.10	(0.84)	1.06^{+}	(0.57)
Phase 1 MS4	0.060	(0.20)	-0.083	(0.13)
Stormwater Credits Provided	0.25	(0.17)	0.19	(0.14)
Private Retention Required	0.33^{+}	(0.20)	0.20	(0.16)
Percent of Assets Inventoried	-0.22	(0.31)	0.38	(0.26)
Master Plan	0.049	(0.18)	0.0024	(0.17)
Tropical Storm and Thunderstorm Count	0.11**	(0.034)		
Flood Damages per Capita (IHS)			0.28	(0.18)
First Stage Residuals			-0.22	(0.19)
2016	-0.20	(0.19)	0.22	(0.17)
Constant	-3.85	(28.8)	-44.7	(27.1)

Note: Cluster robust standard errors in parentheses. Control function results in endogeneity test not adjusted for two stage nature of estimation; $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < .01$

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CHAPTER 5: CONCLUSION

Flooding, stormwater management, and sea level rise are critical threats that citizens, public officials, and elected officials must work to overcome. While floods are the most damaging natural disaster, flood damages can be mitigated with cost-effective investments (Cigler, 2017; Congressional Budget Office, 2007; Government Accountability Office, 2021; National Academies of Sciences, Engineering, and Medicine, 2019). Flood control and stormwater infrastructure must be first financed and ultimately built before providing any protection. Investing in flood control and stormwater management to combat sea level rise requires governments to understand and invest based on the physical characteristics of their environment. However, because floods are risky events and future sea level rise is defined by uncertainty, investing in resiliency is difficult (Sweet et al., 2022).

Rubin (2006) describes budget outcomes as the result of actors who make micro and macro expenditure, revenue, balance, implementation, and process decisions within the context of their budgetary environment. Budgetary decisions about flood control infrastructure and sea level rise resiliency are made in an environment defined by risk and uncertainty. Different cognitive biases, mental heuristics, and learning processes have been used to describe human decision-making under conditions of risk and uncertainty (Meyer & Kunreuther, 2017). While learning from disasters is possible, decision-makers tend to over-weight the probability of risky events when making decisions from stated probabilities and under-weight the probability of risky events when making decisions based on experience (Hertwig et al., 2004; Meyer & Kunreuther, 2017; Zhang et al., 2018). This research examines how local governments budget for flood control, sea level rise, and stormwater management by assessing macro-level budgetary outcomes and costs and micro-level decisions about sea level rise resiliency investments through three separate, but interrelated, studies.

The first study, in Chapter Two, assesses local governments' flood control infrastructure investments based on the demand for flood control infrastructure of the median voter (Bates & Santerre, 2015; Chen et al., 2019; Fisher & Wassmer, 2015). Conflicting theoretical arguments posit that voters may 1) rationally demand flood control infrastructure because they perceive flood damages as a risk worth mitigating, 2) demand no flood control infrastructure because they are unable to distinguish necessary and risk-seeking capital investments, or 3) myopically fail to demand flood control infrastructure at all (Gailmard & Patty, 2019; Healy & Malhotra, 2009). While these three outcomes are observationally equivalent when voters are uncertain about future flooding levels, they can be distinguished by studying local governments' investment responses to informational shocks that reveal flood risks (Gailmard & Patty, 2019). If local governments invest in response to scientific information about their flood risks, the median voter may be said to rationally demand flood control infrastructure based on the objective level of risk in their environment. If local governments invest in response to damaging floods, voters may be said to be biased by their exposure to recent flood events through the representativeness heuristic (Dumm et al., 2020; Grether, 1980; Volkman-Wise, 2015). Finally, if voters fail to invest even when environmental conditions or scientific studies reveal their risk to flooding, they may be considered myopic (Healy & Malhotra, 2009).

Evidence from 67 Florida counties demonstrates that local governments' investment patterns appear to take the form of a corner solution, whereby voters first determine if they want flood control infrastructure before demanding a certain level of protection (Wooldridge, 2010). While counties with histories of frequent flooding and properties in the floodplain are no more likely to develop flood control infrastructure than those without, recent damaging floods appear to drive counties to take the first step in developing flood control capital stocks. Local governments with recent, damaging flood events were more likely to have developed capital stocks than those without. However, once counties choose to invest, they appear to react to changes in scientific information. Updates to the regulatory floodplain established by the Federal Emergency Management Agency's Flood Insurance Studies appear to cause counties to increase their capital stocks of flood control infrastructure. Overall, the results suggest that the median voter tends to exhibit a recency bias, whereby recent flood events increase the probability that they demand flood control infrastructure, but rationally demand investments based on changes in the objective level of flooding in their environment once flood control infrastructure has initially been built.

