MANAGING DEMAND FOR SCARCE WATER RESOURCES: AN EVALUATION OF CURRENT APPROACHES

Ahmed Rachid El-Khattabi

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Approved by:

T. William Lester

Maryann Feldman

Nikhil Kaza

Dale Whittington

Andrew J. Yates

ABSTRACT

Ahmed Rachid El-Khattabi: Managing Demand for Scarce Water Resources: An Evaluation of Current Approaches
(Under the direction of T. William Lester)

Increasing water scarcity due to droughts and competition for water resources is threatening the ability of cities all over the world, even those that are well-resourced, to provide their residents with basic water services. My three-paper dissertation addresses three different areas of intervention aimed at addressing water scarcity.

In my first paper, I address incentives to create technologies that address water scarcity. Concerns of a "deficit" of water-related technologies question the widely held belief that we can innovate our way out of water crises. In the context of the United States, I exploit temporal and spatial variation in the incidence of drought and the implementation of water technology clusters to explain changes in water-related patenting activity. I find that patenting activity does not increase following droughts, which suggests few incentives to innovate exist. I do find that water technology clusters boost water-related innovation, suggesting that additional policy interventions may be warranted.

In my second paper, I provide insights into price-based rationing for managing residential water demand, an increasingly popular demand management tool. The efficacy and distributional impacts of this approach depends on households' heterogeneous price sensitivity. I estimate heterogenous price responses for single family households in Chapel Hill, NC using a household-level panel dataset that features a large change in marginal water prices and a

novel measure of local hydrological stress. Contrary to prior research, I find households with presumably strong preferences for irrigation are no less price sensitive than other households.

In my third paper, I examine water utility compliance with state-imposed mandates for water conservation during severe droughts. States use mandates as a policy intended to address conflicting incentives for conservation by water utilities. Using data on urban water utilities in California subjected to a year-long mandate, I provide evidence that mandating higher conservation objectives does not lead to water utilities increasing water conservation. Moreover, I show that compliance is higher for water utilities where customers actively complain about "water waste." In this context, private citizen activism appears to be an overlooked aspect of local agency compliance.

To my parents, Drs. Elizabeth and Mohamed El-Khattabi, and my siblings, Omar and Meriem. All for one and one for all.

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PREFACE

"We will never miss the water till the stream gets dry. It is not like human nature to prize highly that which costs us nothing, but the taking."

-S.J. Rosamund, 1905

In 1994/95, I experienced firsthand one of Morocco worst droughts on record. In Tangier, my hometown, reservoir levels fell to about 10% of overall capacity; levels so low that desperate measures had to be taken. Four tankers (bateaux-citernes) were chartered to barge in from Jorf Lasfar, a port city 461km (286mi) away. For seven months, city planners rationed water, limiting running water to only three days a week for four hours on each of those days. At home and at school, water dominated all aspects of everyday life. I can still recall helping to fill up empty bottles at every possible opportunity so that my family could wash, cook, drink, and clean. Even then, I realized that this event made an indelible mark on my way of thinking and living. Water insecurity is all too real and traumatic. To this day, my family still keeps an emergency supply of water stockpiled for fear of future water cutoffs or shortages despite improvements in water management and infrastructure.

These memories came flooding back in 2014, a year in which California—a state that I have strong personal connections to—was experiencing severe drought conditions which continued to worsen, leading to California's first-ever statewide mandate for water conservation in 2015. Concurrently, the ALS ice-bucket challenge had people dumping buckets of ice-water on themselves, many of whom were living in drought-stricken California. This struck me as a glaring oddity. Water is one of our most precious resources, yet it is continually taken for granted. In developed countries, people expect water to come out of their faucets 24/7 without giving a second thought to where the water comes from, where it goes, and with little knowledge of the costs associated with its provision. More importantly, it seems as if people are willing to use water with an almost callous disregard even when faced with the realization that it is a scarce resource. Not long afterwards, there was intense concern over the effect that a drought was having on the largely agriculture-based economy back in Morocco. Though 2014 had been an abundantly wet year, I remember the calls for national prayers for rain and predictions that 2016 would be as dry as 1994/95 during one of my visits to Morocco in 2015. By late 2016, Tétouan—a city only 63km (39mi) away from Tangier—had to resort to rationing water.

Though droughts are an increasingly important reason why water resources are scarce, they are not the only cause for concern. Notably, cities all over the world are growing thirstier due to rapid urbanization and economic development. As a result, cities are constantly seeking out new water supplies and often competing over water resources to keep up with demand. Traditional strategies that focus purely on managing water supplies are therefore not enough. It is increasingly important to explore options that manage the demand for water and delay the need for expensive capacity expansions, rather than increasing capacity to meet demand.

At a professional inflection point, I decided to pursue a PhD in City and Regional Planning with a focus on water resource management to help work towards solutions from an interdisciplinary perspective. The role of planners is especially complex because the challenges facing water management are multifaceted and interconnected. In addition to ensuring supply in the face of population growth and environmental threats resulting from climate change, water management involves addressing challenges on social, economic, technological, and institutional fronts. Planners in the water sector, at both the local and state levels, need be aware of how to manage water resource and minimize conflict in the context of increasing urban growth and climate change.

The foresight that I had about going into this field was borne out a few months before I defended my dissertation proposal in March 2018. On January 19th, 2018, the Western Cape Water Supply District—the water utility serving the city of Cape Town, South Africa—announced that it was coming dangerously close to running out of water due to drought. Experts predicted that the city would run out of municipal water (referred to in the media as “Day Zero”) in a matter of months. Cape Town’s near brush with what is arguably every water utility manager’s worst nightmare serves a powerful reminder that increasing water scarcity is threatening the ability of cities all over the world, even those that are well-resourced, to provide their residents with basic water services.

I structure my dissertation as a series of three papers on distinct policies related to water demand management. My aim is highlight successes and failures in current approaches to provide guidance in the years to come.

In my first paper, I focus on the role of technological innovation in addressing water scarcity because while there is a belief that we can innovate our way out of water crises, there is also a longstanding concern that there is a “deficit of innovation” in the water sector that questions whether technology can deliver “solutions commensurate to the impending stresses on urban water systems” (Kiparsky et al 2013). Some countries have attempted to address this by establishing initiatives to promote water-related innovation by identifying and supporting local efforts with increased funding and other assistance. In the U.S., for example, Environmental Protection Agency to establish a Water Technology Innovation Clusters Initiative in 2011. A similar initiative was launched by Scottish Water in 2018 (the Water Test Network) to increase market opportunities in North-West Europe. In the academic literature on innovation, however, there is a marked absence of studies on the drivers of water-related technologies (Wehn and Montalvo, 2018). This is problematic because if we are to innovate our way out of water scarcity, we must first understand what drives—or does not drive—the creation of new water technologies. An often-cited concern is that water resources are underpriced because prices are not set through the market but through highly political processes. In the absence of market prices, an important question is whether existing institutional mechanisms signal scarcity, a necessary step for encouraging innovation.

This paper contributes to the literature in two ways. First, I shed light on the extent to which water scarcity prompts innovative activity, using droughts as observable and exogenous events that generate water scarcity. I empirically test this by examining patenting activity following droughts. Second, I assess the effectiveness of a public policy intervention, the establishment of a Water Technology Innovation Clusters Initiative, as a potential solution to increase water-related technological innovation. Overall, I find evidence that patenting activity does not change following the incidence of droughts, suggesting that water-scarcity alone does not induce more innovation. This finding supports the notion that there is a lack of innovation in the water sector. I also find evidence to suggest that water technology clusters increase overall patenting activity. Together, these findings suggest that additional policy interventions may be warranted to support innovation in the water sector.

In my second paper, I collaborate with economists, engineers, and hydrologists to study the use of prices to manage demand for residential water. In recent years, price-based approaches have gained popularity among water utilities as a tool to manage demand, especially among residential users. Little is known, however, regarding its effectiveness in managing demand for households that are most likely to maintain lawns. In part, this is because implementing price increases can be challenging. Notably, increasing prices can hurt financially vulnerable households and potentially conflict with the social principle of "the human right to water." This challenge has meant that large price changes have been relatively rare. It is also the case, however, that data maintenance can be poor. For instance, it is common for water utilities to lose data when upgrading to a new billing software. If prices are to be used effectively as a demand management tool, water utilities need to analyze their data to understand the effect of pricing policies.

This study contributes to the rich literature on water demand in two ways. First, I define households in terms of past usage and wealth simultaneously instead of in isolation to underscore the fact that both dimensions are necessary for understanding household responses, but neither is sufficient by itself. For example, households with similar wealth levels may have different preferences for outdoor water usage, or households with comparable levels of past usage may respond to changes in price differently given the resources at their disposal. Second, I estimate price responses for single family residential households under price variation that is much larger than typically observed in studies of the water sector. I use a highly detailed panel of households' monthly water usage in Chapel Hill and Carborro, NC from 1999-2005 with a change in pricing policy that generated price changes of about 40%. To my knowledge, no other study has conducted a household-level longitudinal analysis for water under the same magnitude of price variation. Contrary to previous studies, I find that households that are most likely to irrigate are no less price-sensitive than other households. If anything, the point estimates suggest that heavy-usage households are more price elastic than households that are less likely to irrigate. These results provide an optimistic assessment of the utilities' ability to use prices to reduce water consumption by households with high-usage.

In my final dissertation paper, I focus on the role of state governments in managing drought. During drought, local water utilities may face conflicting incentives to conserve water. On the one hand, water utilities want to ensure continuity of service and avoid supplies falling below minimum reserve levels. On the other hand, water utilities face several disincentives for engaging in conservation due to local situational factors. Water utilities, for instance, may shy away from increasing prices or implementing usage restrictions due to social and political pressures exerted by their customers (Mullin, 2009; Teodoro, Zhang and Switzer, 2018). To address conflicting incentives for conservation at the local level, states often rely on mandates that require water utilities to conserve. Mandates promote conservation through two mechanisms: (1) increasing political acceptance of local conservation efforts by shifting some of the responsibility from local water utilities to the state agency, and (2) the threat of fines and potential legal action against the water utility for noncompliance. To pursue conservation, water utilities implement one or more strategies to manage demand, including public awareness campaigns, rebates for turf replacement or water efficient fixtures, mandatory watering restrictions (caps on usage), and pricing strategies. Conservation is therefore ultimately a result of reductions made by water utility customers. The two-part nature of the problem presents a challenge for states because they often do not observe water utilities actions, or if they do, may not easily interpret them as water utilities implementing the same strategy may do so with varying degrees of "implementational intensity" (Halich and Stephenson, 2009).

I contribute to the literature by accounting for the two-part nature of the problem using a double-principal-agent framework as a heuristic device. I consider local situational factors to account for differences at the customer level that may affect water utilities' ability to conserve. Notably, I account for the degree to which customers actively complain about "water waste." During droughts, water utilities often encourage customers to anonymously report instances where other customers are using water in ways that are deemed "wasteful" as a passive enforcement mechanism. Using evidence from California during the 2015-2016 drought, I do not find evidence that mandating objectives leads to intended results. I do show, however, that both conservation and compliance is higher in service areas where customers actively complain about "water waste" than in service areas where customers do not. In this context, private citizen activism appears to be an overlooked aspect of local agency compliance.

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1.1 Introduction

Technological innovation has played a pivotal role in addressing resource scarcities by relaxing binding resource constraints for resources such as food, copper, iron, nickel, silver, tin, coal, and natural gas through the development of new processes that enable the use of substitutes, improve efficiency, or enable access to untapped resources (e.g. Krautkraemer, 2005). In this context, longstanding concerns of a “deficit of innovation" in the water sector have led scientists and policymakers to question whether technology can deliver “solutions commensurate to the impending stresses on urban water systems" (Kiparsky et al., 2013).[1] Given the substantial welfare consequences associated with water shortages,[2] these concerns prompted the U.S. Environmental Protection Agency (EPA) to spearhead the *Water Technology Cluster Initiative* in 2011 to identify and support local efforts with funding and other types of assistance.[3]

[1]Stressors include increased demand (Averyt et al., 2013), uncertain precipitation patterns (Milly et al., 2008), aging infrastructure (Kalogo, Monteith and Eng, 2008), and contamination of water supplies (Addams et al., 2009).

[2]Water scarcity negatively impacts energy production (Gleick, 1994; Spang et al., 2014), food security (Schmidhuber and Tubiello, 2007), and public health (Haines et al., 2006).

[3]Similar initiatives have since been launched in other parts of the world (e.g. Water Test Network in Europe).

In this paper, I analyze the extent to which water scarcity prompts innovative activity by treating droughts as observable and exogenous events that generate water scarcity and patent data as an observable measure that proxies for innovative activity and R&D expenditure. In addition, I assess the impact of the *Water Technology Innovation Clusters Initiative* as a public policy solution aimed at increasing water-related technological innovation. I construct a panel data set that allows me to describe changes in regional water-related patenting activity using variation in the timing and geographic location in both the incidence of droughts and establishment of water technology clusters. Overall, I find evidence that patenting activity does not change following the incidence of droughts, suggesting that water-scarcity alone does not induce more innovation. This finding supports the notion that there is a lack of innovation in the water sector.[4] I also find that the support provided by the EPA initiative significantly increased water-related patenting activity. Together, these findings suggest that additional policy interventions may be warranted to support innovation in the water sector.

Innovating our way out of water scarcity requires inventing (and deploying) appropriate technologies quickly enough to address continuously emerging needs.[5] Specifically, arguments that “necessity is the mother of invention" hinge on our ability to recognize scarcity quickly enough to act. Notably, the economic argument rests on the assumption that scarcity drives prices upwards. These increased prices then signal to innovators that they can make a profit by inventing new processes that enable the use of substitutes, improve efficiency, or enable access to untapped resources (e.g. Shumpeter, 1934). Prices in the water sector, however, are not set through the market but instead through highly political processes. As a result, water

[4] The “water sector" is used broadly to describe actors who participate and are dependent on water for day-to-day operations such as utilities, end-users, firms, and others.

[5] Adoption of water-related technologies is a significant barrier to innovation. Adoption of technologies is beyond the scope of this particular study.

resources are often under-priced (e.g. Renzetti, 1999; Elnaboulsi, 1999; Timmins, 2002). The inability to price water using market-based principles is often cited as a reason for the lack of water-related innovative activity. In the absence of market prices, the question is whether other institutional mechanisms encourage innovation.

Some scholars have posited that the threat of scarcity itself may be sufficient to spark human ingenuity (e.g. Boserup, 1981; Simon and Bartlett, 1985). In support of this argument, previous droughts over the past few decades garnered significant media attention and triggered significant policy changes (Wiener, Pulwarty and Ware, 2016). For example, several droughts (1976-77, 1988, 1998, 2000-2004, 2011-12) have led to requirements to create water shortage response plans, long-range water plans, land-use integration policies, and other frameworks to better manage water supplies. Droughts have also spurred interest in water markets[6] and crop insurance.[7] With respect to technological innovation, previous studies have documented high financing gaps (Krozer et al., 2010) and low rates of water-related patenting activity (Ajami, Thompson and Victor, 2014). Little is known, however, on the dynamics of innovation in the water sector.[8]

I contribute to body of work on environmental innovation by shedding light on the inventive phase (i.e. the timing of inventions) of water-related technologies. This paper also

[6]The first major economic investigation of water marketing and the property right to water occurred in the context of policy debate over a state and federal involvement in a California water project in the middle of a drought (Hirshleifer, De Haven and Milliman, 1969).

[7]In 2014, for example, the USDA announced additional targeted assistance for areas affected by the most extreme and exceptional drought, namely in California and Texas (USDA, 2014). The USDA manages several insurance programs related to drought (USDA, n.d.).

[8]The absence of academic studies on water innovation led to the publication of a special issue in the *Journal of Cleaner Production* (Volume 171, Supplement, 10 January 2018) to serve as a foundation for future studies on water innovation (Wehn and Montalvo, 2018).

connects the environmental innovation literature to the growing literature on the economic effects of natural disasters (Becerra, 2012; Kellenberg and Mobarak, 2011; Miao and Popp, 2014), further contributing to the literature on endogenous technological change by assessing the impact of droughts as a stimulus for innovation (Miao and Popp, 2014).

My approach contrasts with previous work on environmental innovation by examining innovative activity through the lens of regions instead of at the firm level (e.g. Hemmelskamp, 1999; Horbach, 2008; Di Stefano, Gambardella and Verona, 2012).[9] In doing so, I bridge the literature on environmental innovation to the body of work on Regional Innovation Systems (RIS), two literatures that have largely operated independent of each other. I ground my study in the RIS literature because firms do not innovate in isolation but through interactions with other and industry-related actors in their regional ecosystem (e.g. universities and public administrations). These interactions produce regionally specific knowledge that then generates more innovation (Cooke, 1992, 1998; Feldman and Florida, 1994; Feldman and Audretsch, 1999; Feldman, 2001; Camagni, 1995; Asheim, 1996; Crevoisier, 2004).[10] Moreover, these interactions create dense regional "learning networks" of mutually reinforcing industries that allow innovators to quickly capitalize on new ideas and innovative solutions to pressing problems in a process that Alfred Marshall once described as being "in the air." More importantly, the RIS literature explains the basis for the *Water Technology Innovation Cluster Initiative* as an explicit attempt to leverage learning networks to increase and accelerate the rate of water-related innovation.

[9]A few studies have examined innovative activity at national levels (e.g. Miao and Popp, 2014).

[10]See Stuck, Broekel and Revilla Diez (2016) for a review of the RIS literature.

1.2 Conceptual Framework

In this paper, I investigate whether droughts generate interest in creating technologies that address water scarcity. Though prices for water resources are not set through market mechanisms, water scarcity may still promote innovation because individuals, firms, and other organizations that heavily reliant on water resources for daily activities may seek to reduce the risk and uncertainty of drought-related disruptions to water supplies.

Moreover, drought-related water scarcity may generate increased competition over water resources that may in turn generate interest in water-related technologies. Resource-based theory of organizational behavior, for instance, holds that an organization faced with scarcity will engage in increased competitive behavior if it can secure access to scarce resources that can confer it with a competitive advantage (Selznick, 1957; Andrews, 1971; Barney, 1986; Chandler, 1990).[11] Similarly, firms may seek a competitive advantage by developing technologies that increase local water supplies (e.g. process that recycle water resources) or by developing new processes or technologies that reduce the intensity with which water resources are used.[12] Innovation is therefore an important means of creating and maintaining a sustainable competitive advantage. Transaction cost economics (TCE) holds environmental uncertainty will entice firms for vertical integration (e.g. Helfat and Teece, 1987; Williamson, 1988). This theory holds that the process of vertically integration itself may help the acquiring firm reconfigure resources or integrate resources, increasing innovative activity (Iansiti, 1995). Alternatively, resource dependence theory (RDT) contends that firms will attempt to reduce

[11] Organizations, for instance, might adopt a "race to the bottom for extraction-profit" strategy by developing technologies to access water resources at lower depths (Maldonado and del Pilar Moreno-Sanchez, 2016).

[12] Firms may also choose to mitigate against local scarcity by importing water. Transferring water over long distances, however, can be expensive and not feasible in many situations.

environmental uncertainty by renegotiating interorganizational relationships to minimize dependency (Pfeffer and Nowak, 1976; Pfeffer and Salancik, 1978). For instance, support industries often re-purpose their technological know-how to create technologies that can be applied to other sectors of the economy (Kuramoto and Sagasti, 2006; Lorentzen, 2015).

Assuming that disruptions to water supply caused by droughts is sufficient to generate interest in creating water technologies, the question that naturally arises is where one would expect innovation to occur. One the one hand, innovative activity may not necessarily be confined to a particular geographic location. Innovators, for example, can create a technology and market it anywhere where there is demand for that technology. Innovators could learn about droughts occurring in areas far from their own locations through media or other sources. In the United States, for example, several droughts have received nationwide attention (Wiener, Pulwarty and Ware, 2016). Depending on where a particular firm decides to locate its R&D facility, they could be creating solutions to address problems experienced by another branch experiencing drought.