The second study, Chapter 3, turns to the individual level to study how public works directors prioritize assets at risk of sea level rise. Coastal local government roads, stormwater systems, water supply systems, and other key assets all may be at risk if seas continue to rise (Allen et al., 2019; Fisk, 2019; Price, 2019). Local governments across the Southeast United States are beginning to recognize, understand, and develop options to respond to rising seas (Grandage et al., 2023). Eventually, options to adapt infrastructure systems will need to be prioritized for sequencing into capital budgets. Public works directors lead departments with direct responsibility for infrastructure systems, and, as such, will have the considerable responsibility for protecting their government's assets from rising tides. Prioritizing key assets will require public works directors to make judgements about assets' criticality and probability of failure if seas rise. Cumulative prospect theory, a leading theory of risky decision-making, argues that decision-makers tend to be decreasingly sensitive to the size of gains or losses, decreasingly sensitive to probabilistic changes as they move away from conditions of impossibility and certainty, and more sensitive to losses than to gains (Tversky & Kahneman, 1992). Of course, assets' probability of failure and criticality are not the only factors that public works directors must consider when prioritizing assets. They must also consider managerial, economic, and political factors.

Results from the behavioral experiment engaging 16 public works directors from across the coasts of the United States show that public works directors are risk averse. These directors participated in a choice experiment: each was asked to prioritize 40 assets with different probabilities of failure, levels of criticality, degree of adaptability, abilities to be cost-effectively made resilient, levels of alignment with their government's strategic goals, and levels of support from current elected officials. The results reveal that these directors' decision-making patterns align, in part, with the predictions from cumulative prospect theory. Public works directors tended to be decreasingly sensitive to increases in an asset's criticality and an asset's probability of failure as failure rates increased. While decision-makers were decreasingly sensitive as probabilities depart from conditions of impossibility, they were not increasingly sensitive to probabilistic changes approaching certainty. Results indicate that most public works directors are risk averse across the full range of presented failure probabilities rather than for low probability losses, and risk seeking for high probability losses, as implied by cumulative prospect theory (Tversky & Kahneman, 1992). Following prior research, public works directors displayed substantial heterogeneity in their prioritization of threatened assets, with some placing more importance on political factors (e.g., the support of current elected officials) and others being more sensitive to economic factors (e.g., the cost-efficiency of the planned repair) (Thurmaier & Willoughby, 2001; Willoughby, 1991; Willoughby & Finn, 1996).

The third study, presented in Chapter 4, assesses the cost-drivers of stormwater management and asks if recommended best practices from the systematic capital budgeting literature, like master planning and asset inventories, are able to improve stormwater utilities' cost-efficiency (Ermasova, 2020; Srithongrung, 2008; Srithongrung et al., 2019). Stormwater utilities aim to reduce stormwater quantity to prevent flooding and improve stormwater quality to prevent pollution (Grigg, 2013). This is an especially important mission, as urbanization continues to pressure the waterways and waterbodies of the United States. This chapter develops public sector cost functions for stormwater utilities, which model stormwater costs as a multiplicative function of their performance, population served, environmental conditions, and the labor and capital prices they face (Donahue, 2004; Duncombe, 1992; Duncombe & Yinger, 1993, 2011). Public sector cost functions assume that organizations work to minimize costs. Those which spend above the minimum required to achieve a given level of performance, given their other cost factors, may be considered cost inefficient (Donahue, 2004; Duncombe & Yinger, 2011). The systematic capital budgeting best practices literature has advanced master planning and asset inventorying processes as best practices that should improve organizational effectiveness and efficiency. The third study tests the impact of those practices on stormwater utilities' cost-efficiency.

Results from this study show that environmental factors impact stormwater utilities' costs, but not that recommended practices from the systematic capital budgeting best practices literature are able to improve cost-efficiency. First, stormwater utilities' scale matters. Stormwater utilities that serve more people in larger areas have higher costs. Similarly, stormwater-specific environmental factors appear to influence costs as well. Stormwater utilities serving cities with more impervious surfaces and more properties at risk of flooding tended to have higher costs. While it was expected that stormwater utilities that experienced fewer flood damages would have higher costs, because they would have to spend more to achieve higher levels of protection, the opposite is the case. It is possible that stormwater damages may reflect underlying, unmeasured environmental conditions that make flooding more likely or increase the demand for stormwater services, in a mechanism similar to the representativeness heuristic explored in the first study. Contrary to expectations, private retention requirements did not reduce costs, and stormwater credits tended to increase costs. It is possible that stormwater credits increase the demand for stormwater infrastructure by increasing the perceived fairness of stormwater fees. After modeling stormwater utilities costs, it was not found that counties which develop master plans or inventory a higher percentage of their assets are able to increase their level of cost-efficiency.

Within Rubin's (2006) Real Time Budgeting (RTB) model, budgetary actors are constantly adjusting their revenue, balance, process, implementation, and expenditure decisions over the course of the budget cycle based on budgetary shocks and the information in their environment. The empirical chapters in this dissertation explored how local governments' environmental conditions impact their budgetary outcomes at the macro and micro levels. A complete perspective on budgetary decision-making requires the integration of macro and micro perspectives of budgetary decision-making. The following sections integrate findings from the three empirical chapters, and tease out broader implications for the political foundations of the budgeting process and the policy results of budgeting under conditions of risk and uncertainty.

Implications for the Political Foundations of the Budget Process

At the macro level, the results from the first chapter demonstrate that the median voter's initial decision to demand infrastructure is influenced by their experiences with damaging floods, (Bates et al., 2011; Chen et al., 2019; Fisher & Wassmer, 2015; Gailmard & Patty, 2019; Healy & Malhotra, 2009). This has broader implications for understanding the degree of rationality voters exhibit when determining whether to support politicians who promise to prevent disaster. Instead of being myopic and failing to reward prevention spending generally, voters may simply underweight risks that they have not experienced, such that they are biased by the representativeness heuristic (Dumm et al., 2020; Grether, 1980; Volkman-Wise, 2015). While such learning processes are retrospective and cannot be optimal, they imply that voters are able to learn from damaging disasters and ultimately increase their resiliency over time.

Once they demand protection, it appears that voters are reactive to changes in scientific information. As estimated in the first study, counties had approximately 44.0% larger capital stocks two years after experiencing a flooding insurance study (FIS). This relatively strong response is intuitive, because flood map updates are often infrequent (Government Accountability Office, 2021; Highfield et al., 2013). As of September 2020, the Government Accountability Office (2021) estimated that 14.5% of flood maps were over 15 years old. In response to outdated maps, the U.S. Federal Emergency Management Agency (FEMA) has been working to more frequently update flood maps and develop additional non-regulatory flood products to better communicate flood risks to the public (Government Accountability Office, 2021). The results of this study suggest that such efforts are not in vain, and may stimulate local governments to invest. Similarly, the results imply that scientific information on communities' risks may be able to help them better prepare if it is presented after a disaster. The results imply that voters can use scientific information on the extent of their risks to evaluate their need for protection, inform themselves, and support policies which prevent disaster (Gailmard & Patty, 2019). Once demanded at the macro level, flood control infrastructure, as well as stormwater management infrastructure and sea level rise resiliency projects, must be developed, prioritized, and implemented at the micro level by public works directors, their staffs, and elected officials.

Local government public works departments provide critical stormwater management, transportation, water supply infrastructure, and other key systems. However critical, these infrastructure systems tend to be out of sight and out of mind until challenges arise, like a major flood. Local governments' budgetary processes bring together the views of the public through their elected officials and the professional opinions of public works directors. As shown in the experimental results from the third chapter, public works directors exhibited different types of budgetary rationalities when prioritizing assets (Thurmaier & Willoughby, 2001; Willoughby, 1991; Willoughby & Finn, 1996). As long established in the public budgeting literature, as department heads, public works directors must navigate the political aspects of the local budgetary process by accounting for the perspectives of their elected officials (Rubin, 2006; Wildavsky, 1964). Still, while all participating public works directors noted the importance of considering the public mood and the agendas of their elected officials when making decisions, the weight they placed on political factors and the discretion they described receiving tended to vary.