On the other hand, one would expect innovative activity to be particularly strong in geographic locations that experience drought. Droughts represent exogenously determined instances of local scarcity (i.e. unusual departures in average precipitation levels for a particular climate).[13] Power-plants, oil and gas companies, farmers, and others that are heavily dependent on water for operations may invest in developing new technologies to address their particular operational concerns. Furthermore, one would expect competition over water resources to be a a largely localized phenomenon since transporting water over long distances may cost-prohibitive or illegal in some situations.

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[13]Definitions include a lack of precipitation (meteorological drought), a lack of soil moisture (agricultural drought), or by reduced streamflow or groundwater levels (hydrologic drought) (USGS, n.d.).

The RIS literature contends that innovation is largely a local process that arises due to both competitive and cooperative interactions between firms and other innovative agents in local economic environments. This literature describes innovation as these interactions that lead to innovation in terms of "learning networks," an interactive process determined by the interdependent choices that innovative agents, users, and other market actors make. For instance, firms often compete with each other over resources and often draw on the same labor pool but also cooperate with other each other on projects and obtain advice from neighboring firms. These "learning networks" are thought to generate and diffuses knowledge locally. Firms and organizations that are part of these networks are often interdependent and mutually reliant on each other for resources, often acting as external supply chain partners. Industries also tend to cluster spatially around universities and other public research institutions (Feldman, 1994).[14]

The RIS literature attributes the development of "learning networks" primarily to spatial proximity (e.g. Asheim and Gertler, 2005; Cooke et al., 2008; Stuck, Broekel and Revilla Diez, 2016). The importance of spatial proximity can in part be explained by the role of regional institutions. Firms and industry-related actors in close spatial proximity share a common institutional framework. In the United States, for instance, legal doctrines for water management have evolved differently in western states relative to eastern states. Moreover,

[14] Firms rely significantly on academic research (Arora, Belenzon and Patacconi, 2018) and may also have a direct influence on the topics that academics work on (Furman and MacGarvie, 2007; Evans, 2010; Sohn, 2014). Universities are a key local industry-related institution as they produce skilled labor and act as engines that help create, diffuse, and deploy new knowledge in economically useful ways (Feldman et al., 2002). A key mechanism through which universities diffuse and deploy knowledge to the private sector is through licensing patents to spin-off businesses or industrial partners (university-to-industry transfers).

state governments have significant autonomy over environmental regulation.[15] For instance, water-related technologies must get approved by each state in which it is marketed and sold. In some states, regulation may be highly localized, enacted at a municipal level rather than a state level. Institutions–both formal and informal–are important for shaping incentives for technical innovation and provide the basis for the type of social interactions between organizations. The sharing of a common institutional framework can be also be related to sharing common social and cultural understanding necessary to build trust (Lundvall, 1992). The spatial proximity to universities and other public research institutions have been associated with positive effects on R&D expenditure (Fritsch and Slavtchev, 2011).

The importance of spatial proximity for innovation can also be explained by the reductions in transaction costs associated with exchanging and communicating knowledge and information locally. This gives rise to locally specific tacit knowledge that is facilitated through face-to-face contact with individuals or organizations in close spatial proximity. There is substantial evidence that the importance of local relationships are important for innovation even in the context of modern information and communication technologies (e.g. internet) (e.g. Kaufmann, Lehner and Tödtling, 2003). Though internet-based communication technologies lower transaction costs of co-operating with potential innovation partners around the world, they are not perfect substitute for face-to-face interaction. Notably, innovation requires interactions between innovators with different sets of specialized knowledge (Grant, 1996) and the development of a shared language and overlapping knowledge structures that cannot be easily accomplished using internet-based communication technologies (Kaufmann, Lehner

[15] On the one hand, the Porter-Linder hypothesis states that environmental regulation can drive innovative activity (Porter and Van der Linde, 1995). Recent regulations, for instance, motivated by water scarcity is pushing the power generation industry away from once-through cooling systems towards closed systems (White, Shelton and Dennis, 2014). On the other hand, the pollution haven hypothesis states that firms may avoid regions with strict regulations as these regulations may represent an added cost to doing business (Brunnermeier and Levinson, 2004).

and Tödtling, 2003). Moreover, physical proximity can facilitate "serendipitous encounters" that in turn lead to creative opportunities (Campa, 2008; Brinks et al., 2018).

The emphasis on local knowledge is especially relevant for the water sector as water availability is largely determined by local physical and social processes. Differences in institutions, culture, and conceptualizations of what solutions may be socially acceptable play an important role in how water is managed (Cosgrove and Loucks, 2015). Solutions are therefore contingent on local factors and would depend on local knowledge for appropriate design of technologies and products to address local challenges (Andersen, Marìn and Simensen, 2018). To motivate this anecdotally, many Israeli innovators–leaders in water-related technologies–have moved to California to work on solutions to address the issue of water scarcity locally instead (Peleg, 2018). Firms may locate in proximity to suppliers and customers to better market their technologies to downstream customers (e.g. Fujita, Krugman and Venables, 1999) or to facilitate testing and prototype work (Howell and Higgins, 1990).

Instead of studying innovation at an individual firm-level, I draw on the RIS literature and study innovative activity through the lens of regions. I model each region's capacity for innovation, i, at time t, as:

$$C_{it} = f(I_i, F_{it}, W_{it}) \tag{1.1}$$

where I represents the presence of key institutional actors (e.g. universities), F represents overall economic activity in the regional economy, and W represents the presence of water resources. In this paper, I use Metropolitan Statistical Areas (MSA) as the geographically relevant spatial unit to capture regions.[16]

[16]MSAs represent localized and economically coherent areas based on commuting and employment information therefore would be large enough to capture "learning networks."

I draw on the natural hazards literature to model the effect of drought. Previous studies have found that experience with natural disasters shape the perceived risk associated with the disaster. In order for a drought to elicit a response, however, organizations must first notice and recognize the incidence of a drought as a significant event that affects their respective objectives (Cowan, 1986). This information is processed at the organization level and converted to response (Gresov and Drazin, 1997). For instance, the severity level of a natural disaster can play an important role in shaping responses (Perry and Lindell, 2008). This suggests that more severe droughts may have a greater impact on innovation than less severe droughts.

The perceived risk of drought can also be affected by previous experience with the particular hazard. On the one hand, previous experience with natural disasters may increase risk perceptions and levels of preparedness, though these increases may often be short-lived in nature (Perry and Lindell, 1986). On the other hand, previous experience may have a desensitizing effect.

I model the perceived risk of drought, R_{it}, is as a function of attributes of contemporaneous drought and experience with prior droughts, given by (1.2):

$$
\begin{aligned}
R_{it} =& f(d(l, s)_{it}, h_{it}) \qquad (1.2)\\
h_{it} =& \sum_{x=0}^{t-1} d_{i,x}
\end{aligned}
$$

where d_{it} represents drought episodes experienced in MSA, i, in year, t, with each drought episode modeled as a function of its duration, l, and severity level, s. Experience with prior droughts is given by h_{it}.

Using this, I express regional-level innovative activity, P_{it}, as:

$$P_{it} = f(C_{it}, \sum_{t=0}^{t-1} R_{it}, d_{-it}) \tag{1.3}$$

where d_{-it} represents drought conditions in other regions. This model can then be simplified as the following reduced-form model:

$$P_{it} = f(I_i, F_{it}, W_{it}, d_{it}, h_{it}, d_{-it}) \tag{1.4}$$

The lag between d_{it} and innovation, P_{it} is of particular interest because pressing concerns over relatively low patenting activity would be allayed if patenting activity increases following instances of scarcity. Specifically, this finding would lend credence to the argument that the threat of scarcity is sufficient to spark "human ingenuity," suggesting that innovators are attuned to the needs of the water sector and the presence of institutions and economic infrastructure necessary to support innovative activity.

Patents are generally filed at the end of the applied research phase. If water scarcity does lead to an increase in patenting activity, one would expect to see an increase approximately 6-8 years following a drought as that is the average duration of the applied research phase for water technologies (O'Callaghan et al., 2018).[17]

[17] Patents are generally filed at the end of the Applied Research Stage when the scientific basis for the technology can be proven (proof of concept).

1.3 Data

1.3.1 Hydrological Drought

I measure droughts using the Palmer Drought Severity Index (PSDI), a measurement of dryness based on a physical water-balance model, to capture water stress and relative dryness.[18] The index ranges from -10 (extreme dryness) to 10 (extreme wetness). A major strength of this index is its effectiveness in quantifying long-term drought.[19] This accounts for possibility that it may take several rain cycles to refill reservoirs and aquifers or restore soil moisture conditions. I follow the United States Drought Monitor in their classification of drought, shown in Table 1.3.1.[20]

Table 1.3.1: Drought Classification using Palmer Drought Severity Index

Classification	**Range**	**Definition**
Abnormally dry	-1.0 to -1.9	Lingering water deficits
Moderate drought	-2.0 to -2.9	Streams, reservoirs, or wells low; some water shortages developing or imminent; voluntary water-use restrictions typically requested
Severe drought	-3.0 to -3.9	Water shortages common; water restrictions generally imposed
Extreme drought	-4.0 to -4.9	Widespread water shortages or restrictions
Exceptional drought	-5.0 or less	Shortages of water creating water emergencies

Notes: Values between -0.9 and 0.9 indicate normal conditions. Values greater than 1 indicate wet conditions.

[18] The model uses primarily relies on precipitation and temperature as inputs.

[19] Other measures include PHDI, SDI.

[20] The United States Drought Monitor is a collaboration between National Drought Mitigation Center (NDMC) at the University of Nebraska-Lincoln, the National Oceanic and Atmospheric Administration (NOAA), and the U.S. Department of Agriculture (USDA).

A historical time series of the PDSI is collected from the National Oceanic and Atmospheric Administration (NOAA) from 1930-2018.[21] I define drought episodes as two or more years of uninterrupted drought, where a year of drought is defined as a calendar years with at least 6 months with PDSI $\leq$ -2.0 (moderate, severe, extreme, or exceptional drought). Table 1.3.2 summarizes drought characteristics for all MSAs by Census Region. For each drought episode, I identify the most severe drought year.

1.3.2 Patent Data

Following standard practice in prior work on innovation, I use patent data to proxy for innovative activity. Patents are the most commonly used proxy used in the literature on innovation as they represent innovations that are: (i) novel; (ii) nonobvious; and (iii) useful (Brunnermeier and Cohen, 2003; Jaffe and Palmer, 1997; Horbach, 2008; Johnstone, Haščič and Popp, 2010; Horbach, Rammer and Rennings, 2012). Patenting activity has been shown to be a good proxy for general innovative activity since they are strongly correlated with R&D spending (e.g. Griliches, 1998). Though patents do not cover innovation in financial or managerial practices, innovation in these areas may positively impact technological innovation (Benner and Tushman, 2002). More importantly, there are very few examples of inventions that have had significant economic and social welfare impacts that have not been patented (Pakes and Griliches, 1980; Griliches, 1990; Gallini, 2002).

Patent data used in this study consists all utility patents filed in the U.S. between 1976 and 2018, compiled from bulk data files made available by USPTO's Bulk Data Storage

[21] These data are available at the USGS climate division level. For MSAs that intersect with multiple climate divisions, PDSI values are weighted averages, using the percentage of the MSA that intersects with each climate division as weights.

Table 1.3.2: Drought Characteristics

	Census Region of the United States			
	MIDWEST	***NORTHEAST***	***SOUTH***	***WEST***
Drought Episodes				
Duration (years)	1.60	1.89	1.65	1.73
	(0.90)	(1.24)	(1.01)	(1.15)
Years Between Episodes	11.18	13.83	8.14	5.21
	(7.22)	(11.02)	(7.61)	(5.39)
Total Count (since 1950)	4.83	3.71	7.28	10.71
	(1.63)	(1.44)	(2.08)	(3.18)
Years Spent in Drought Since 1950				
Any	7.72	7.07	12.04	18.60
	(3.11)	(1.86)	(4.29)	(7.14)
Mild	4.35	4.68	7.17	10.21
	(2.15)	(1.47)	(2.62)	(4.01)
Severe	3.38	2.39	4.88	8.38
	(1.82)	(1.31)	(2.73)	(4.45)
MSAs Experiencing Drought (%)				
1950s	0.86	0.54	0.94	0.79
1960s	0.83	1.00	0.60	0.79
1970s	0.57	0	0.28	0.90
1980s	0.67	0.14	0.81	0.92
1990s	0.20	0.71	0.60	0.83
2000s	0.59	0.54	0.92	0.98
2010s	0.54	0.32	0.76	1.00
Number of MSAs	69	28	121	52

Note: 27 MSAs intersect more than one Census region. These MSAs are assigned to the region with the largest overlap. Where appropriate, Combined Statistical Areas (CSAs) are used instead of MSAs.

System.[22] Patents are published with an average publication lag of 18 months after the actual filing date. This would primarily affect the ability to observe many of the patents filed during 2018 and would also affect 2017, though to a more limited extent.

[22] I restrict the data to utility patents to as they protect the way a manufactured article is used and works (35 U.S.C. 101) as opposed to design patents that protect the way the article looks (35 U.S.C. 171). I exclude patents that are marked as being reissued or reexamined. Information on all patent applications published as of September 26th 2019 are obtained from XML and PDF files USPTO's Bulk Data Storage System.

Following Hascic and Migotto (2015), water-related patents are identified using sets of International Patent Classification (IPC) and Cooperative Patent Classification (CPC) codes that are closely associated with specific types of inventions. The main advantage of using these codes is that they are heavily reliant on the detailed knowledge of patent examiners (Haščič and Migotto, 2015). Technologies produced in the water sector are produced for a variety of different end-users, including residential, industrial, and agricultural users. Technologies range from low-flow devices, aimed at reducing water consumption, and smart meters, devices to help monitor water usage to water purification and treatment technologies developed for industrial users and utilities to help meet stricter environmental standards and reduce costs of compliance. Water reuse and water recycling technologies, for example, help relieve pressure on traditional sources of water (Bichai, Grindle and Murthy, 2018). Water-related are therefore further categorized as technologies that promote conservation, technologies that augment water supply, and technologies that aim to improve water quality (also referred to as water pollution abatement or treatment technologies).[23] All IPC and CPC codes used to identify water-related patents are presented in Appendix 1.3.[24] Between 1975 and 2018, a total of 4,336,280 patents were filed by inventors in the the United States.[25] Of these, 4,215,624 patents were filed by at least one inventor living in an MSA. Of the patents with at

[23]Droughts affect water quality by increasing the concentration of point source pollution—sewer outfalls, industrial discharges, and thermoelectric power plant return flows—and non-point source pollution—stormwater runoff. This makes it harder to filter and decontaminate drinking water. Furthermore, reduced water flows can lead to saltwater intrusion, further burdening most water treatment plants, many of which are not equipped to remove salts (Mosley, 2015).

[24]The categorization a patent is mutually exclusive as the same patent can have multiple IPC or CPC codes assoicated with different areas of innovation.

[25]Entire database consists of 8,427,024 patents.

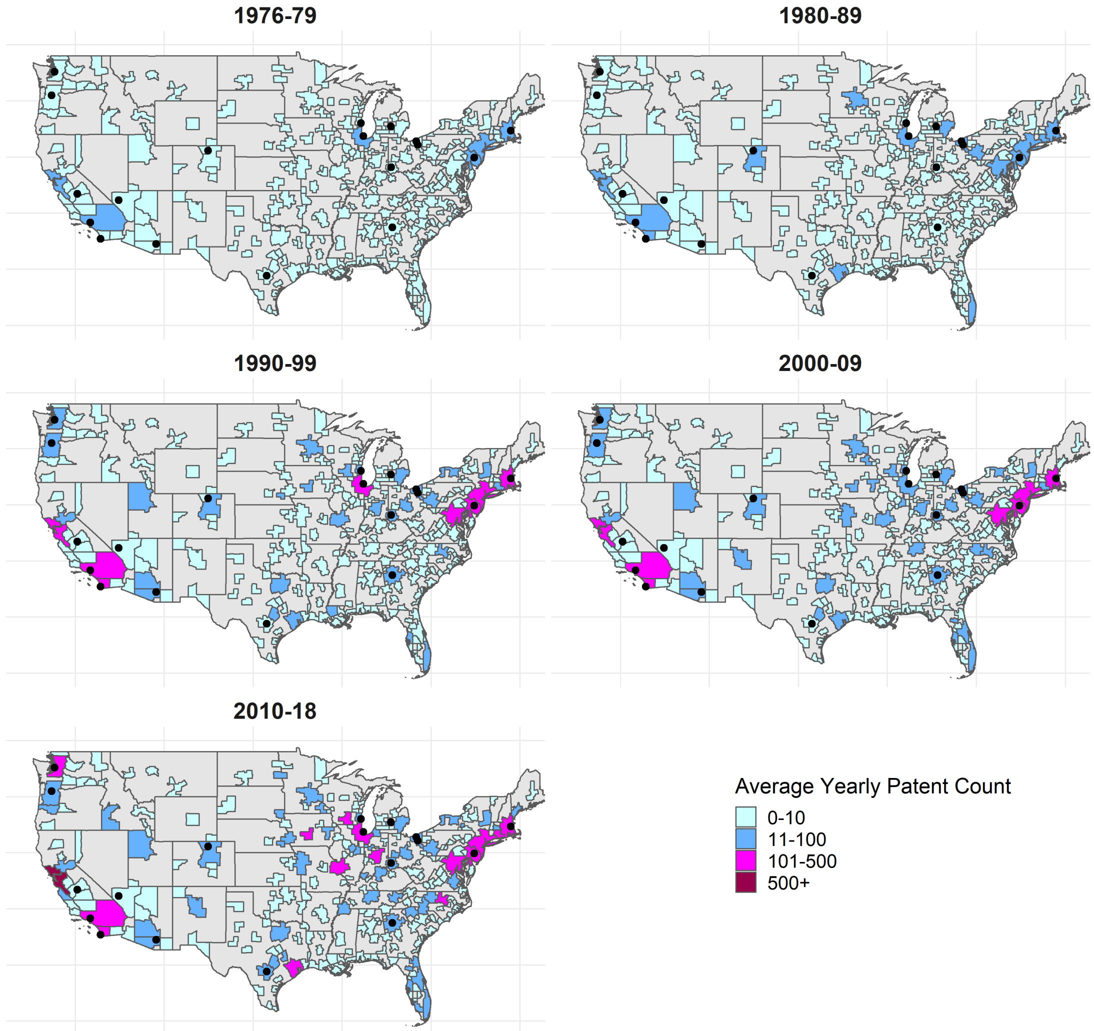
least one inventor geographically located within an MSA, 121,197 patents are identified as water-related.[26]

I measure of innovative activity using the count of patents filed in each year by MSA. Where appropriate, Combined Statistical Areas (CSAs) are used instead, resulting in a total of 270 geographic regions. I use the location information associated with the patent inventor(s) listed on the patent application to assign each patent to a MSAs. This location reflects the inventors' location at the time the patent was filed. If the patent had two or more inventors located in the same MSA, the patent count for the MSA is only incremented by one to avoid counting the same invention more than once for a particular region. If the patent had two or more inventors located in the different MSAs, the patent count for each MSA associated with the patent is incremented by one to reflect that each location was involved in the creation of the invention. The average yearly patent count for each MSA is displayed by decade in Figure 1.3.1. There has been an increase in water-related patenting since the 1990s. This trend is observed in MSAs located in the West, Northeast, and the Midwest regions of the US.

I trim the data to remove outlier MSAs at the bottom of the distribution for patenting activity. Specifically, I remove MSAs in the lowest percentile of overall innovative activity (unrelated to water) and MSAs in the top 5% percentile of zero water-related patents to exclude MSAs that don't have the necessary economic infrastructure in place to support innovative activity in the water sector. This removes a total of 29 MSAs from the sample.

[26] 160,298 patents in the entire database were identified as water-related.

Figure 1.3.1: Water-Related Patenting Activity Over Time



Note: The figure represents average patenting activity for all water-related patenting activity for each MSA by decade. Black points on the maps represent the locations of the 18 recognized water technology clusters. Black points included in all time periods to help visualize patenting activity in locations that establish a water technology cluster across time and space.

1.3.3 Water Technology Clusters

Technology clusters have been an important part of innovation policy since the mid-to-late 1990s (Porter, 2000; Braunerhjelm and Feldman, 2007; Delgado, Porter and Stern, 2014). The creation of technology clusters is intended to promote cooperation among the various stakeholders to leverage regional strengths and bridge the gap between research and ideas and successful commercialization of new products (Fieldsteel, 2013). Technology clusters are therefore largely built around industries with an already established presence and the presence of key regional stakeholders which include end-users, universities, research centers, large firms, government and other relevant institutions.

Water utilities are a key stakeholder in the water sector, responsible for the provision of water services and waste-water treatment. Many water utilities, however, are cash constrained which may limit their ability to collaborate or innovate. In particular, many innovators in the water sector aim to improve water utilities' ability to recover resources from wastewater and reduce the energy intensity of water utility operations (Daigger, 2009; Naik and Stenstrom, 2014).

A key goal of water technology clusters is to mitigate some of the risk associated with the development of new technologies. Many of the water technology clusters provide funding and opportunities to test, validate, and verify new technologies, serving as a credible third-party vetting system to screen new technologies. The screening of technologies is important for two reasons. First, water-related technologies are expensive to test and scale. More importantly, development of water technologies generally require long testing and review periods because of factors such as requirements that technologies be piloted in each state as a pre-condition to commercialized nationally (e.g. Forer and Staub, 2013). Adoption of several successful technologies in the water sector have taken up to 14 years after pilot testing (O'Callaghan et al., 2018). Private venture capital funding for the development of water-related technologies is relatively scarce because of want to take on projects with shorter time horizons.

Second, end-users generally view new technologies as risky, preferring proven technologies despite the potential gains that newer technologies could offer. This risk aversion often dampens demand for new technologies and reinforces inertia. This is especially the case for water utilities as they are primarily preoccupied with continuity of service (e.g. Worm, 2018; Garrone et al., 2018). More generally, this is important as many technologies fail because they often do not address actual market needs due to a lack of end-user engagement during the development process (EPA, 2014).

In 2011, the EPA established a *Water Technology Innovation Cluster Initiative* (WTICI) to jump-start innovation in the water sector by supporting the development of local water technology clusters. In this paper, reference to technology clusters specifically refers to the technology clusters that are managed as part of the WTICI.[27] The EPA's official recognition of water technology clusters represents formal and additional support to reduce barriers to innovation. As part of the initiative, for example, EPA and other federal agencies help ease regulatory hurdles and provide support for meetings, networking, planning, coordination to promote the creation of new technologies that address pressing environmental and public health challenges and encourage sustainable economic development. In 2018, the EPA transferred coordination of the water technology program to the Water Environment Federation to be managed as part of the Leaders Innovation Forum for Technology (LIFT) program, whose goal is to "establish the conditions that promote accelerated development and implementation of innovative technologies and approaches" in the water sector (Barillo, 2018).

A total of 18 water technology clusters across the United States are recognized by the WITCI.[28] Each of the established clusters' technology focus vary based on each regions' particular needs or strengths. These foci range from water scarcity, reuse, agriculture challenges, aging water infrastructure, and water quality. A list of the 18 existing water-related technology clusters, along with their relative foci, is provided in Appendix Table 1.4.1 in Appendix 1.4. Several of the water technology clusters existed prior to WTICI. For the

[27]There is no universally accepted definition of a technology cluster (Arthurs et al., 2009). Existence of a technology clusters for various industries, including water, is measured in several ways (Wood, Harten and Gutierrez, 2018).

[28]The location of each cluster is geocoded then assigned to the MSA in which is located.

technology clusters that formed prior to WTICI, I use 2011, the start of the initiative, as the first year.

1.3.4 Additional Data

The main goal of this study is to examine the relationship between scarcity and water-related technological innovative activity. It is therefore important to control for other drivers of innovative activity unrelated to scarcity. Additional data is collected at the MSA level to capture attributes at a regional scale that may affect the level of water-related innovation and innovative activity, more generally.

1.3.4.1 Toxic Release Inventory.

Water Quality is measured using data from the Toxic Release Inventory (TRI) from 1986-2017, which is maintained by the EPA (EPA, 2019).[29] The program requires facilities in various industries which manufacture, process, or use significant amounts of toxic chemicals, to report annually on storage, use, and releases of these chemicals, including information on the medium in which the substance is released (e.g. air, water, landfill). An advantage of these data is that firms are not fined for the content of their reports. Firms are fined for not reporting information. This minimizes concern over incentives for misreporting.[30]

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[29]Congress created the Toxic Release Inventory (TRI) in 1986 under Section 313 of the Emergency Planning and Community Right-to-Know Act (EPCRA) in response to a deadly chemical release at a chemical plant in West Virginia in 1985.

[30]Other potential data sources on water pollution include federal data repositories: Storet Legacy, Modern Storet, and the National Water Information System (NWIS). Though these sources contain valuable water quality information, they suffer from several issues. First, they are not easily accessible by the public. Second, locations of stations are not exogenous. Lastly, the timing of the readings themselves are highly endogenous.

The main purpose of the data compiled by TRI is to provide information about industrial management of potentially dangerous chemicals to inform the public, help communities plan for potential chemical emergencies, and assist local governments in accessing information on possible exposures. A count of the number of chemicals released that are known carcinogens is used to capture the effect of informal regulation on innovative activity. Given that the program was established in 1987, these measures do not exist prior to 1987. These measures are set to 0 in years before the program was established to reflect the fact that this type of informal regulatory pressure was non-existent.

1.3.4.2 Census Data

Decennial censuses from 1970–2010 are used to collect data on education to proxy for the availability of a skilled workforce, measured as the proportion of the population with a college degree or higher. Data for years in between collection are linearly interpolated.[31] Yearly population estimates for MSAs are obtained from the Complete Economic and Demographic Data Source (CEDDS). Using these data, a measure of population growth is constructed to capture development pressures that may put strain on existing water supply.

1.3.4.3 Municipal Financial Records

The state of the existing water-related infrastructure may affect both firm location as well as firm investment in water-related technologies. Municipal spending on water-related infrastructure is measured using data from the 1967-2015 Annual Survey of State and Local Government Finances. These data include reports for annual capital and total expenditures for waste-water, solid waste management, and natural resources for each local government.

[31] Data collected from IPUMS NHGIS (Manson et al., 2017) and Longitudinal Tract Data Base (Logan, Xu and Stults, 2014)

These annual estimates are averaged at the MSA level and linearly interpolated for missing years.

1.4 Estimation

I adopt a "treated-within-the-treated" approach, extending the difference-in-difference framework to evaluate both the impact of establishing a Water Technology Cluster on water-related patenting activity in addition to changes in patenting activity following the incidence of drought. This approach makes use of variation in both the timing and geographic location in the incidence of droughts and the recognition of water technology clusters to explain differences in patenting water-related patenting activity.

In this setup, MSAs that experience drought are considered exposed to a "water scarcity treatment." Following the event study literature, I capture the dynamic effects of a drought shock in MSA i, using indicator variables. Let d_i denote a year in which MSA i experiences a drought shock; $t - d_i$ therefore represents the number of years elapsed since a drought shock, i.e. "relative time" (Borusyak and Jaravel, 2017; Schmidheiny and Siegloch, 2019). Indicator variables for each year following a drought shock can be expressed as $\sum_{\tau=1}^{\infty} \mathbb{1}\{t - d_i = \tau\}$, where $\tau = 1$ represents the first year following a drought shock and $\tau = \infty$ is the maximum lag possible given the data. Pre-trends (i.e. $\tau \leq 0$) are not included because the incidence of a drought episode is considered to be as-good-as-randomly assigned.[32]

Additionally, MSAs in which a water technology cluster is established are considered to have received a "policy treatment." These MSAs are treated at various times and, once treated, remain treated thereafter. Specifically, the policy treatment is defined as, $T_{it} \in [0, 1]$,

[32]Droughts are usually predicted up to a month in advance. In certain rare instances, droughts are predicted up to a year in advance (Huang et al., 2014).

where $T_{it} = 0$ if MSA i has not established a Water Technology Cluster by year t and $T_{it} = 1$ if it has. MSAs that never establish a Water Technology Cluster are included in the analysis as control locations. An interaction term, $\sum_{\tau=1}^{\infty} \mathbb{1}\{t - d_i = \tau\}T_{it}$ is included to capture the dynamic effect of a drought shock that occurs in MSAs with an established water technology cluster. The basic modeling approach is given by (1.5):

$$P_{it} = \sum_{j}^{J_i} \sum_{\tau=1}^{\infty} \gamma_\tau \mathbb{1}\{t - d_{ij} = \tau\} + \beta T_{it} + \sum_{j}^{J_i} \sum_{\tau=1}^{\infty} \theta_\tau \mathbb{1}\{t - d_{ij} = \tau\}T_{it} + \delta X_{it} + \eta_i + \epsilon_{it} \tag{1.5}$$

where i indexes MSAs, t indexes calendar years, and j indexes drought events. MSA fixed effects, η_i, are included to capture time-invariant characteristics that vary by MSA. Specifically, η_i would account for the general propensity to generate water-related patents and capture factors that account for these differences, such as institutions, regulatory environments, the presence of water resources, or differences in knowledge stocks that would affect the level of patenting across MSAs. Standard errors are adjusted for both heteroscedasticity and autocorrelation due to potential persistence of drought shocks that would be captured by ϵ_{it}. I estimate this equation separately for each technology type (All, Conservation, Supply, Water-Quality) to account for heterogeneous effects across the broad range of activities that droughts affect.

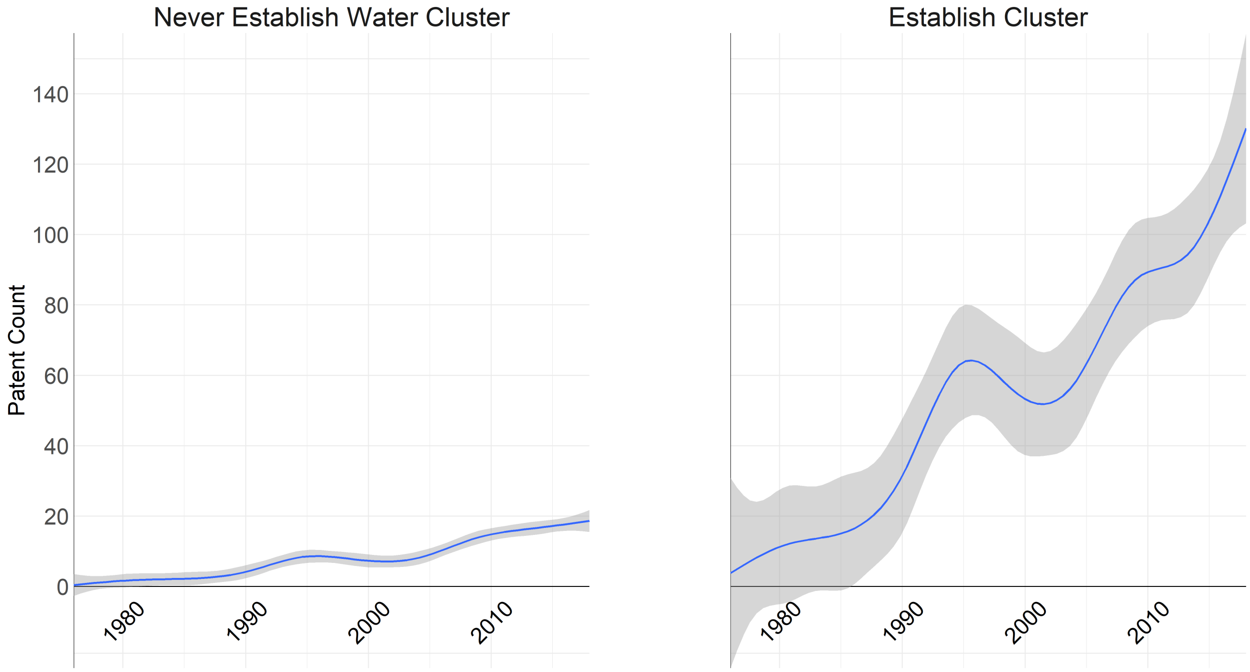
The coefficient γ_τ represents patenting activity in years following droughts in MSAs without a water technology cluster and the coefficient θ_τ any additional patenting activity that occurs in MSAs with an established technology cluster. Identifying the the effect of a drought shock on patenting activity depends on the assumption that an innovator files for a patent in the same location that they experience drought, i.e. they do not move locations between when drought occurred and when patent is filed.[33]

The vector X_{it} represents time-varying observed covariates to controls for factors may affect water-related patenting activity. First, I control for local innovative activity using a measure of per capita patenting activity unrelated to water as proxy for the general propensity to patent in each year t and MSA i. Second, I control for regulatory pressure to create new water-related technologies unrelated to scarcity using a count of the number of chemicals released that are known carcinogens. Lastly, I control for temporal variations in patenting incentives for water-specific technologies using the number of successful U.S. applications in year t in non-MSA areas, including those filed by foreign corporations (Jaffe and Palmer, 1997). I also include US census region-specific linear time trends to capture long-term patenting trends due to differences in climate and regional institutions.

The coefficient, β, captures the mean change in patenting activity observed pre- and post-establishment of a water technology cluster. Causal interpretation of β requires that the establishment of a water technology cluster be uncorrelated with water-related patenting activity. A priori, there is reason to be concerned that the location of a technology clusters is not random because its establishment is a result of local initiatives. The policy treatment, T_{it}, may therefore be endogenous as MSAs select into treatment. Simply comparing locations with that establish a water technology cluster to those that do not is not sufficient because locations in which a cluster was created may be systematically different than those where one was not created. More importantly, these differences might due to unobserved characteristics that would also be systematically correlated with the outcome of interest (i.e. water-related patenting activity). These unobserved characteristics will be subsumed in ϵ_{it}. As shown

[33]This is a common assumption made in literature on innovation.

Figure 1.4.2: Water-Related Patenting Activity in MSAs that do and do not Establish a Water Technology Cluster



Note: The solid lines represent average patenting activity. The shaded region represents the associated 95% confidence interval.

in Figure 1.4.2, patenting trends in MSAs that eventually establish a water technology cluster are significantly different from MSAs that have not established a cluster.

In the main specification, I account for the potential endogeneity of the policy treatment using a parametric control function approach motivated by Heckman (1978) extensively used in the literature (Semykina and Wooldridge, 2010; Papke and Wooldridge, 2008; Imbens and Wooldridge, 2009; Semykina and Wooldridge, 2010; Fernández-Val and Vella, 2011; Wooldridge, 2015; Kawatkar et al., 2018). As a robustness check, I also estimate the effect of water technology clusters using a Baysian Structural Time-Series approach in Appendix 1.6. This alternative approach constructs a synthetic control using untreated MSAs. The results from this alternative approach are consistent with the results presented in this section.

The parametric control function approach approach is implemented in two stages. In the first stage, a selection equation is specified and estimated using a Probit regression at each cross-section, year t, to obtain estimates of time variant unobserved heterogeneity that explains the selection into treatment. These estimates are then used to construct the Inverse Mills Ratio, $\hat{\lambda_{it}}$. The control function is then included as a regressor in the outcome equation to purge ϵ_{it} of the factors that led to selection. This approach is inherently an instrumental variable method. The first stage is specified as follows:

$$P(T_i = 1|z_{it}) = \phi(z_{it}\delta_t + \bar{z}_i\xi_t) \tag{1.6}$$

where z_{it} are instrumental variables and $\bar{z}_i$ are time means of these instruments.[34] The set of exclusion restrictions used in the first stage consist of factors related to water-specific concerns and the RIS literature. These variables are summarized in Table 1.4.3 and discussed in Appendix 1.2.

In the second stage, the $\hat{\lambda_{it}}$ is included as an additional explanatory variable to control for selection bias.[35] MSA fixed effects are replaced with time means of the instruments to purge the idiosyncratic error term of the factors that led to selection in addition to including the constructed control function as an additional explanatory variable. The resulting error

[34]Binary instrumental variables are not time-meaned.

[35]This approach is the basis for Heckman two-step estimator for endogeneity.

Table 1.4.3: Control Function Exclusion Restrictions

Variable	**Description**	**Data Source**
	Time-Invariant Factors	
EPA office	Distance to the nearest regional EPA office	EPA
CEE	MSA with a Civil and Environmental Engineering Dept.	SR
	Time-Varying Factors	
Previous drought episodes	the total number of drought episodes that a MSA experienced from 1930 through time $t-1$	NOAA
WaterExp	Expenditure on operation, maintenance, and construction of public water supply systems	ASSLGF
SewExp	Expenditure on provision, maintenance, and operation of sanitary and storm sewer systems and sewage disposal and treatment facilities	ASSLGF

Notes: EPA- Environmental Protection Agency; SR- Shanghai Ranking; NOAA-National Oceanic and Atmospheric Administration; ASSLGF - Annual Survey of State and Local Governments

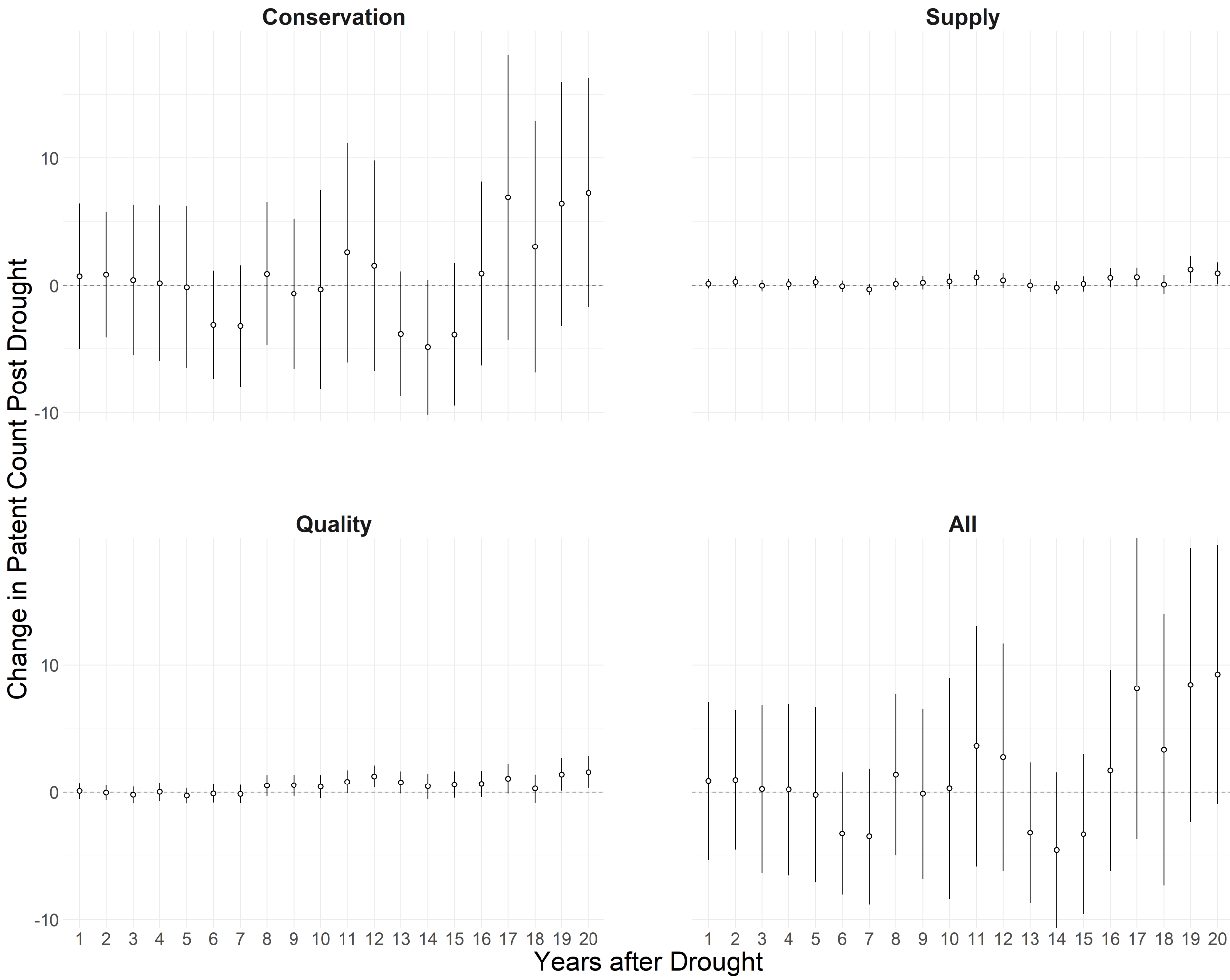
term in the new outcome equation is theoretically orthogonal to the explanatory variables.[36] The second stage is specified as follows:

$$P_{it} = \sum_{j}^{J_i} \sum_{\tau=1}^{\infty} \gamma_\tau \mathbb{1}\{t - d_{ij} = \tau\} + \beta T_{it} + \sum_{j}^{J_i} \sum_{\tau=1}^{\infty} \theta_\tau \mathbb{1}\{t - d_{ij} = \tau\} T_{it} + \delta X_{it} + \hat{\lambda_{it}} + \bar{z}_i + \epsilon_{it} \tag{1.7}$$

The results of estimating (1.7) are shown graphically in Figure 1.4.3 through Figure 1.4.4 for various subsets of the coefficients of interest. The full numerical results are given in Appendix Table 2.2.1. Starting with patenting activity following the incidence of drought,

[36]This was first proposed by (Mundlak, 1978) and (Chamberlain, 1979). In the absence of selection bias, the transformation produces the same results as a fixed effects approach (Semykina and Wooldridge, 2010).