In interviews, public works directors described their collaborative relationships with elected officials, in which the directors bring their technical expertise into the political budgetary process. Many directors described working to justify projects that, while relatively unglamorous or expensive, were critical to complete from an engineering perspective. For instance, one interviewed public works director described his ability to communicate as one of the most important skills he brought to the job, because translating engineering requirements to public officials helps these officials understand why particular projects are necessary. The dynamic relationship between public works directors and their elected officials reflects past observations that the relationships between elected officials and bureaucrats are reciprocal (Krause, 1999; Meier & O'Toole, 2006). Armed with discretion and expertise, public works directors work diligently and deliberately to balance their accountability to elected officials and the public, and their professional obligations (Bertelli & Lynn, 2003; Friedrich, 1940).

The results in the second study demonstrate that public works directors' prioritization when making decisions about infrastructure tends to reflect risk averse project selection such that unlikely to fail, critical assets are prioritized over more likely to fail, less critical assets. Because most public works directors were decreasingly sensitive to probabilistic changes as they departed from zero, they tended to be sensitive to the probability of asset failure even when it was relatively low. These results mirror similar observations that public financial directors may be more likely to be risk averse (Fennimore & McCue, 2021; McCue, 2000). Observed risk aversion may reflect public works directors' professional obligations and work cultures (Fennimore & McCue, 2021). For instance, when explaining the criteria that most mattered to her, one public works director indicated that she was primarily concerned with the probability of failure because she was an engineer. Similarly, the public likely has an expectation that public infrastructure systems are designed to work. This tendency to heavily weigh an asset's probability of failure may stem from public works directors' professional obligation to ensure critical systems work, and from their accountability to the public and their elected officials as the expert related to the technical nature of infrastructure. Whether or not the public or elected officials prefer risk averse decision-making themselves is an open question. Future behavioral experiments may consider describing a range of risk preferences across other budgetary actors and the public.

Policy Implications

Reactive planning may set the stage for local governments to develop master planning processes which allow them to understand their flooding and sea level rise risks in greater depth. Charleston County, South Carolina provides an example of such practices. As discussed in recent work by Grandage and colleagues (2023), Charleston County experienced terrible flooding in 2015 for which their stormwater drainage system was thoroughly unprepared. In response, the city created an asset management plan and began to identify drainage improvements. In this case, Charleston's experience with a damaging flood led it to invest in planning processes to build a response to flooding risks that were revealed by nature. This example is similar to the statistical results, presented in the first study, suggesting that histories of flooding can prompt communities to take adaptive action (Brody et al., 2010; Landry & Li, 2012; Li & Landry, 2018). In this case, a policy window opened for better asset management processes and new drainage improvements.

Master planning and asset inventories are key parts of the broader normative planning processes discussed in the systematic capital budgeting process literature. Ideally, master plans and asset inventories allow governments to better determine what infrastructure investments are required to meet their communities' overall goals while preserving their current assets (Ermasova, 2020; Srithongrung et al., 2019). However, results from the third study do not indicate that such plans and inventories improve cost-efficiency: macro-level plans and asset inventories may not matter if they are not able to influence micro-level project prioritization and implementation decisions.

Master plans and asset inventories are nested in governments' broader budget processes. Prior research has emphasized the importance of linking strategic planning, long-range fiscal planning, asset monitoring, and implementation for systematic capital budgeting processes to achieve results (Srithongrung, 2008). The results of the third study indicate that master planning processes and asset inventories alone will not improve cost-efficiency. More empirical work is required to understand the conditions under which master planning processes and asset management plans are ultimately able to improve cost-efficiency. Implementation, a part of both the systematic capital budgeting model and Rubin's (2006) RTB theory (Srithongrung et al., 2019), may be a place to start. Yet, there is little research, empirical or otherwise, on public sector project management (Grandage, 2021). Srithongrung (2019, pg. 13) suggests that, "Effective project implementation can be achieved if governments detect and address problems in capital project execution as early as possible." Project management practices like Earned Value Management that detect and respond to budgetary and schedule overruns may be the missing link between cost-efficient plans on paper and cost-efficient results in reality (Grandage, 2022). Alternatively, effective master plans simply may not be well funded. Another source of constraint faced by local governments is their ability to raise revenues and implement expensive projects while balancing their budgets (Rubin, 2006).