Figure 1.4.3: Patenting Activity after Drought

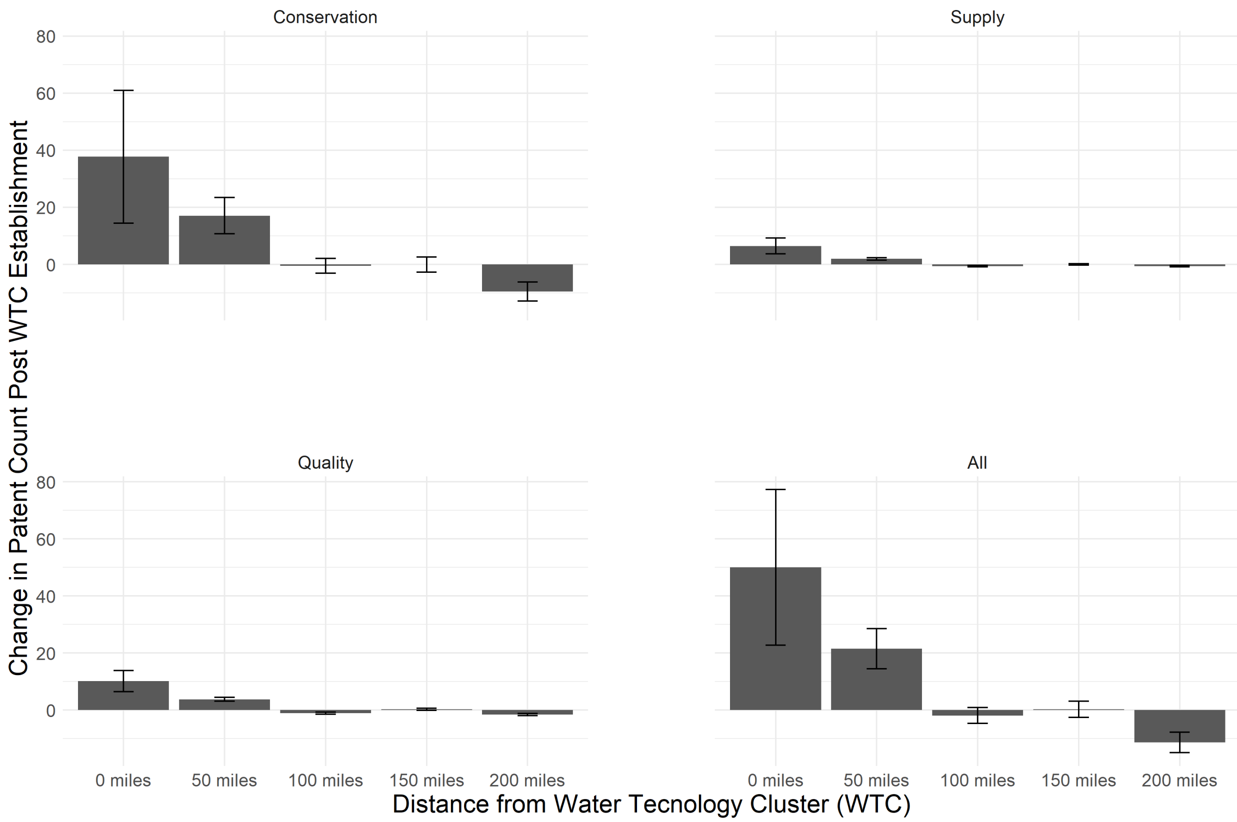


Note: Coefficients represent the change in patent counts at each lag following the occurrence of a drought shock.

the results suggest no evidence that water-scarcity shocks induce more innovation. As shown in Figure 1.4.3, the magnitude of the lagged coefficients, $\sum_{\tau}^{\infty} \gamma_{\tau}$, are relatively small and insignificant from zero, especially for supply and pollution abatement technologies.

With respect to the impact of water technology clusters, the results indicate that establishing a water technology cluster that receives formal recognition by the EPA increases patenting activity. In Figure 1.4.4, this effect is represented in the 0mi column. The effect is strongest for water conservation technologies, with an approximate increase of 41 patents per year. Smaller increases are observed for water supply and water quality technologies,

Figure 1.4.4: Effect of Water Technology Cluster on Patenting Activity

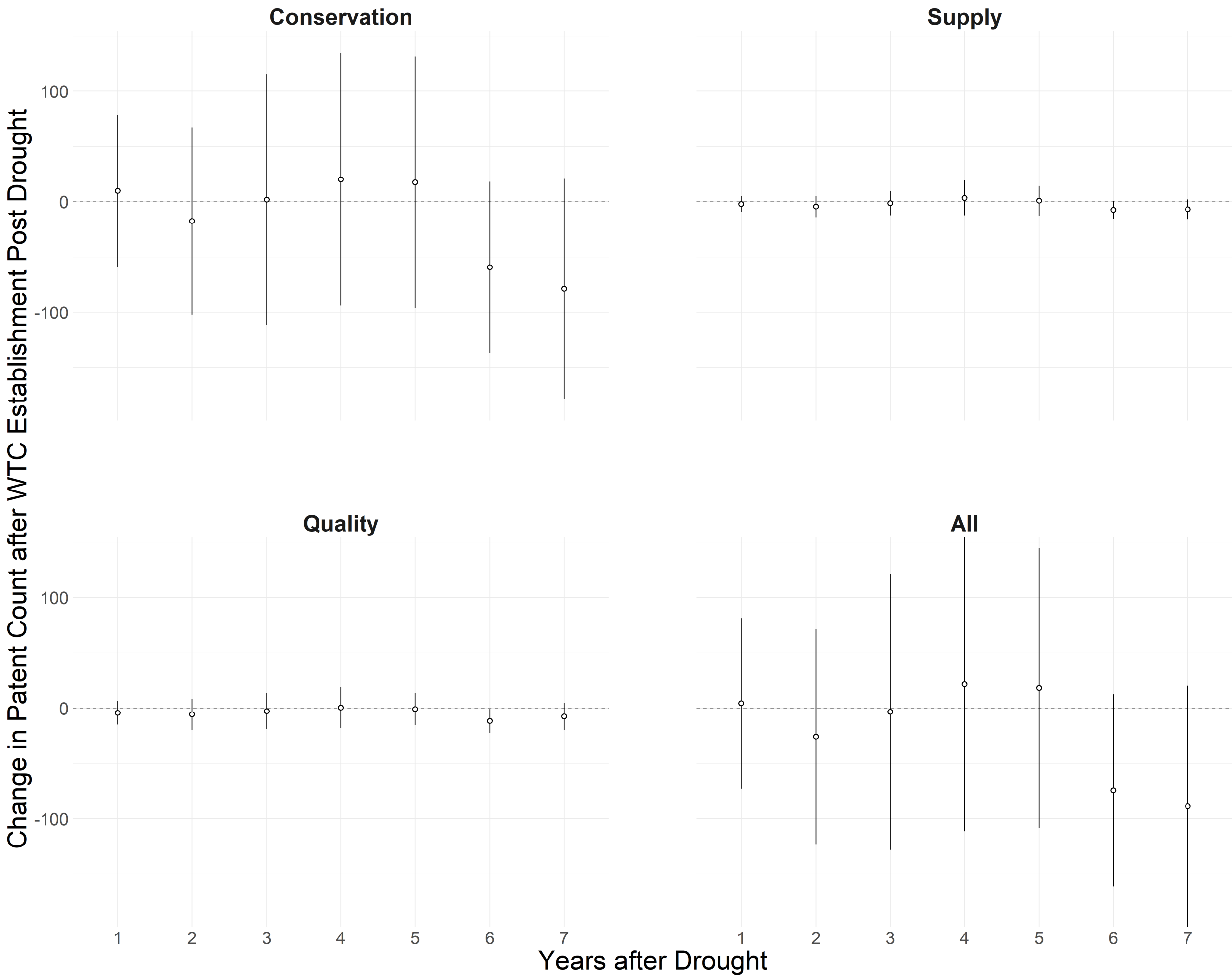


Note: The 0mi column is the additional patenting activity that occurs in MSAs with an established technology cluster. Subsequent columns represent the change in patenting activity for MSAs within the specified radius of a water technology cluster.

with increases in average patent count of approximately 7 and 11 respectively. I also find evidence of spillover effects for MSAs within a 50mi radius of a treated MSA (i.e. MSA with a water technology cluster). I find that MSAs further than 50mi do not significantly increase patenting activity. Moreover, I find evidence that MSAs further between 150-200mi of a treated MSA may decrease patenting activity. One potential explanation for this is that innovators that would have filed for patents in these locations filed for them in the treated MSA instead.

As shown in Figure 1.4.5, results also indicate that droughts do not induce more innovation MSAs with water technology clusters. The magnitude of the lagged coefficients

Figure 1.4.5: Patenting Activity after Drought in MSA with Water Technology Cluster



Note: Coefficients represent the change in patent counts at each lag following the occurrence of a drought shock in MSAs with an established water technology cluster.

for the effect of drought in MSAs with water technology clusters, $\sum_{\tau}^{\infty} \theta_{\tau}$, are not significantly different from zero.

1.5 Conclusion

In this paper, I focus on technological innovation in water sector because of the long-standing perception that water-related innovative activity is lagging. I study the inventive phase of water-related innovation to shed light on whether innovators react to water scarcity, focusing on the timing of the inventions, as opposed to characteristics of the inventions themselves. Specifically, I estimate the extent to which water scarcity motivates innovators to create new water-related technologies, using the incidence of drought as exogenous water scarcity shocks.

In general, findings indicate that patenting activity does not increase following water scarcity shocks. This finding is important as droughts are expected to become more severe.[37] Several explanations exist for why this may be the case. First, it is possible that the droughts observed during the sample period were not considered to be serious 'scarcity signals.'

Second, the uncertainty in the incidences of drought may influence preferences for investmenting in new technologies. Previous research has shown that people tend to overweigh the likelihood of the most favorable outcomes and are consequently less likely to invest or demand technologies (Bernedo and Ferraro, 2017). Similarly, empirical evidence also suggests that government insurance programs that insure against crop losses due to extreme heat (e.g. subsidized crop insurance program) may potentially distort inventivies to create or adopt technologies in the agricultural sector (Annan and Schlenker, 2015).

Third, it is also possible that technologies already in existence are being increasingly adopted following instances of drought. Taking this perspective, adoption of already existing technologies may be considered "innovative" as it would be addressing an issue in a way that is new for that location as water issues intersect strongly with local concerns and solutions are contingent on local conditions. This study points to the need to better understand the adoption behavior of water-related technologies in the context of scarcity.

[37] With few exceptions, most droughts have not lasted that long as the period under study happens to be one of the wettest periods within the last 500 years (Pederson et al. 2015).

Lastly, it is also the case that extreme droughts create conditions that may inhibit innovative activity. For instance, extreme water scarcity can lead to or exacerbate other natural disasters (e.g. wildfires, floods, sinkholes) or lead to social unrest (Westerling et al., 2003; Ichoku et al., 2016; Hand, Thompson and Calkin, 2016; Scasta, Weir and Stambaugh, 2016).[38] These secondary effects may draw resources away from innovating on water-related issues.

With respect to water technology clusters, I find that the establishment of water technology clusters increases local patenting activity as well as activity in nearby locations. I find no evidence, however, that innovators operating in the context of a water technology cluster increase innovative activity after experiencing a drought. The most likely reason for this finding is that there are too few years of post-drought data to be able to detect a different response. Further research is needed to understand this finding. This finding would support the notion that there are significant barriers to innovation that technology clusters address. Though further work is needed to investigate the attributes of water clusters that specifically enable them to promote innovative activity, this study also points to the need to evaluate policies that leverage market forces to promote water-related innovation.

[38] In California, wildfire related-damages in 2018 totaled over $2.5 billion. Land subsidence can occur as ground dries which can rupture pipelines buried within, causing costly repairs and wasted water. While the occurrence of wildfires is not solely driven by drought conditions, the number of wildfire incidents and the extent of their associated damaged have increased in part due to changing climate (Hand, Thompson and Calkin, 2016).

PAPER 2: HETEROGENEOUS RESPONSES TO PRICE: EVIDENCE FROM RESIDENTIAL WATER CONSUMERS[1]

2.1 Introduction

Public or regulated utilities, such as water and electricity providers, often face demand or supply fluctuations that make it difficult to satisfy all demand with a single year-round price. Utilities may respond to these challenges with rationing, either through prices or explicit usage restrictions, or by increasing capacity. In recent years, price-based rationing has gained popularity as a demand management tool (Cuthbert and Lemoine, 1996; Newsham and Bowker, 2010; Kenney et al., 2011; Mayer, Hunter and Smith, 2018). Price increases can be used to reduce quantity demanded to meet (perhaps reduced) supply while allocating the utility's product to consumers with the greatest marginal benefit. The benefits of this approach are likely to increase in the coming decades due to aging infrastructure, changes in climate and population, and the increasing cost of creating new capacity.[2]

In this paper, we provide new insights into price-based rationing by exploiting a detailed panel of households' monthly water usage. The data allow us to describe how households of different wealth and water usage patterns respond, potentially differently, to variation in water prices, environmental conditions, and usage restrictions. Most notably, we find

[1]Co-authors include Shadi Eskaf, Julien Isnard, Brian McManus, and Andrew J. Yates.

[2]Most of the electrical grid and over 30% of water utilities already operate at or near maximum capacity. Experts have estimated that $1 trillion dollars are required to maintain and expand service to meet demand over next 25 years (Fynn et al., 2007; American Society of Civil Engineers, 2017; American Water Works Association, 2019).

that heavy-usage households are no less price sensitive than other households, regardless of household wealth. These findings are in contrast with the previous literature. Explanations for these differences include our treatment of heterogeneity as well as the richness of our data.

Understanding heterogeneity in demand for residential water is important for evaluating the impact of using prices to manage demand. Water supply networks are typically designed based on peak usage, which generally occurs during the summer when up to 50% of all usage is for lawn and garden irrigation (Swamee and Sharma, 2008; Lucas, Coombes and Sharma, 2010; Dandy, Nguyen and Davies, 1997; Mayer et al., 1999; Balling, Gober and Jones, 2008). It is therefore important to quantify the relationship between price and consumption of heavy-usage households who are likely to irrigate. Estimating heterogeneous responses to price changes is also a necessary precursor for the analysis of distributional effects.

The previous literature on water demand's price elasticity has explored heterogeneity along two dimensions, independently of one another. First, studies have explored how price responses vary with wealth, usually proxied by assessed home value or income. These studies suggest that wealthier households have less elastic demand for outdoor water usage as well as for water usage overall (Mansur and Olmstead, 2012; Wichman, Taylor and von Haefen, 2016). Second, studies have explored heterogeneous responses by usage. Wichman, Taylor and von Haefen (2016), for instance, find that higher-usage households with irrigation systems are generally less price sensitive.[3] Taken together, these previous results suggest that price-based policies may not be effective in reducing demand by heavy users, and may generate distributional effects by raising water expenditures by poor households.

[3] Wichman, Taylor and von Haefen (2016) examine how price responses vary by wealth and usage characteristics but not the interaction of the two characteristics.

We depart from previous work in several ways. First, we examine heterogeneous responses in terms of usage and wealth simultaneously instead of in isolation. This highlights the fact that both dimensions are necessary for understanding household responses, but neither is sufficient alone. Households with similar wealth levels may have different preferences for outdoor water usage and households with comparable levels of usage may respond differently to price changes given the resources at their disposal.

Second, we characterize households' usage heterogeneity in terms of temporal patterns and levels over the course of a year. We use machine learning cluster analysis techniques to group households according to similarity in their usage. These groupings, which we call "usage profiles," can be used to identify households that likely irrigate, making use of available data without the need for costly interventions (DeOreo et al., 2011) or strong assumptions to explicitly distinguish between indoor and outdoor usage.[4] Furthermore, characterizing households in terms of usage profiles is intuitively meaningful and of practical relevance.