Local governments face budgetary constraints that may limit their ability to invest in flood control infrastructure or sea level rise responses. Over the next 30 to 50 years, adaptation efforts, likely to be extremely expensive, will only add to the financial burden faced by local governments working to adapt to flooding now. The results from the first study indicated that counties with high levels of poverty and in which the median voter's tax share was higher were less likely to have flood control infrastructure. Grant funding may be able to ease the fiscal burden created by rising seas. Results from this study did show that counties which received stormwater grants may be more likely to have flood control capital stocks, and counties which received a higher percentage of their total revenue from intergovernmental sources developed larger infrastructure stocks. Grants may be able to spark investment, but given the U.S. federal government's tendency to provide disaster response assistance, rather than prevention, it is reasonable to suspect that grants may not provide the amount of support that local governments truly need (Cigler, 2017; Healy & Malhotra, 2009).

This situation may be further complicated by the fact that aid may not actually flow down to the small governments with less capacity that need it most. For instance, a recent news article described the struggle faced by Tybee Island, Georgia, which is dealing with a stormwater drainage outfall that commonly gets covered with sand, leading to backups during high tide events (Jones, 2023). As described by Jones (2023), local governments pursuing federal funding for resiliency offered recently through the Inflation Reduction Act often had a hard time applying for or coming up with the required match. Interviewed public works directors from smaller, rural communities mentioned similar issues when describing their struggle to finance necessary stormwater drainage improvements. One interviewed director whose community had limited resources and substantial need noted that he had to conserve his budget when considering which matching grants to seek. Though he needed, and qualified for, many federal grants, meeting the matching requirements often proved difficult.

Future Research Directions

This dissertation modeled budgetary outcomes either from the perspective of the median voter, a public works director, or as the cost of providing stormwater services given environmental factors. While each provides insight to a slice of the budgetary process, no single perspective can capture the entire story of budgetary decision-making for environmental conditions under uncertainty. Future research should explore the potentially endogenous relationship between public officials, elected officials, and voters, to understand how they collaboratively respond to their own and regional risks. It is possible that case studies on local government stormwater management utilities, flood control investments, and sea level rise resiliency projects could offer a richer description of their behavior that captures how different actors' risk perceptions and the influence of cognitive biases on budgeting under conditions of environmental uncertainty.

This research indicates that the production of new information on local governments' flood risks through FISs leads governments to invest in their flood control responses. The U.S. National Oceanic and Atmospheric Administration (NOAA) has produced sea level rise forecasts for the nation, and included these forecasts in risk communication tools like its online Sea Level Rise viewer (Sweet et al., 2022). Such sources of information are critical at the local level. Interviewed public works directors often referenced state and federal sources when describing their expected level of sea rise. However, it remains an open question if the production of scientific information on the extent of a local government's exposure to sea level rise will be enough to prompt action by the government if it has not yet begun to develop policy responses to sea level rise.

Across the United States, local governments are beginning to respond to sea level rise (Ekstrom & Moser, 2013; Lubell & Robbins, 2021; Vella et al., 2016). However, evidence from Florida and the southeastern United States indicates that while many governments have recognized and begun to plan for rising seas, far fewer have developed robust plans of action in which they have generated data on the extent of their sea level rise problem, applied it in risk assessments, and used that scientific data to develop responsive options (Grandage et al., 2023; Hines et al., 2022). It remains to be seen if scientific information on the extent of the sea level rise threat will be enough to prompt residency investments, or if local governments will ultimately respond to the consequences of rising tides as they happen. Understanding and evaluating policies which promote local sea level rise planning will be critical in future research.

Similarly, new studies will need to evaluate the outcomes of sea level rise resiliency policy. This dissertation primarily focused on understanding a local government's budgetary outcomes in response to floods and in terms of stormwater management, as localities are just beginning to plan for rising seas. As seas continue to rise, local governments will have to put their sea level rise resiliency plans into action and account for such in their budgets. Future work will need to evaluate the efficiency and effectiveness of local efforts to budget for resiliency.