Third, our data have several advantages over those used in past studies. We observe a transition from year-round uniform pricing to seasonal pricing in which summer prices are about 40% above winter prices. To our knowledge, no other study has conducted a

[4]In water demand studies, it is often difficult to distinguish between outdoor and indoor usage. One common approach is to assume that a household's outdoor usage is equal to the difference between its usage during irrigation season and the "base usage" of winter months (Howe and Linaweaver, 1967; Danielson, 1979; Maidment, Miaou and Crawford, 1985; Miaou, 1990; Mini, Hogue and Pincetl, 2014). In addition, water demand studies generally have not addressed household-level heterogeneity; see the review by House-Peters and Chang (2011) and Fuente (2019). Exceptions include Renwick and Archibald (1998); Mansur and Olmstead (2012); Klaiber et al. (2014), and Wichman, Taylor and von Haefen (2016). Similar issues exist for residential energy demand; see Reiss and White (2005); Borenstein (2012); Auffhammer and Rubin (2018) and Swan and Ugursal (2009).

household-level longitudinal water demand analysis with similar degree of price variation.[5] Additionally, severe drought conditions during part of the sample period triggered the use of command-and-control (CAC) policies that imposed restrictions on outdoor usage. This provides an opportunity to also examine the effects of CAC policies. Finally, we use a hydrological model, calibrated to the local area, to calculate a measure of local hydrological stress. This enables us to captures the amount of moisture available to residential lawns.[6]

Our estimates of water demand shed new light on the efficacy and distributional consequences of price-based policies. In particular, we show that households that are most likely to irrigate (i.e. high wealth, heavy-usage households) are not less price sensitive than other households, and price sensitivity does not vary across wealth levels. If anything, the point estimates suggest that heavy-usage households are more price elastic than households that are less likely to irrigate. For example, we find that wealthy heavy-usage households have a price elasticity of -0.104, while wealthy low-usage households have a price elasticity of -0.063 and non-wealthy low-usage households have elasticity equal to -0.046. By contrast, the previous literature typically finds elasticities in the range of -0.92 to -0.27 for low-wealth or low-usage households, and elasticities in the range of -0.48 to 0.12 for households with high-wealth or high-usage. Elasticities for this latter group presumed to have higher prefereces for outdoor water usage are generally statistically indistinguishable from zero.[7] Why are our

[5]Seasonal pricing is also sometimes referred to as "peak-load" or "time-of-use" pricing. Previous studies of residential water demand under seasonal pricing (Renzetti, 1992; Lyman, 1992; Reynaud, 2010) have focused on aggregate demand rather than household-level demand.

[6]Previous water demand studies vary in how they model environmental factors. See Arbués, García-Valiñas and Martínez-Espiñeira (2003), Worthington and Hoffman (2008), or House-Peters and Chang (2011) for comprehensive reviews of the literature.

[7]See Mansur and Olmstead (2012); Baerenklau, Schwabe and Dinar (2014); Klaiber et al. (2014); Wichman, Taylor and von Haefen (2016).

results different from the previous literature? One potential explanation is that our joint characterization of households in terms of both wealth and usage profiles more effectively isolates households' preferences for outdoor water usage from their price sensitivities. Indeed, we show that ignoring this heterogeneity can lead to differences in the price elasticity estimates. Another possible explanation is that the large price increases we observe provide a better opportunity to accurately estimate elasticities.

We complement our elasticity estimates with descriptive evidence of transitions in usage profiles over time. This provides insight into the extent to which households make substantial changes in water usage following the introduction of higher prices. These descriptions reveal that a large share of households, in each wealth level, reduced water usage significantly after the implementation of seasonal pricing.

2.2 Data

2.2.1 Water Usage Data

The Orange Water and Sewer Authority (OWASA) in Orange County, North Carolina has provided monthly water usage and rate data from February 1999 through September 2005 for single-family residential properties. We match this data with each property's parcel-level characteristics using Orange County Land Records' geographic information system. These characteristics include lot size, square footage, year built, assessed value of the home in 2000, and the Census Block Group.[8] During the sample period, OWASA staff recorded usage from household water meters approximately monthly, with different households' usage recorded on different days of the month. We define monthly usage for each household in terms of these

[8]In OWASA's service area there are 42 Block Groups which contain, on average, about 190 households each.

read periods. In recording households' usage data, OWASA truncates to the nearest thousand gallons the total quantity of water used during a read period. Usage above a truncation point carries-over to the next read period, which effectively delays payment rather than allowing some usage to be unbilled entirely.

To prepare the sample we use for empirical analysis, we remove observations that may be incomplete or contain errors. First, we eliminate households that, despite OWASA's billing designation, may not be single-family households.[9] Next, we drop households with usage data that begins later than October 1st, 1999. This insures that we observe all households for more than two years prior to OWASA implementing seasonal pricing in May 2002. From this set of households, we exclude those with any missing data between October 1999 and September 2005. We eliminate outliers by dropping households with monthly usage values that ever exceed the 99.9th percentile of usage; some of these extreme outliers are due to meter misreads or catastrophic leaks. We also drop households with zero-usage readings in 2+ consecutive periods or 12+ periods in total, in order to exclude households with frequent absences due to travel or intermittent rental activity.[10] Our final sample contains 4,455 households, roughly 52% of the starting data.

2.2.2 Water Prices

OWASA is among the first water utilities to use prices as part of a broader strategy to manage demand during non-drought periods. On May 1st 2002, OWASA replaced uniform

[9]For example, we eliminate customers with multiple location identifiers as they may represent households that own multiple homes or properties managed by rental agencies. We also eliminate customers whose land record information is inconsistent with a single-family property.

[10]A zero-usage reading may also be due to meter rounding for very low usage amounts, or it could indicate a water shutoff due to non-payment.

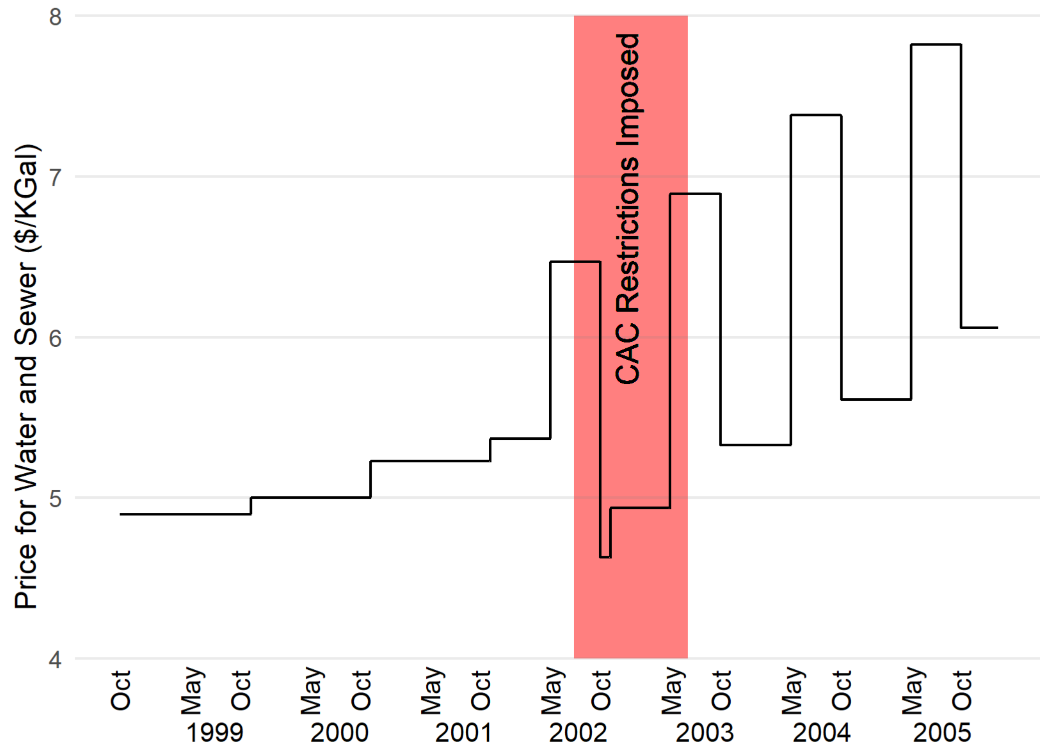
year-round prices with seasonal prices that are higher in the summer.[11] The decision to adopt seasonal pricing was part of a longer-term plan to manage water resources and not in response to a particular event. OWASA sets its prices yearly based on the average cost of service for the residential sector as a whole. Similar to many utilities, OWASA charges households a combination of volumetric and fixed fees. The volumetric portion of the bill includes separate per-unit charges for both water and sewer services. Because households are billed for both services on the same bill, we follow the literature in assuming that the effective marginal price is the combined price for water and sewer services.

We show the nominal marginal prices per thousand gallons (KGals) from October 1999 to October 2005 in Figure 2.2.1. Prior to 2002, price changes were limited to small increases on October 1st of each year. The introduction of seasonal prices, which we refer to as the treatment, began in May 2002. This pricing scheme features marginal prices that are 40% greater during summer months (May-September) relative to the rest of the year. Water prices during non-summer months are largely unchanged with the introduction of seasonal prices. Fixed fees and volumetric sewer charges remained constant throughout the year. In our empirical analysis, we convert all prices to January 1999 dollars using the seasonally-adjusted U.S. city average monthly consumer price index (CPI) from the U.S. Bureau of Labor Statistics.

Approximately two months after the implementation of seasonal pricing in 2002, drought conditions led to falling reservoir levels, triggering the use of CAC restrictions, indicated with shading in Figure 2.2.1. Given the coincidence of seasonal pricing and CAC restrictions, we

[11] In October 2007, OWASA transitioned to a different pricing schedule in which marginal prices depend on usage, referred to as increasing block pricing.

Figure 2.2.1: Seasonal Prices and CAC Restrictions



Notes: Prices are nominal US dollars. CAC restrictions were imposed from July 11th 2002 through June 2003. The dip in the marginal price observed in October 2002 was due to a brief administrative error.

identify households' responses to seasonal pricing through their usage choices after OWASA lifted the CAC restrictions.

2.2.3 Command-and-Control Restrictions

CAC restrictions target outdoor water usage to encourage conservation. These restrictions are determined by reservoir levels and are independent of OWASA's introduction of seasonal prices. Violations of CAC restrictions were considered misdemeanors and enforced through fines by the local townships and Orange County. OWASA implemented CAC restrictions in three stages, with stricter requirements imposed during each subsequent stage. On July 11th, 2002, the first restriction, *Stage 1*, was implemented, restricting irrigation of lawns, gardens, trees, or shrubs to three days out of each week. Approximately one month later, the second restriction, *Stage 2*, was implemented, further restricting irrigation to only one day a week. Two weeks after the implementation of *Stage 2*, OWASA implemented water supply *Emergency* restrictions as reservoir levels continued to fall. This restriction prohibited the use of outdoor water for any purposes other than fire suppression or necessary emergency activities. OWASA began the process of lifting CAC restrictions after heavy rains in October 2002 ended the drought. Definitions of each CAC restriction and a timeline of their implementation are in Appendix 2.3.

Following the 2002 drought, OWASA revised its restriction policy in June 2003 to include a *Year-Round Conservation Requirement*. The conservation requirement strongly encouraged the use of reclaimed or harvested water, the installation of water-saving fixtures, and limitation of activities such as spray irrigation to three days per week during non-drought conditions. Outdoor usage behavior following the drought, therefore, may have been influenced by factors other than prices. To supplement the main analysis, discussed below, we estimate several specifications to ensure that our results are robust to our treatment of the conservation requirement. The results from these additional specifications do not differ from the main specification.

2.2.4 Usage Profiles and Wealth

We use Ward's agglomerative hierachical clustering algorithm (Ward, 1963) to identify yearly usage patterns during October 1999-September 2001, the two pre-treatment years that feature constant within-year prices and small price changes between years. We define years to coincide with how OWASA implemented price changes. Combining the two pre-treatment years to create a representative year, we apply the clustering algorithm to identify yearly usage profiles based on the amount of water used in each respective month.[12] We allow the algorithm to create three usage profiles; additional levels did not add clear value for our empirical approach. As a practical matter, we need the profiles to capture enough households so that they can be further divided by other household characteristics (i.e. wealth).[13] We illustrate the usage profiles – which we refer to as *Heavy*, *Moderate*, and *Light*– in Figure 2.2.2.[14]

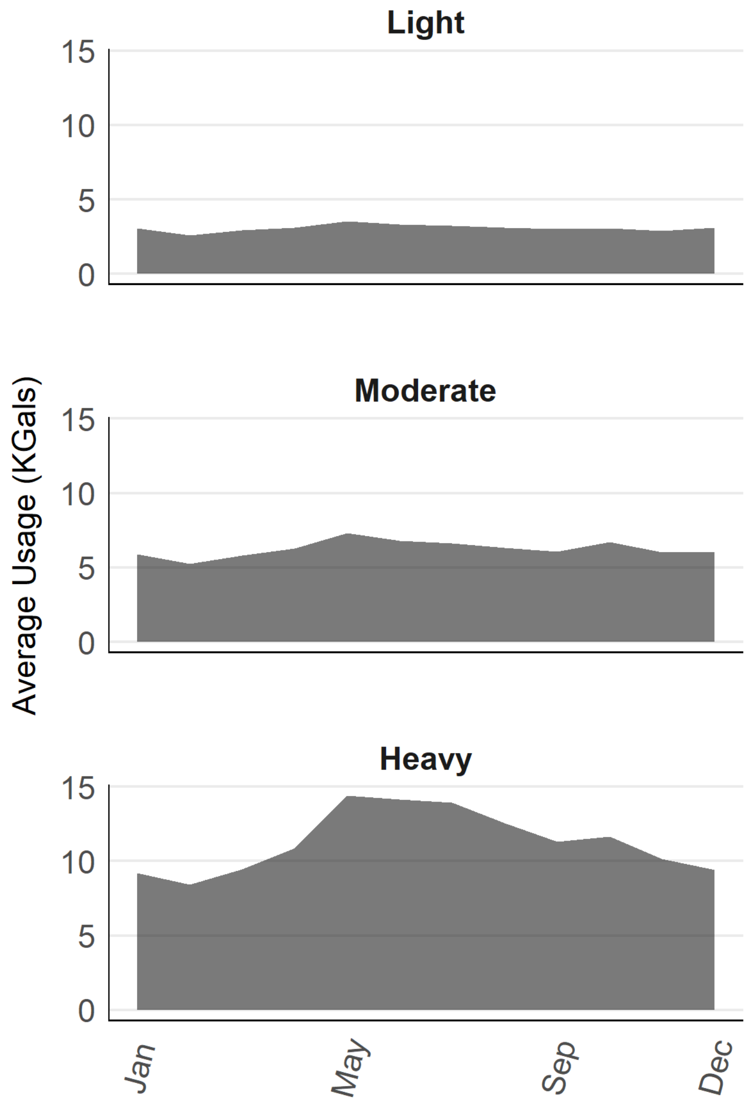
The usage profiles are instructive in describing differences in how households use water over the course of the year. They intuitively describe annual usage patterns, conforming with informal classifications of residential water usage. The timing and magnitude of water usage of the *Heavy* profile, for example, is consistent with lawn care. In particular, the large quantities of water usage during peak summer months suggests outdoor irrigation, and the significant amount usage late in the fall suggests watering of re-seeded lawns in preparation for the following summer. Conversely, the *Light* profile reflects consistently low water usage month-to-month, indicative of no outdoor water usage. Finally, the *Moderate* profile reflects usage in between the two other profiles. Relative to the *Light* profile, the *Moderate* profile has higher usage during the winter and small but distinct peaks during the summer and fall, likely reflecting occasional outdoor water use.

[12]To apply the machine learning clustering algorithm, we convert usage amounts from read periods to calendar months under the assumption that per-day usage is constant within a read period.

[13]When we experimented with adding a fourth usage profile, we found that it did not add information about the timing of water usage within the year, just its level.

[14]Ward's agglomerative hierarchical clustering method groups-together time series that are closest to each other in multivariate Euclidean space. The agglomerative coefficient, a measure of the clustering structure, for this method is 0.993 in our data, indicating a strong clustering structure.

Figure 2.2.2: Usage Profiles from Clustering



This profile, which has higher usage than during the winter, has small but noticeable peaks during early summer and fall, likely reflecting occasional outdoor water usage.

These usage profiles are useful because they also capture household characteristics that we do not observe directly, such as the number of people in the household or preferences for outdoor water use. We assign each household to a profile based on its usage from October 2000 to September 2001, immediately before seasonal pricing's introduction. We use k-nearest neighbors, a supervised learning algorithm, to perform the match (Batista et al., 2014). As a robustness check, we redo all analyses using October 1999 to September 2000 usage to match households to profiles, and we find that our results are not sensitive to the choice of pre-treatment year. These results are provided in Appendix 2.4.

We follow the convention in the literature and define household wealth using assessed value of the home (Jones and Morris, 1984; Dandy, Nguyen and Davies, 1997; Arbúes, Barberan and Villanua, 2004).[15] Specifically, we create an indicator for relative wealth based on the median assessed home value ($192,647) in the area of study in 2000.[16] We identify a household as *High* wealth if the home value is above the median, and *Low* wealth otherwise. Columns 2 and 3 of Table 2.2.1 summarize parcel-level household characteristics by wealth level. As indicated by the average house value for lower-wealth households ($131,369), OWASA's service area is generally wealthier than the rest of North Carolina (median home value $108,300) and the United States ($119,600).

As shown in Table 2.2.1, there is a correlation between wealth and higher usage, consistent with the literature (Dalhuisen et al., 2003; Harlan et al., 2009). However, 25% of the households with *Heavy* usage profiles have lower-than-median home values. In addition, the set of households with higher-than-median home values and *Heavy* usage profiles only represent 21% of wealthier households.

[15]Studies that have explored how price responses interact with wealth measures have used homes' assessed values or income as a proxy. Wealth may be more appropriate than income in understanding a household's ability to pays its bills, due to former capturing savings, access to credit, and other financial resources (Meyer and Sullivan, 2003).

[16]This approach is consistent with previous work. For example, Olmstead and Mansur (2012) define households with incomes and lot sizes both above the sample medians as "rich, big lot" household and those with incomes and lot sizes both below the medians are categorized as "poor, small lot."

Table 2.2.1: Usage and Parcel Characteristics

		Wealth Level		***Usage Profile***		
	All	***Low***	***High***	***Light***	***Moderate***	***Heavy***
Usage (KGals)	5.63	4.65	6.49	3.25	5.93	9.78
	(4.31)	(3.30)	(4.87)	(2.22)	(3.45)	(6.40)
House size (sq. ft.)	2346	1700	2910	1923	2444	2923
	(878.20)	(494.57)	(740.38)	(748.10)	(792.35)	(983.17)
Number of bedrooms	3.56	3.14	3.93	3.24	3.64	3.97
	(0.96)	(0.85)	(0.91)	(0.91)	(0.92)	(1.02)
Number of bathrooms	2.55	2.04	3.00	2.19	2.64	3.01
	(0.85)	(0.66)	(0.75)	(0.80)	(0.76)	(0.95)
Yard size (acres)	0.44	0.35	0.51	0.39	0.45	0.50
	(0.34)	(0.26)	(0.39)	(0.33)	(0.35)	(0.34)
House value (1000 USD)	206.65	131.37	272.31	162.93	216.27	268.20
	(98.18)	(36.68)	(87.28)	(79.08)	(90.24)	(117.67)
Year built	1975	1969	1981	1972	1977	1979
	(18)	(17)	(17)	(18)	(18)	(17)
Number of households						
Total	4455	2080	2375	1481	2301	673
High wealth				478	1389	508

Note: Values are means and standard deviations in parenthesis.

2.2.5 Environmental Conditions

Environmental conditions are important factors that drive demand for outdoor water usage such as lawn irrigation. The standard approach has been to account for this with an *ad hoc* collection of weather variables. By contrast, we introduce a novel measure based on hydrological stress. This measure more directly captures the water needs of a household's lawn. We use a hydrology model to account for how water moves through the hydrological cycle, while also accounting for land use and vegetation cover patterns. Specifically, we introduce an index derived from a spatially-explicit eco-hydrological model known as Regional Hydro-Ecologic Simulation (RHESSys) (Tague and Band, 2004; Lin et al., 2019; Gao et al., 2018) to summarize the exogenous factors that determine lawn and soil dryness. This approach builds on previous hydrological research that has found that calculations of soil water deficits are better than weather variables (which mostly capture atmospheric conditions) at identifying periods in which plants are likely to be water-stressed in agricultural settings (Yao, 1974; Torres, Lollato and Ochsner, 2013).