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APPENDIX A: INSTRUCTIONS FOR COMPLETING THIS SURVEY

This survey concerns the ways in which you approach your assessment of capital projects given sea level rise. The decision-making simulation may be different from surveys you have completed in the past. The simulation portion of this survey presents you with hypothetical capital project profiles that vary across several defined criteria.

Imagine you are creating a system for scoring different projects that protect capital assets threatened by rising seas. In this case, your government assesses each asset assuming that emissions continue to rise, stabilizing around 2050. This scenario aligns with the International Panel on Climate Change's Representative Concentration Pathway (RCP) 4.5 scenario. The following questions ask you to prioritize each capital project assuming the 4.5 scenario using your best professional judgment.

The level of prioritization is a "1 to 10" scale. A "1" prioritization, at the lowest end of the scale, indicates the project should not be pursued in favor of other projects, and a "10" prioritization, at the highest end of the scale, indicates the project should take priority over other current projects. This simulation contains profiles of different capital projects with criteria representing different characteristics of each project. The criteria are explained below.

Percent Chance of Failure: Indicates the probabilistic assessment of asset failure ranging from 0 to 100 percent under the RCP 4.5 sea level rise scenario.

Asset Criticality: Indicates the importance of the threatened asset. Lower scored assets are not critical. Lower scored assets provide general quality of life services. If they failed, lower scored assets would not be challenging to replace, and their failure would not threaten life or property. Higher scored assets are critical. Higher scored assets provide essential services. If they failed, higher scored assets would be challenging to replace, and their failure would threaten life or property.

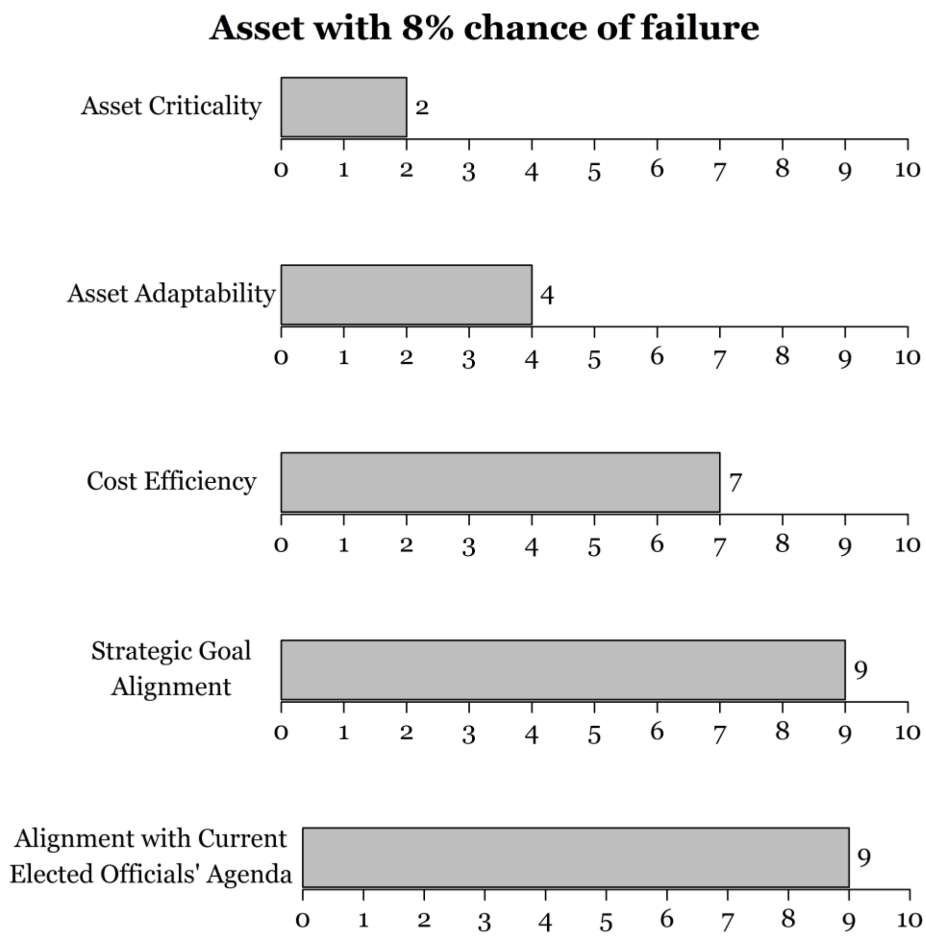
Asset Adaptability: Indicates the ability to improve the asset's resiliency as more is learned about sea level rise. Lower scored assets will be difficult to modify once seas rise whereas higher scored assets will be simple to modify once seas rise.