We construct the index in two steps. First, RHESSys produces estimates of actual evapotranspiration and potential evaporation, which are measurements of the amount of moisture transferred from lawns to the atmosphere. The two measurements differ in that actual evapotranspiration is a conditional measure, limited by the amount of soil moisture currently available, whereas potential evapotranspiration is an unconditional measure that reflects the maximum amount of moisture that could theoretically be transferred. To produce these estimates, the model combines a high-resolution landcover database (Pickard et al., 2015; NLCD, 2001) with other model inputs (e.g. precipitation, soil water potential, air temperature, solar radiation) to model spatial and temporal dynamics of soil moisture. We calibrate and validate the model using United States Geological Survey gauges to derive estimates of soil moisture specific to lawns. In the second step, we use the resulting estimates of actual and potential evapotranspiration to produce a "water stress" index, $WS \in [0, 1]$, that captures soil conditions for each Census Block Group in OWASA's service area. A value of $WS = 0$ indicates minimally stressed (i.e., wet) conditions, and $WS = 1$ indicates maximally stressed (dry) conditions. In Appendix 2.1, we provide further details on water stress as well as an illustration of its temporal and spatial heterogeneity. In our estimation models, we also include a measure of average temperature to capture demand for seasonal recreational water uses (e.g. water used to fill swimming pools or car washing) that water stress does not capture.

The use of water stress presumes that households water their lawns when their plants are stressed. It is possible, however, that households respond to weather variables instead. We also collect weather data and construct environmental controls like those typically used in the literature. In Appendix 2.5, we compare our results to estimates obtained when controlling for environmental factors using *ad hoc* collections of weather variables. We show that commonly used collections of weather variables generally produce smaller estimates of price sensitivity among wealthier households with *Heavy* and *Moderate* usage profiles. We also show that is possible for collections of several weather variables to approximate our results when we use water stress. The advantage of using water stress is that it summarizes environmental factors in a single variable. This allows us to estimate differential responses to environmental factors in a parsimonious way.

2.3 Water Demand Estimation

We estimate a demand function for water. In considering the demand model's components and parameterization, it is useful to consider households' constrained optimization problem. We assume that households are heterogeneous in two dimensions: their taste for landscaping and their budget constraints. In our empirical model, we allow usage profiles and house values, respectively, to proxy for these sources of heterogeneity. In addition to the utility from landscaping (and other consumption, including indoor water use) and the budget constraint, a household must consider the "technology" that produces healthy landscaping. This technology requires water as an input, and in general the need for watering or irrigation is greater during hot, dry weather. As the price of water increases, households with different landscaping tastes and budget constraints may respond differently to this price variation. This motivates one characteristic of our empirical specification, which allows a different price elasticity term for each usage-wealth combination. Similar to the heterogeneous effect of prices, when changes in environmental conditions affect water's productivity in maintaining a lush lawn, households of different tastes or wealth may respond differently in their water choices. This motivates a second characteristic of our empirical specification, which allows a different response to water stress for each usage-wealth combination. Some households may view command-and-control restrictions as hard limits on the total amount of outdoor water to be used, but others may view CAC policies as an increase in water's price, whether through levied fines or their neighbors' opprobrium. Therefore, households' responses to CAC restrictions may also vary with usage-wealth combinations.

We assume that household i's demand for water during read period t is a function of water's contemporaneous marginal price.[17] To account for demand heterogeneity, the demand model's parameters vary with a household's usage profile, $u \in \{Heavy, Moderate, Light\}$, and its wealth, $w \in \{High, Low\}$. For each household and combination of u and w, we define a set of indicator variables, τ_{iuw}, that are equal to one if i has usage profile u and wealth level w, and zero otherwise. We specify demand as:

$$q_{it} = \sum_{u}\sum_{w} \tau_{iuw}\beta_{uw}p_t + \sum_{u}\sum_{w}\sum_{k} \tau_{iuw}X_{it}\phi_{uwk} + \sum_{u}\sum_{w} \tau_{iuw}Z_{it}\theta_{uw} + \eta_i + \epsilon_{it}, \tag{2.1}$$

The dependent variable, q_{it}, is the log of the total quantity of water demanded by household i during read period t. The variable p_t is the log of the marginal price in effect during read period t. The coefficient β_{uw} therefore represents price-elasticity for wealth level w and usage profile u.

The vector X_{it} records CAC restrictions, $k \in \{$*Stage 1, Stage 2, Emergency*$\}$, that were implemented during the drought. The restrictions are mutually exclusive, and we record in X_{it} the number of days restriction k was in place during each read period. The coefficient ϕ_{uwk} represents the percent change in usage per day due to CAC restriction k for households with wealth level w and usage profile u. Responses to CAC policies are identified with

[17] Alternative assumptions, used elsewhere in the literature, include the assumption that households respond to lagged prices (because they believe that prices printed in recently-received bills also apply to the current period) or they respond at the margin to an average of fixed and marginal prices (because the true marginal prices are difficult to decipher).

variation across households in exposure to restrictions per read period, due to asynchronous meter-reading and billing.

The vector Z_{it} contains controls for other factors that influence water demand during each read period. These include Census Block Group level water stress, average temperature, and the number of days in each household's read period t. We standardize the values of both Census Block Group level water stress and average temperature, demeaning then normalizing them by their standard errors, to put them on the same scale. Their effects on usage are interpreted in terms of changes in their standard deviations. We account for intra-year usage patterns with a sixth-order polynomial in a read period's average week number. We account for long-term usage changes with a pair of linear time trends. The first trend applies until the introduction of the *Year-Round Conservation Requirement*, and the second for the remainder of the sample period.[18]

We leverage the panel nature of the data to control for time-invariant unobserved household characteristics that may be correlated with water demand. These characteristics are absorbed by the fixed effect η_i. Lastly, ϵ_{it} is an error term that captures unobservable demand shocks that households experience during individual read periods.

The results of estimating (2.1) are shown graphically in Figure 2.3.3 - Figure 2.3.5 for various subsets of variables. The full set of coefficient estimates are in Appendix Table 2.2.1 in Appendix 2.2. Starting with the estimates for the price elasticities shown in Figure 2.3.3, we see that, all else equal, households with *Heavy* usage profiles are just as price-sensitive as other households. Tests for significant differences in the price elasticity estimates for high

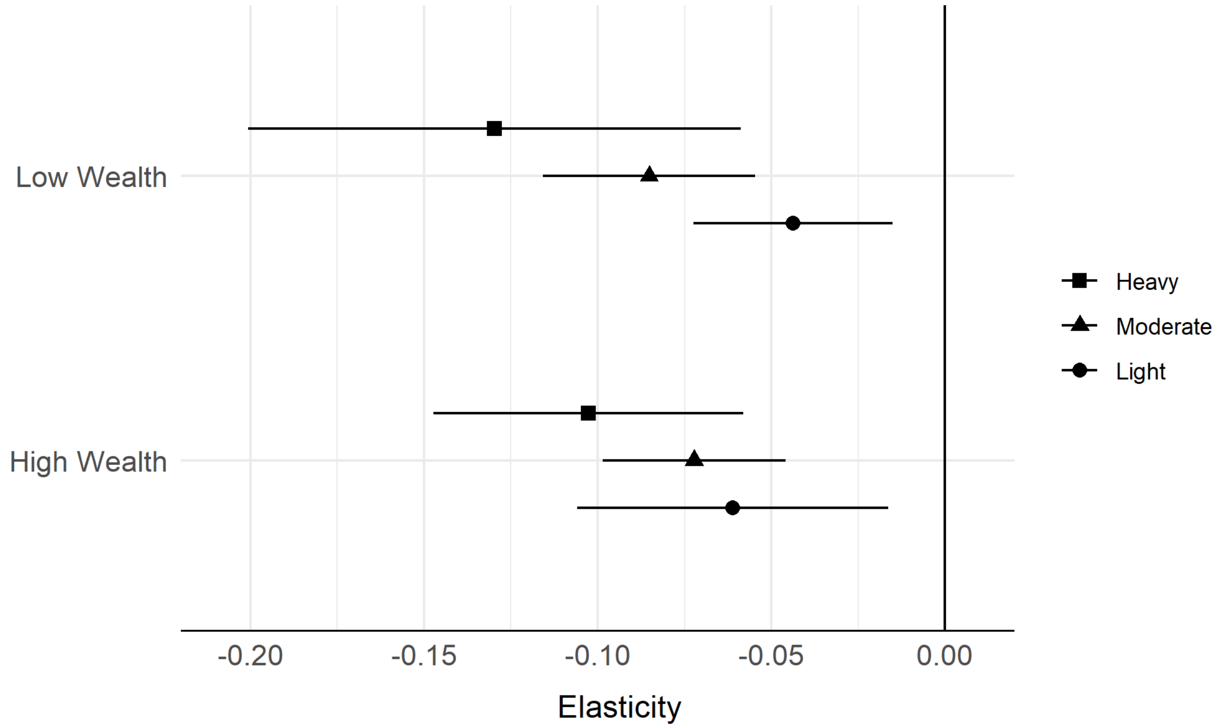
[18] We include distinct intercept and slope terms following the introduction of the *Year-Round Conservation Requirement*, which provides greater flexibility in fitting households' responses to OWASA's post-drought policies and messages about conservation.

wealth households with *Heavy* usage profiles relative to high wealth households with *Moderate* and *Light* usage profiles yield p-values of 0.48 and 0.22, respectively. If anything, the point estimates suggest that households with *Heavy* usage profiles are the most price sensitive, followed by households with *Moderate* usage profiles. We estimate that high-wealth, *Heavy* households have price elasticity of -0.104, while *Moderate* and *Light* high-wealth households have price elasticities of -0.082 and -0.063, respectively. Similarly, low wealth-households with *Heavy* usage profiles have price elasticity of -0.134, whereas low-wealth households with *Moderate* and *Light* usage profiles have elasticities of -0.067 and -0.046, respectively. These findings are particularly important as they suggest prices are no less effective at curbing the water usage by households with *Heavy* usage profiles than other households. We find very little heterogeneity across wealth levels. A test of the difference in price elasticity estimates for high and low wealth households with *Heavy* usage profiles yields a p-value of 0.53. This finding is inconsistent with previous studies that have found that prices induce a larger reduction in demand among poorer households (Renwick and Archibald, 1998; Mansur and Olmstead, 2012; Wichman, Taylor and von Haefen, 2016).

One potential explanation for our findings diverge from previous studies is that our characterization of households in terms of wealth and usage profiles does a better job of isolating preferences for outdoor water usage that are separate from price sensitivities. Indeed, the water stress and average temperature coefficients, graphically represented in Figure 2.3.4, suggest that each wealth and usage profile has distinct preferences for outdoor water usage. For instance, households with high wealth and heavy usage profiles increase water usage the most due to drier environmental conditions, possibly due to the stress to their plants or landscape. Conversely, households with high wealth and light usage profiles are least responsive to drier environmental conditions.

To illustrate the validity of this explanation, we show that ignoring differential impacts of environmental factors leads to bias in price elasticity estimates due to positive correlation

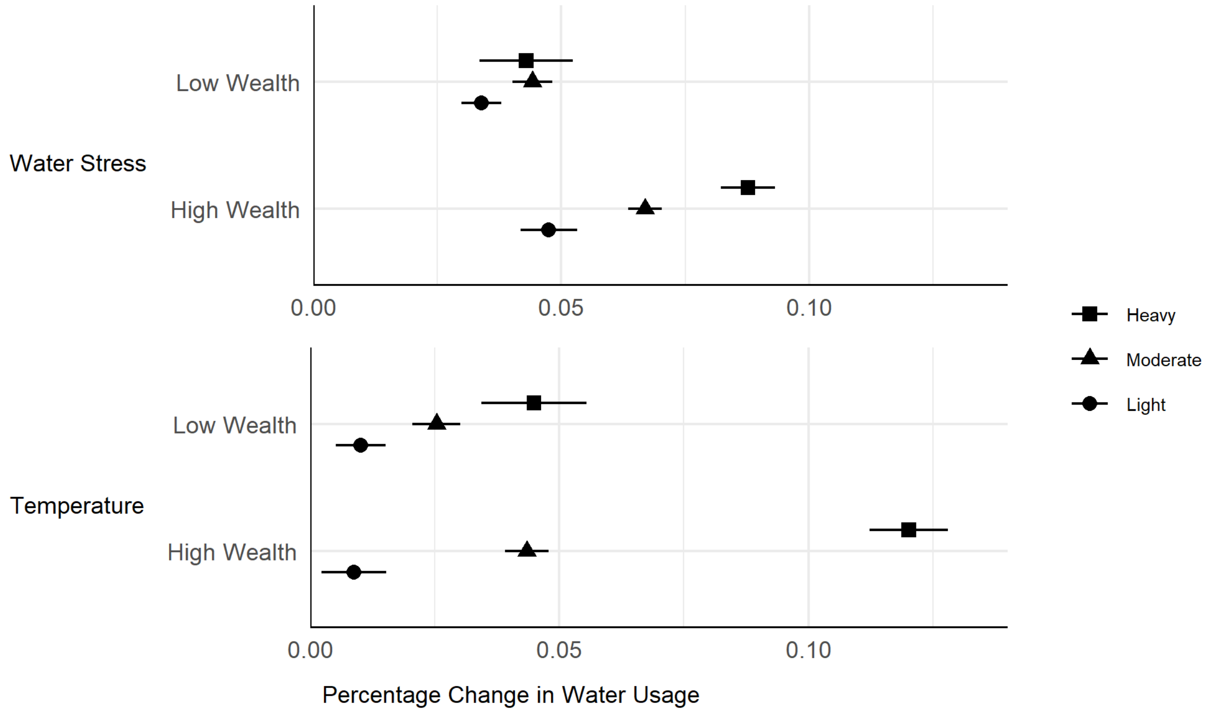
Figure 2.3.3: Water Price Elasticities



Note: Geosolids represent point estimates and lines represent 95% confidence intervals.

between higher prices and drier environmental conditions. If we do not allow environmental factors' impacts to vary by wealth, for example, we essentially assume that changes in environmental conditions have the same effect on both high- and low-wealth households for a given usage profile. If wealthier households have stronger preferences for outdoor usage, this specification would understate the true effect of drier conditions on their demand for water. During peak summer months when prices are higher and conditions are drier, one would then incorrectly attribute increases in usage to increases in price, and conclude that households that irrigate are insensitive to price. This would also explain why some studies find positive price elasticity estimates for households presumed to irrigate (Wichman, Taylor and von Haefen, 2016). Although other studies did not estimate demand under seasonal pricing, they estimate demand demand under increasing block pricing, a price structure in which marginal prices depend on usage. The same effect would be observed under increasing block prices since households with higher usage levels face higher prices. The opposite would be true

Figure 2.3.4: Effect of Environmental Factors on Water Usage

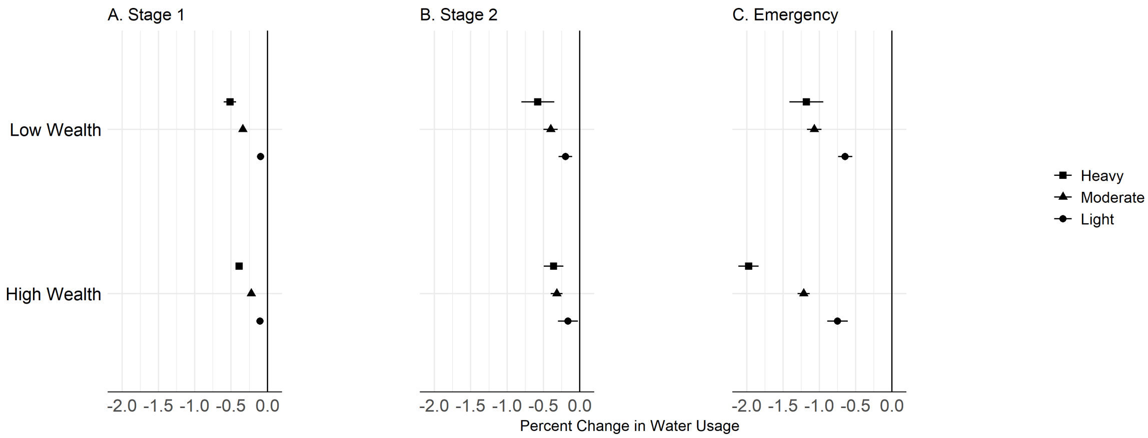


Note: Point estimates (geosolids) represent percentage change in water usage per standard deviation change in environmental control. Lines represent 95% confidence intervals.

for lower wealth households, as the estimates would imply overly-strong responses to dry conditions. Then, when prices and dryness increase in the summer, the absence of increased usage would be attributed to strong price elasticity in order to counter-balance the upward bias in expected response to environmental conditions (Appendix Table 2.2.2). A similar argument holds for not allowing responses to water stress to vary by usage profile, as this specification assumes that changes in environmental conditions affect households with similar wealth levels in the same way. As shown in Table 2.2.1, not all high wealth households have the same preference for outdoor water usage. Following similar reasoning, we show that not allowing for differences in usage profiles results in biased price elasticity estimates (Appendix Table 2.2.3).

Turning now to the effect of CAC restrictions used during the 2002 drought, we find little wealth-based heterogeneity. As shown in Figure 2.3.5, the estimated reductions in

Figure 2.3.5: Effect of Command and Control Policies on Water Usage



Note: Geosolids represent point estimates and lines represent 95% confidence intervals.

usage attributable to each CAC restriction do not differ across wealth levels, except in the case of high wealth households with heavy usage who reduced consumption significantly more their low wealth counterparts. Instead, we find them to be increasing as a function of both the severity level of the restriction as well as usage profiles. Reductions attributable to *Stage 1* and *Stage 2* restrictions are relatively modest relative to reductions from the water supply *Emergency* restriction. Furthermore, we find evidence that all households reduced consumption during the declared *Emergency*, including households with *Light* usage profiles.

Finally, our results also suggest some heterogeneity in how usage trends changed after the drought. The introduction of the *Year-Round Conservation Requirement* led to a decrease in usage for all wealth and usage groups, with the largest changes for wealthier households (see Appendix Table 2.2.1). Usage was generally lower for all groups once the conservation requirement was enacted.

2.4 Additional Evidence on Usage Profiles

For the elasticity estimation conducted in Section 2.3, we grouped households according to their usage profiles. Though the results suggest that households with *Heavy* usage profiles were most sensitive to price (given the point estimates), the way in which these households reduced usage is unclear. In this section, we examine how households move across usage profiles over time to provide supplementary information about the effects of seasonal pricing on usage. This information is relevant to water utilities, which are concerned with both price elasticities and peak-usage timing when setting policies for reservoir management. We use a k-nearest neighbors algorithm to match each household's usage in each year to one of the three usage profiles previously identified (*Heavy* *Moderate* and *Light*).

We start by providing the fractions of households in each usage profile over time in Table 2.4.2. Panel A shows that, in the first year of the sample, 34% of households had *Light* usage profiles. This fraction stayed relatively constant for two more years before increasing to about 45%. Overall, the fractions are generally stable in the sample's first couple of years, move around in the middle two "transition years" – October 2001-September 2002 and October 2002-September 2003 – and then are generally stable at a new level in the sample's final years. These patterns suggest a qualitative shift in usage following the introduction of seasonal pricing. Panels B and C show that a similar effect holds within both high- and low-wealth households.

The two transition years are particularly interesting because they were affected by the introduction of seasonal prices, the onset of drought, and the implementation of CAC restrictions. Although we do not explicitly decompose these various effects on how households sort into usage profiles, it is important to note that there are two opposing forces at play during the summer months of seasonal pricing's first year (October 2001-September 2002). On one hand, the onset of drought conditions put upwards pressure on usage. From Section 2.3, we expect that this "drought effect" would primarily affect high-wealth households with outdoor usage, as drier conditions increase watering needs for landscaping. On the other hand, the implementation of higher seasonal prices and CAC restrictions put downward pressure on usage. For the full population (Panel A), we note a small, but noticeable, increase

Table 2.4.2: Usage Profile Shares

	Light	Moderate	Heavy
Panel A	*All Households (N=4455)*		
Oct99-Sep00	0.34	0.49	0.17
Oct00-Sep01	0.33	0.52	0.15
Oct01-Sep02	0.34	0.49	0.17
Oct02-Sep03	0.49	0.44	0.07
Oct03-Sep04	0.45	0.44	0.10
Oct04-Sep05	0.45	0.45	0.10
Panel B	*Lower Wealth Households (N=2080)*		
Oct99-Sep00	0.48	0.43	0.09
Oct00-Sep01	0.48	0.44	0.08
Oct01-Sep02	0.49	0.43	0.08
Oct02-Sep03	0.61	0.35	0.04
Oct03-Sep04	0.59	0.36	0.05
Oct04-Sep05	0.59	0.37	0.04
Panel C	*Higher Wealth Households (N=2375)*		
Oct99-Sep00	0.21	0.55	0.24
Oct00-Sep01	0.20	0.58	0.21
Oct01-Sep02	0.21	0.54	0.25
Oct02-Sep03	0.37	0.52	0.11
Oct03-Sep04	0.34	0.51	0.15
Oct04-Sep05	0.33	0.52	0.15

in the fraction of households with *Heavy* usage profiles during the transition years, and essentially no change in the fraction of households with *Light* usage profiles. These patterns suggest that the upward pressure exerted by the drought was generally greater than the downward pressure exerted by increased prices. Consistent with the results in Section 2.3, panels B and C show that the “drought effect" was particularly strong among high-wealth households.

In the following year (October 2002-September 2003), changes in usage profiles reveal large, observable decreases in usage. Since the drought officially ended in October 2002, these changes can be attributed to either seasonal prices or CAC restrictions. In particular, CAC restrictions were in place from October through the end of June, which would have affected

Table 2.4.3: Transitions in Usage Profiles

Oct00-Sep01	*Light (N=1481)*			*Moderate (N=2301)*			*Heavy (N=673)*		
	L	*M*	*H*	*L*	*M*	*H*	*L*	*M*	*H*
Oct01-Sep02	0.82	0.17	0.00	0.12	0.76	0.11	0.01	0.24	0.75
Oct02-Sep03	0.89	0.11	0.00	0.35	0.62	0.03	0.05	0.56	0.39
Oct03-Sep04	0.86	0.13	0.01	0.31	0.63	0.06	0.04	0.49	0.46
Oct04-Sep05	0.85	0.14	0.01	0.31	0.64	0.06	0.06	0.49	0.44

the ability to irrigate during critical periods. We observe small increases in *Heavy* usage profiles between October 2002-September 2003 and October 2003-September 2004, suggesting a return to outdoor water usage following the lifting of CAC restrictions. Panels B and C indicate that wealthier households increased usage more strongly than low-wealth households.

To shed additional light on the reduction in usage after the implementation of seasonal pricing, we report in Table 2.4.3 changes in household-level usage profiles relative to usage profiles in the year prior to treatment (October 2000-September 2001). We illustrate how to understand the entries in this table using the transitions of households with *Heavy* usage profiles. As shown in the "Oct00-Sep01" row, 673 households were classified as having a *Heavy* profile during October 2000-September 2001. Of the households in the "Oct00-Sep01" row, 75% were in that same profile the following year ("Oct 01-Sep02"), while 24% moved to *Moderate*, and 1% moved to *Light*. The next row, labeled "Oct02-Sep03," shows that 56% of initially-*Heavy* usage households in "Oct00-Sep01" row moved to the *Moderate* profile during the second year of seasonal pricing. Among households identified as *Moderate* prior to seasonal pricing, many more reduced their usage to *Light* than increased to *Heavy*. Similarly, relatively few households initially identified as *Light* moved to a higher usage profile. We provide a table of transitions by wealth in Appendix 2.6.

The information in Table 2.4.3 corroborates the finding that there seems to have been a permanent downward shift in usage for many households. It also provides further insight into the overall impact that seasonal pricing had on usage. In particular, the adoption of seasonal pricing was effective at reducing usage during peak summer months, resulting in observable decreases in *Heavy* usage profiles among both high- and low-wealth households. Examining transitions also provides additional information on the effects of price that were not detectable in Table 2.4.2 during the onset of drought conditions. In particular, we observe some households increasing usage and others decreasing usage in the "Oct01-Sep02" row. This would suggest that increased prices may have been effective at mitigating the effect of drought on usage, although some of these decreases may have been attributable to CAC restrictions.

2.5 Conclusion

Water utilities are increasingly using price-based demand management strategies as an alternative to infrastructure expansions. Evaluating these strategies requires an understanding of the consequences of price increases. In this study, we estimate demand for residential water using household-level panel data. The richness of our data allows us to estimate elasticities that vary by both household wealth and usage profile. Our results indicate that households with higher usage profiles are no less price-sensitive than low-usage households, for any wealth level. Relative to previous research, these results provide a more optimistic assessment of the utilities' ability to use prices to reduce water consumption by high-usage households.

We complement the analysis with an examination of how households are matched to usage profiles over time. Following the introduction of higher marginal prices during summer months, a large fraction of households with heavy usage transitioned to usage profiles with lower and flatter usage. Moreover, we observe similar transition patterns across wealth levels.

Our findings have implications for several areas of related research. First, from the perspective of a water utility, the effect of a price change on revenues is an important consideration because utilities tend to recoup a large percentage of their fixed costs from variable charges (Beecher, 2010). Second, water utilities may be concerned with the welfare impacts of higher prices on various customer classes. In contrast to previous findings, we show that poorer households have similar demand elasticities as wealthier households. This provides the basis for future research exploring welfare implications of price changes and the affordability of water services.

PAPER 3: COMPLIANCE WITH STATE MANDATES FOR WATER CONSERVATION: THE ROLE OF SOCIAL OPPROBRIUM

3.1 Introduction

Decentralized management of natural resources is often promoted as a policy objective because local agencies have better knowledge of the environmental and socio-economic problems that they face than do higher-level government institutions (Ostrom, 2000; Kwon, Berry and Feiock, 2009). However, local agencies may make decisions based on short-term objectives that often result in socially inefficient outcomes (e.g. Yaffee, 1997). Consequently, higher-level government institutions (e.g. state, federal, or national governments) intervene to coordinate local actions through a centralized, top-down mandates with specific requirements (Brewer and Stern, 2005). Significant implementation gaps, however, arise between legislative objectives and real-world outcomes because compliance with mandates is not automatic (Stewart, 1977; Cullingworth, 1994). Local agencies' priorities often diverge from those of higher-level governments (Vig and Kraft, 2012; Burby et al., 2013).[1]

In this paper, I provide new insights into the extent to which local agencies comply with centralized government mandates in the context of water conservation.[2] Overall, I do not find evidence that mandating objectives leads to intended results. Moreover, I show

[1]Diverging priorities is especially prominent in the context of planning for natural hazards (Rossi et al., 1982; Cigler, Stiftel and Burby, 1987; Godschalk, Brower and Beatley, 1989).

[2]In the United States, states have the legal authority to establish priorities for how water is used among users at various spatial scales (e.g. Hanemann, Dyckman and Park, 2015)

that compliance is higher in service areas where customers actively complain about "water waste" than in service areas where customers do not. During droughts, water utilities often encourage customers to anonymously report instances where other customers are using water in ways that are deemed "wasteful" as a passive enforcement mechanism. In this context, private citizen activism appears to be an overlooked aspect of local agency compliance.

I study the use of mandates for water conservation using data on urban water utilities in California subject to a drought-related conservation mandate–Executive Order (EO) B-29-15. Under EO B-29-15, the State of California mandated that large urban water utilities collectively reduce water production (i.e. conserve water) by 25% between June 2015 through May 2016 (SWRCB, 2015*a*).[3] Typically, this 25% target would be uniformly applied to all water utilities. However, the designated state agency–State Water Resource Control Board (SWRCB)–assigned each water utility a different conservation target using a multi-threshold assignment rule based on the average amount of water used by residential users (SWRCB, 2015*b*).[4] Each utility, in turn, was responsible for managing demand among their residential customers. This institutional feature of EO B-29-15 provides an opportunity to study a large number of heterogeneous local agencies facing a common drought shock with potentially different externally imposed incentives to pursue water conservation.

Over the course of EO B-29-15, urban water utilities collectively achieved reduced water production by 24.5%, just shy of the intended 25% objective. From a policy perspective, EO B-29-15 was notable because it was the first in a series of policy decisions to promote

[3]Produced water refers to the total amount of potable water from groundwater, surface water, and water purchased from other water utilities. Water that was produced but not used in a service area did not count towards the total.

[4]This is measured in terms of residential gallons per capita per day (R-GPCD).

"conservation as a way of life" in California.[5] At the water utility level, however, the extent to which the mandate itself led to increased conservation is unclear because there were many cases of both under and over compliance. For instance, approximately 18% of water utilities subjected to EO B-29-15 reduced water production by more than 10% above the conservation target assigned to them while 28% failed to meet their target. Studying California's experience with EO B-29-15 can help shed light on the extent to which mandated objectives explain conservation outcomes. Understanding the extent to which mandating objectives induces conservation at the water utility level can inform future conservation policy.

My approach builds on previous work that examines decentralized management through the lens of principal agent theory (Tommasi and Weinschelbaum, 2007; Estache, Garsous and da Motta, 2016).[6] Unable to perfectly control or monitor local water utilities, state governments need the cooperation of local-water utilities to implement programs to achieve desired policy objectives and provide sufficient incentives to do so. Mandates promote conservation through two mechanisms: (1) increasing political acceptance of local conservation efforts by shifting some of the responsibility from local water utilities to the state agency, and (2) enforcement through a coercive regulatory approach consisting of a threat of monetary fines and legal action against the water utility as punishment mechanisms for noncompliance.[7] Divergent priorities in the context of drought manifests through conflicting incentives that

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[5]"Making conservation a way of life" is a slogan used the State Water Resources Control Board and the Department of Water Resources.

[6]Other studies largely focus on welfare implications. Water conservation mandates, for instance, often curtail or limit access to water. These limitations in water access are conceptualized as supply disruptions that may translate into significant welfare losses (Buck, Nemati and Sunding, 2016) but reduced greenhouse gas emissions (Spang, Holguin and Loge, 2018).

[7]This characterization is based on May and Williams's (1986) conceptual framework of state approaches for managing natural hazard risks. See Berke et al. (2006) and Dyckman (2016) for reviews on how state mandates are characterized.

local water utilities may face to conserve water. On the one hand, water utilities want to ensure continuity of service and avoid supplies falling below minimum reserve levels. On the other hand, water utilities face several disincentives for engaging in conservation depending on local situational factors (Dalton and Burby, 1994). Notably, water utilities may be sensitive to social and political pressures exerted by their customers against aggressively pursuing conservation (Mullin, 2009; Teodoro, Zhang and Switzer, 2018).

Given the uncertainty in drought duration, water utility managers therefore often "weigh the risks of delay against the potential public relations problems caused by 'false alarms' " (TCEQ, 2005). As a result, water utilities often delay pursuing conservation as long as possible (Walker, Hrezo and Haley, 1991). State governments, however, have a clear stake in reducing the risks of drought given the significant economic costs, including the costs of disaster assistance (Schwab et al., 1998; Wilhite, 2000).[8]

In the case of mandates for water conservation, however, there is a second problem as water utilities must rely on their customers to reduce their water consumption to achieve desired outcomes. To pursue conservation, water utilities may implement one or more strategies to manage demand, including public awareness campaigns, rebates for turf replacement or water efficient fixtures, mandatory watering restrictions (caps on usage), and pricing strategies. These strategies are referred to as demand-side management (DSM) strategies. The amount of conservation achieved at the water utility level is therefore ultimately due to reductions by residential customers. The two-part nature of the problem presents a challenge for states as they usually do not observe water utilities actions. In the event that states observe water utilities' actions, states may not easily interpret these actions because water

[8]The cost that a typical drought episode incurs on a state's economy, for instance, is approximately $9.5 billion (National Integrated Drought Information System, 2018).

utilities may implement the same strategy with varying degrees of "implementational intensity" (Halich and Stephenson, 2009). To account for the two-part nature of the problem, I use a double-principal-agent framework as a heuristic device. This framework has been used in several studies on managing fisheries (Jensen and Vestergaard, 2001; Bailey et al., 2016). To my knowledge, this is the first paper to use this framework to study a mandate in the context of droughts.

Empirically, I assess the extent to which the mandate drove water utilities' reductions in produced water by exploiting quasi-experimental policy variation in the assignment of conservation targets (SWRCB, 2015*b*). Significantly, water utilities under the California mandate had no direct control over the specific conservation target they were assigned. At each cutoff used to assign conservation targets, water utilities with similar average residential water usage were therefore assigned different conservation targets. This policy therefore approximates a random assignment mechanism around the cutoffs. Thus, I build treatment and control groups and estimate the amount of conservation that can be attributed to the mandate using a regression discontinuity design.

I show that public involvement in reporting instances of "water waste" helps explain reductions in water production. Water utilities heavily relied on private citizens anonymously reporting cases of "water waste." Customers and the public at large were encouraged through media campaigns to report sightings of water running down the street, sprinklers on during the middle of the day, or other potential instances of water waste.[9] A plausible explanation is that people who call in with a water waste complaint were likely driven by a combination of strong sense of environmental responsibility, referred to as "warm glow" in the literature on

[9]Media campaigns were largely local initiatives. The State Water Resource Control Board and other state agencies were also involved in media efforts by issuing press releases, giving interviews, and were also active on social media platforms.

intrinsic motivation (e.g. Van Der Linden, 2015), and preferences that depend on the actions of others, referred to “nosy” preferences (e.g. Danchin et al., 2004; Dave and Dodds, 2012). As a result, increased community involvement should result in higher levels of conservation.

My findings suggest that, in the case of California, the ability of higher-level government to achieve designated water conservation goals through mandated objectives may be limited in spite of aggressive efforts to promote conservation at the local level. I find that the water utilities serving customers that actively participate in the enforcement process by reporting instances of water waste are able to achieve higher amounts of conservation during the mandated conservation period. These findings are in line with previous studies on the efficacy of enforcement (Halich and Stephenson, 2009) and the literature on the importance of intrinsic motivations for environmental sustainability (Van Der Linden, 2015).

3.2 Conceptual Framework

My approach builds on previous work that examines decentralized management through principal agent theory. Principal-agent models have been widely used to study situations in which two parties with differing incentives depend on each other to achieve objectives. Specifically, one party, the agent, acts on behalf of the second party, the principal, in a context in which the principal usually cannot perfectly monitor the agent. Moral hazard arises in situations where agents must undertake costly unobservable actions to cooperate with the principal (e.g. Stiglitz, 1974).

In the context of water conservation, higher-level governments can be thought of as acting as a de facto social planner with strong incentives to address externalities that arise from lack of conservation. For instance, the role of the SWRCB is to develop policies and regulations “to preserve, enhance, and restore the quality of California’s water resources and drinking water for the protection of the environment, public health, and all beneficial uses, and to ensure proper water resource allocation and efficient use, for the benefit of present and future generations" (SWRCB, 2018).[10] Because of the decentralized management of water resources, higher-level governments must rely on the cooperation and ability of water utilities to implement and achieve desired policy objectives.

Adopting a moral hazard framework, the use of a mandate can be thought of as an attempt by higher-level governments (principal) to vertically align water utilities' (agents) incentives with its own by "contracting" with them based on conservation outcomes. A challenge for higher-level governments is that they are generally unable to directly observe if a water utility is complying with its requirements. Notably, the actions taken by water utilities (henceforth referred to as effort) is generally not observable.

California's EO B-29-15 deviates from the classic principal-agent model in that effort is partially observable. As part of the mandate, the SWRCB required water utilities to generate monthly reports with several key pieces of information. In addition to reporting information on water production levels in each month, water utilities were required to report the number of days in the week that their customers could water outdoor landscapes and the number of actions taken to enforce their policies (e.g. number of warnings and citations issued to customers). Water utilities, however, were not explicitly required to report on other specific conservation policies that they used (e.g. pricing, rebates). These reports are the primary data source used in this study.

Though effort is partially observable, a moral hazard framework is nonetheless useful as a heuristic device to understand compliance with EO B-29-15. Notably, it is often the

[10]Though it is well recognized that there may be significant differences between scientific assessments of environmental problems and legislative objectives (Sebek, 1983; Sorian and Baugh, 2002; Dodson, Geary and Brownson, 2015), they are beyond the scope of this paper.

case that a water utility will adopt DSM strategies but not enforce them even in the context of a state mandate for water conservation. Water utilities may also implement the same DSM with varying degrees of "implementational intensity" (Halich and Stephenson, 2009).[11] Importantly, DSM strategies vary in the amounts of monitoring and enforcement they require. Price-based strategies, for instance, are appealing because they theoretically require little enforcement. Implementing price-based strategies can be difficult because of equity concerns (Maggioni, 2015). Use of mandatory usage restrictions requires water utilities to exert effort (e.g. dedicate staff and resources) to monitor compliance. Water utilities must also monitor for compliance with other non-price DSM strategies such as rebates for turf replacement and indoor water fixtures. The financial and implementational onus of monitoring and enforcement is borne by the water utilities, with little to no help from the state. Water utilities must trade off the costs and benefits of complying with the mandate.

The SWRCB used conservation outcomes to evaluate water utilities' compliance with the mandate. Using water utility-reported information on monthly water production levels, the SWRCB reviewed water utilities' progress with their assigned target on a monthly basis. The SWRCB sent warning letters to water utilities between 1-5% below their assigned target, and notices of violations to those less than 5% of their assigned target.[12] Water utilities' performance was ultimately judged at the end of the mandate in May 2016. Specific actions depended on the size of the implementation gap, ranging from providing the SWRCB with further information documenting their effort to in person meetings.

[11] Differences may include the scope of the DSM and efforts to communicate the program was promoted to customers.

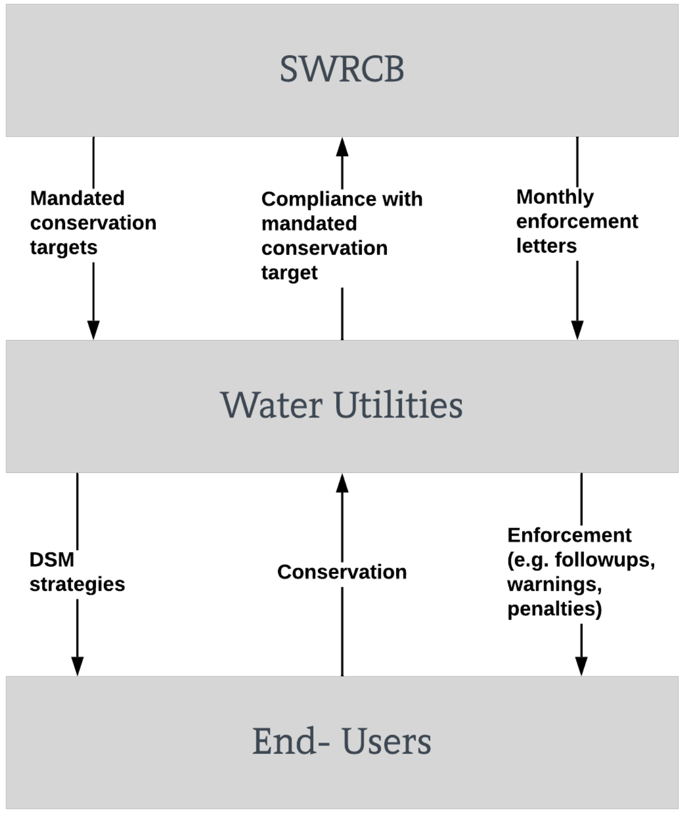
[12] Water utilities who were within 1% or that had production savings in excess of their target received notices of congratulations.