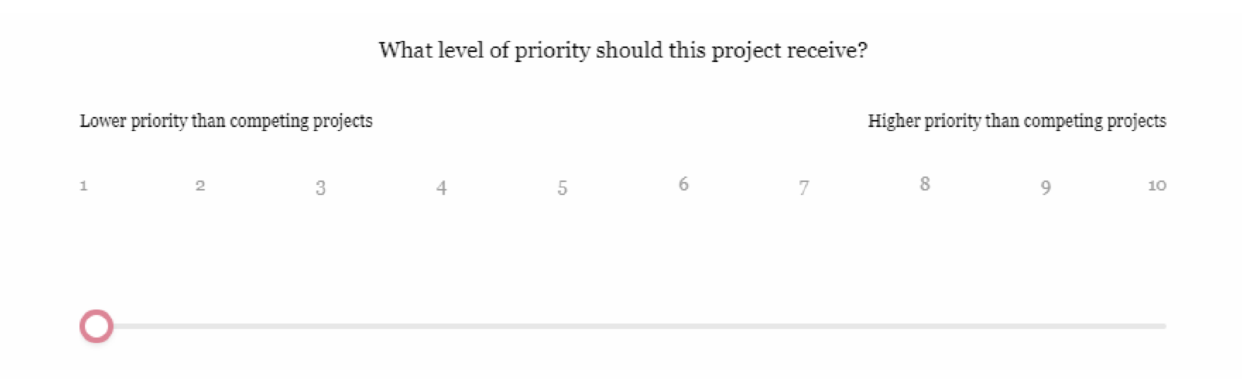
Cost Efficiency: Indicates the cost-effectiveness of the planned repair. Lower scored assets are relatively expensive compared to their benefits whereas higher scored assets are relatively inexpensive compared to their benefits.

Strategic Goal Alignment: Indicates the degree to which the asset aligns with the goals of your government. Lower scored assets do not align with your government's vision for its future whereas higher scored assets directly align with your government's vision for its future.

Alignment with Current Elected Officials' Agenda: Indicates the degree to which the asset aligns with current elected officials' stated priorities. Lower scored assets do not align with current elected officials' agendas whereas higher scored assets directly align with current elected officials' agenda.

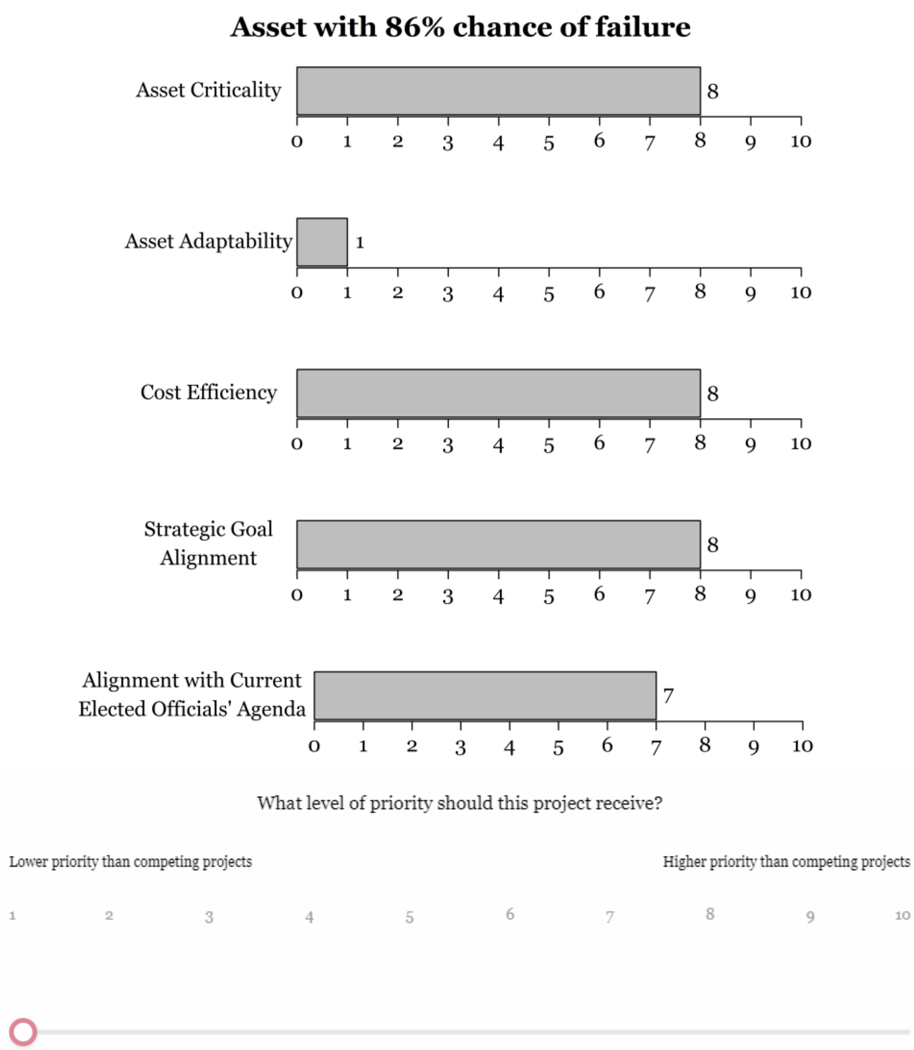
APPENDIX B: EXAMPLE PROFILE





APPENDIX C: PRACTICE PROFILE 1

This profile represents a threatened asset of your government. As indicated by the text at the top of the profile, the asset has an 86 percent chance of failing if seas rise in accordance with the RCP 4.5 scenario. The individual bars below the text describe the key features of the asset on a 1-10 scale. The **Asset Criticality** score of 8 indicates that this a very critical piece of infrastructure that could threaten life and property and would be very challenging to replace if it failed. The **Asset Adaptability** score of 1 means that it would be highly difficult to modify this asset once seas rise. The **Cost Efficiency** score of 8 shows that the repair is very inexpensive relative to its potential benefits. The **Strategic Goal Alignment** score of 8 indicates that the asset is very aligned with your governments' vision for its future. Finally, the **Alignment with Current Elected Officials' Agenda** score of 7 means that the asset is aligned with current elected officials' agenda.



APPENDIX D: FOLLOW-UP QUESTIONS

Government Characteristics

1. What government do you work for?
    a. ____
2. How many years have you served as public works director in this government?
    a. Sliding scale from 0-30 years
3. Check “Yes” or “No” regarding your work and that of your department.
    a. Do you work with local elected officials during the capital budgeting process?
    b. Do you have access to a sea level rise forecast for your government?
    c. Does your department assess the risk that sea level rise poses to planned projects?
    d. Has your department assessed the risk sea level rise poses to your current assets?
4. By how many inches do you expect global mean sea levels to rise by 2050?
    a. Sliding scale from 0 through 30 inches.

APPENDIX E: PERSONAL CHARACTERISTICS

1. What is your age?
    b. ____
2. What is your gender?
    a. Male
    b. Female
    c. Other, please specify ________________
3. Please select all racial/ethnic categories that describe you.
    a. American Indian or Alaskan Native
    b. Asian
    c. Black or African American
    d. Native Hawaiian or Other Pacific Islander
    e. White
    f. Hispanic or Latino
    g. Other, please specify ________________
4. Please select all levels of education that you have completed.
    a. High School Graduate
    b. Technical Education beyond High School
    c. Some College
    d. College Graduate, please specify________________
    e. Master's or Professional Degree, please specify________________
    f. Other, please specify ________________
5. Please use the space below for your thoughts and comments about this project.
    a. ____
    ____
    ____

APPENDIX F: INTERVIEW PROCEDURE

Pre-Simulation

1. Can you describe your professional journey?
    a. How many years have you served as public works director in this government?
    b. What are the greatest challenges and benefits of your work.

Administer simulation allowing for follow up questions.

Post-Simulation

2. Did the simulation capture how you prioritize threatened assets during your government's capital budgeting process?
    a. Why or why not?
3. How many inches do you expect global mean sea levels to rise by 2050?
4. Does your department assess the risk that sea level rise poses to your government's planned projects or current assets?
    a. If so, how does your government assess sea level rise risk?