There are three possible explanations for implementation gaps. First, it is possible that local agencies may be unable to comply with mandated requirements due to financial or institutional capacity constraints (Faguet, 2014). Notably, many water utilities struggle financially or have insufficient staff to enforce policies. Second, implementation gaps may arise because local agencies may be unwilling to comply with mandated requirements due to diverging priorities (Vig and Kraft, 2012; Burby et al., 2013). Third, implementation gaps may also arise if the state is unwilling to enforce regulations and hold local agencies accountable for failing to meet mandated objectives (Berke, 1998; May and Williams, 2012). Notably, enforcing the "contract" may result in lengthy and costly legal action that the SWRCB would like to avoid.[13]

An additional challenge for the state is that water utilities' ability to conserve, in turn, depends on end-users (i.e. customers). Water utilities (principal) must rely on their customers (agents) to reduce their water consumption to achieve desired outcomes, potentially undertaking costly and unobservable actions to do so. Water utilities observe household water usage and can, in turn, "contract" with their customers on outcomes, enforcing their policies in the event of non-compliance. Furthermore, there may be multiple types of customers, some that may be easily encouraged to comply and others that might not. The two-part nature of the problem presents a challenge for the SWRCB because the level of effort that a water utility must exert will depend on characteristics of its customer base that the SWRCB may not observe. I provide a graphical depiction of the double principal-agent in Figure 3.2.1, adapted from Jensen and Vestergaard (2001).

[13]To my knowledge, there is only one instance in which the SWRCB took legal action against a water utility for failing to comply with their mandated conservation target (SWRCB, 2015*c*).

Figure 3.2.1: Illustration of Double Principal-Agent Model



3.2.1 Water Utility Incentives

During drought, water utilities can respond by increasing capacity or by promoting conservation. Despite the wide range of DSM strategies available, water utilities may face disincentives to voluntarily engage in conservation. For instance, increased conservation implies reduced revenue as less water is sold, putting financial pressures on water utilities that may be financially insecure (Kenney, Klein and Clark, 2004). The total amount of forgone net revenue due to conservation during EO B-29-15 is estimated to have been more than $500 billion (Moss et al., 2015). Moreover, pursuing conservation may be met with social pressure and have political consequences. For example, commercial customers may oppose conservation as it may be perceived as being at odds with economic growth and development. Residential customers may resist outdoor watering restrictions because of either strong preferences for lush green lawns or perceived threat to lifestyles (Brown and Hess, 2017).

Consequently, strategies that increase capacity often provide stronger incentives than demand-side strategies (Chesnutt and Beecher, 1998). For example, severe droughts prompt increased interest in reducing non-revenue water (water losses due to leaks), interest in water-sharing agreements (Zeff et al., 2016; Mozenter et al., 2018; Gold et al., 2019; Gorelick et al., 2019), and investments in water recycling and reuse, rainwater and stormwater harvesting, and desalination.[14] Supply-side measures, however, may do little to alleviate short-term constraints as they involve projects that are typically longer-term in nature. Moreover, pursuing supply-side measures can lead to the imposition of externalities on other water utilities and water users because of the shared nature of water resources. There is some evidence to suggest that resource scarcity reduces incentives to cooperate and exacerbates tendencies to act on short-term incentives by adopting a "race to the bottom for extraction-profit" strategy (Maldonado and del Pilar Moreno-Sanchez, 2016). During droughts, water utilities may increase withdrawals from shared water supply sources or excessively withdraw groundwater supplies.

Water utilities, however, also have incentives to pursue conservation voluntarily as they want to ensure continuity of service and avoid supplies falling below minimum reserve levels. These incentives tend to encourage water utilities to pursue increased conservation as droughts condition worsen. Water utilities may also face pressure from other water utilities and stakeholders to reduce withdrawals from shared water supply sources. There is also evidence that water utilities have opted to conserve water during droughts in spite of potential

[14] The Australian government, for instance, invested billions of dollars in water sources such as recycling and desalination in an effort to diversify their water supply portfolio during the "millennium drought" (Radcliffe, 2015).

political costs of doing so. For instance, Mullin (2009) shows that water utilities in Texas adopted water usage restrictions despite strong political resistance to any policies that restrict water use. Mandating water conservation can help increase political acceptance of local conservation efforts by shifting some of the responsibility from local water utilities to the state agency (Berke, 1998).

3.2.2 Household Incentives

Assuming a water utility implements one or more DSM strategies, there are two main channels through which residential households may be encouraged to conserve: extrinsic and intrinsic motivation. For example, households may conserve as a result of increased prices, usage restrictions, or the incentives to adopt new technologies due to rebates. These households would require little monitoring and enforcement.

However, the efficacy of policies that rely on extrinsic motivation may be mitigated by external factors. For example, homeowner's associations (HOAs) may require certain amount of water usage to maintain lawns.[15] It may also be the case that "significant expansion of [water] supplies can inadvertently undermine various demand management policies" (Katz, 2016). Notably, if end-users are aware of potential increases in supply, they may discount the importance of conservation. Palazzo et al. (2017) find that water utilities subject to EO B-29-15 with greater source diversity achieved less conservation. As a result of such mitigating factors, water utilities monitor for compliance and enforce their policies through reminders, warnings, and penalties. Household responses to these efforts may vary depending on the credibility of the threat, the probability of enforcement, and the size of the penalty.

[15] A law was passed to prohibit HOA from taking fining households for lack of lawn care during droughts in June 2015. Anecdotal evidence, however, suggests that HOAs may still have exerted pressure on households to continue watering their lawns during droughts and discourage turf replacement (Abel, 2015).

Households may also conserve water due to intrinsic motivations (De Young, 1985; Corral-Verdugo et al., 2002). Throughout the drought, water utilities relied on public awareness campaigns to spread awareness and the need for conservation.[16] Previous studies, for instance, have shown that the amount of newspaper coverage (Tang, Zhang, and Xu, 2015) and use of social media (Quesnel and Ajami, 2017) may have played an important role in promoting public interest in water conservation. End-users driven by a sense of environmental responsibility, i.e. warm glow, may conserve as a result of receiving information about drought conditions.

Some customers may not only be intrinsically motivated to reduce their own water consumption but may also have "nosy" preferences, i.e. preferences that depend on other customers' actions (e.g. Danchin et al., 2004; Dave and Dodds, 2012). These customers' preferences could manifest through overt opprobrium or, more discretely, through reports to local water utilities. During the drought, private citizens (customers and the public at large) were encouraged to report sightings of water running down the street, sprinklers on during the middle of the day, or other potential instances of water waste.[17] Water utilities could then use this information to follow-up on these reported sightings. This strategy provides an opportunity for citizens with "nosy" preferences to be part of the enforcement process.

3.2.3 Testable Predictions

I rely on a double-principle framework to construct a typology of water utilities based on their level of effort (rows) and of the incentives that may drive residential households to conserve (columns), summarized in Table 3.2.1. To create this typology, I assume a sample of

[16] These campaigns may range from ads on radio and/or TV, sending out flyers, hanging up banners, or sending staff to engage with private citizens at farmer's markets.

[17] These reported sightings were reported to either the state or water utilities directly.

two household subpopulations, one driven by extrinsic motivations only and another that is also driven by intrinsic motivations. In columns 1 and 3, I assume that both subpopulations coexist whereas in columns 2 and 4, I assume that the subpopulation driven by intrinsic motivations is nonexistent. In columns 1 and 2, the population that is driven by extrinsic motivations is motivated by the incentives of DSMs alone. In columns 3 and 4, the incentives of DSMs alone are insufficient, so utilities will require additional enforcement to conserve water. In each box, I generate predictions for the relative amount of effort the water utility will exert as well as the relative number of cases of water waste reported by the public.

In boxes 1 and 2, water utilities willing and able to comply with the mandated requirement do not have to necessarily exert much effort as households respond to DSM incentives. In box 1, citizens motivated by warm glow report any sighted cases of water waste further reducing the need to exert effort to monitor compliance.

In boxes 3 and 4, water utilities that wish to cooperate must now exert effort to implement their policies and households do not respond to the incentives signaled by DSMs. Water utilities in these boxes may fail to conserve sufficiently, but not for lack of effort.

In boxes 5-8, water utilities are not sufficiently motivated to pursue conservation, yet may still reach conservation targets. For instance, in a service area represented by box 5, a water utility may not follow up with publicly reported cases of water waste from intrisincally motivated households. In spite of low effort, compliance may still be achieved in this scenario because households respond to DSM incentives. In comparison, a service area represented by box 7 still has intrinsically motivated households but the population does not respond to DSM incentives. These water utilities will likely have a problem complying with the mandate.

The challenge for the state in evaluating whether conservation targets were achieved due to compliance with the mandated requirements is that service areas with very different underlying water utility and household behavior are difficult to distinguish. For example,

Table 3.2.1: Typology of Service Areas: Effort Exerted by Water Utilities and Reporting by Households

		Residential Population			
		Respond to DSM Strategies		Do Not Respond to DSM Strategies	
		Intrinsic Motivations		Intrinsic Motivations	
		Yes	No	Yes	No
Water Utilities	Cooperating with mandate	(1) Low effort High reports	(2) Low effort Low reports	(3) High effort High reports	(4) High effort Low reports
	Not cooperating with mandate	(5) Low effort High reports	(6) Low effort Low reports	(7) Low effort High reports	(8) Low effort Low reports

Note: Effort refers to relative number of followups taken water utilities and reports refer to the relative number of complaints received from private citizens.

service area types 1, 5 and 7 would all have similar measures of underlying behavior (e.g. monthly effort reports from utilities and a count of citizen complaints). Of these, it is probable that service areas 1 and 5 would achieve compliance. However, only utilities in service area 1 would have been responsive to the mandate. Most importantly, in either case, conservation is likely attributable to household behavior and not to the mandate. Using this framework, I can test two assumptions related to these issues:

- Do mandates resolve the first principal-agent problem? If so, higher conservation target should mean more conservation.

- Do "nosy" preferences matter? If not, there should be no difference in the amount of conservation between water utilities with high and low amounts public reporting of "water waste" for water utilities with similar effort levels (between boxes 3 and 4 in Table 3.2.1).

3.3 Data

3.3.1 State Water Resource Control Board

The SWRCB dataset consists of information for all water utilities serving at least 3,000 residential connections that are subject to the mandate.[18] This information includes each water utility's primary water system identifier assigned by U.S. Environmental Protection Agency's Safe Drinking Water Information System, monthly self-reported water production, average residential usage, 2013 production levels, conservation target, number of residential customers. The dataset also contains information on the number of reported cases of water waste reported by the general public and information on enforcement as well as an optional comment section for additional information related to enforcement.

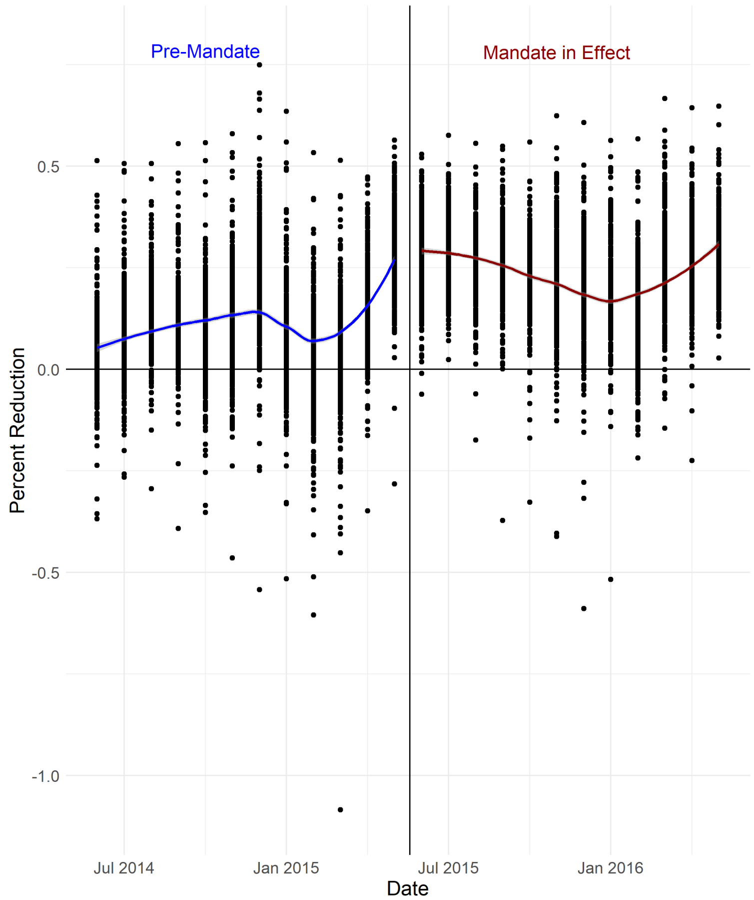
3.3.1.1 Conservation Targets

Overall, statewide conservation amounted to 24.5% (SWRCB, 2016b). Figure 3.3.2 shows average reductions in monthly water production relative to the corresponding month in 2013 for both the year before the mandated conservation period (prior to May 2015) and during the mandated conservation period. Though there was variation in the monthly reductions, water utilities generally reduced water production more during the mandated conservation than during the previous year.

The SWRCB created a tier-based list of conservation targets based on specific ranges of average residential gallons per capita per day (R-GPCD) during July – September 2014 (SWRCB, 2015b). R-GPCD is calculated as total water sold to the residential sector divided

[18] A total of 16 water utilities are dropped from the analysis. Four water utilities are dropped because they received exemptions from initial conservation target were granted. An additional 12 utilities are dropped because they failed to submit at least one month of data to the SWRCB.

Figure 3.3.2: Reductions in Water Production



by the service area population. This approach has been commonly used to measure efficiency in previous conservation efforts (e.g. CA Water Conservation Act 2009) and is also the basis for current policies (Quinn, 2012). Based on these R-GPCD ranges, each urban water utility in the state was assigned a conservation target that ranged between 8% and 36%. These targets represent conservation objectives defined as percent reduction in water production relative to 2013 levels and were judged on a cumulative basis from June 2015 through the end of the mandatory conservation period. Specifically, the SWRCB compared the sum of monthly water consumption starting June 2015 to the sum of corresponding months of 2013 (SWRCB 2015a). Water utilities that met the adjusted conservation standard were considered compliant.

On average, the mean cumulative water production savings over the entire period was 25.9% with a standard deviation of 7.3%.[19] All of the water utilities in the sample reported at least 6.0% savings by the end of the mandatory conservation period, with a maximum savings of 45.4%. Conservation was not uniformly achieved relative to the assigned conservation targets. As shown in Table 3.3.2, only 288 utilities (72%) met or were within one percentage point of their conservation standard (SWRCB, 2016c).

Table 3.3.2: Production Savings Achieved Relative to Conservation Targets (June 2015-May 2016)

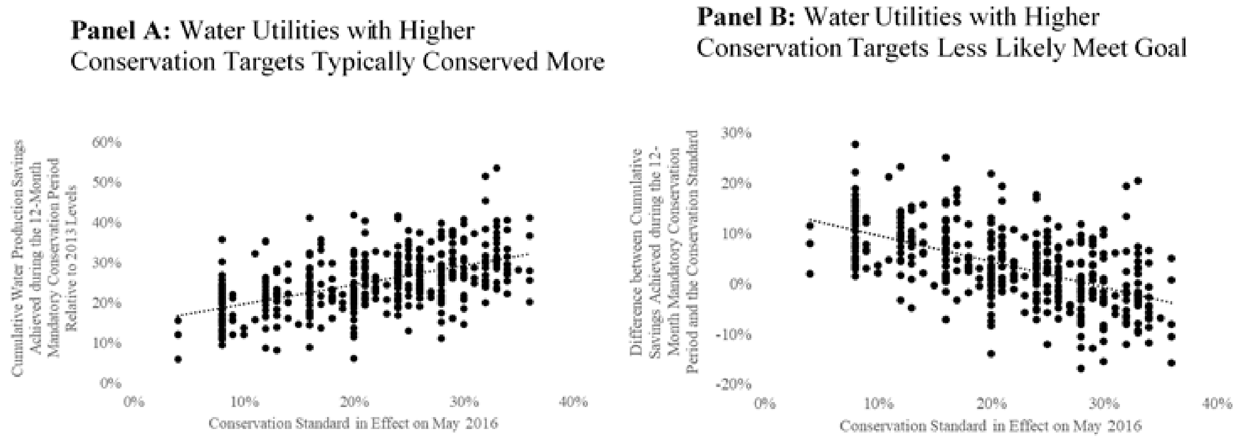
Compliance	**Number of Water Utilities**	**Percent of Water Utilities**
Failed to meet conservation standard by more than 10 percentage points	12	3%
Failed to meet conservation standard by 1 - 10 percentage points	98	25%
Met conservation standard by +/- 1 percentage point	34	8%
Exceeded conservation standard by 1 - 10 percentage points	182	46%
Exceeded conservation standard by more than 10 percentage points	72	18%
Total	398	100%

[19] Aggregate conservation is not necessarily the same as mean conservation:

$$\frac{\sum_i^N X_i^{2015} - \sum_i^N X_i^{2013}}{\sum_i^N X_i^{2013}} \neq 1/n \sum_i^N \left(\frac{X_i^{2015} - X_i^{2013}}{X_i^{2013}}\right) \tag{3.1}$$

As shown in Figure 3.3.3, water utilities with higher conservation targets achieved greater conservation levels (Panel A) but they were also generally less successful in meeting their targets than those with lower targets (Panel B).

Figure 3.3.3: Cumulative Savings Relative to Conservation Targets



3.3.1.2 Reported Cases by the General Public

Public awareness campaigns ranged from ads on radio and/or TV, sending out flyers, hanging up banners, or sending staff to engage with private citizens at farmer's markets. Because these public awareness campaigns are likely to have had spillover effects, I identify each water utility's primary Neilson district market areas (DMAs) to capture the general effect of public awareness of campaigns. Each of these areas represents regions in which households can be expected to have received the same (or similar) media content (e.g. television, radio, newspaper, internet). I obtain spatial boundary information for DMAs from Gaurav (2016).

As part of these campaigns, customers and the general public were asked to be the "eyes and ears of the community" by anonymously reporting instances of leaks, sightings of water running down the street, sprinklers on during the middle of the day, or other potential instances of "water waste" (e.g. Glendale Water and Power). In addition to a statewide portal, many water utilities had their own local hotlines and portals. Most of these reported instances of water waste were reported to a statewide portal.[20] Those reporting instances of water waste did not need to know the name of the local water utility or how to contact them. The only information required was the nature of water waste observed, the address at which it was observed, and had the option of attaching pictures. Water utilities were then able to search for their service area and then follow up on the complaints. Water utilities were required to log the number of publicly reported cases in their monthly reports to the SWRCB, referred to in the dataset as *complaints received*. I use this information to construct a measure of relative private citizen involvement in the enforcement process, identifying a water utility's service area as being highly involved if the total number of complaints per capita received over the course of the mandate is above the median, and low otherwise.

3.3.1.3 Water Utility Enforcement

Water utilities reported several metrics related to how intensely they implemented their policies. First, they reported on the total number of reported cases they followed up on, referred to in the dataset as follow-ups. The number of follow-ups includes both cases that were reported by private citizens–*complaints received*–from hotlines or online portals and those reported by water utility staff. Water utilities also reported on the number of warnings issued to violators as well as the number of penalties issued, referred to in the dataset respectively as *warnings* and *penalties*. Water utilities were also required to report the number of drought-surcharge penalties issued, referred to as *rate penalties*.

In reading the optional enforcement comments, it is evident that there were several inconsistencies in how water utilities defined and reported information on *warnings*, *penalties*,

[20]The state portal for reporting instances water waste can be accessed at https://savewater.ca.gov/.

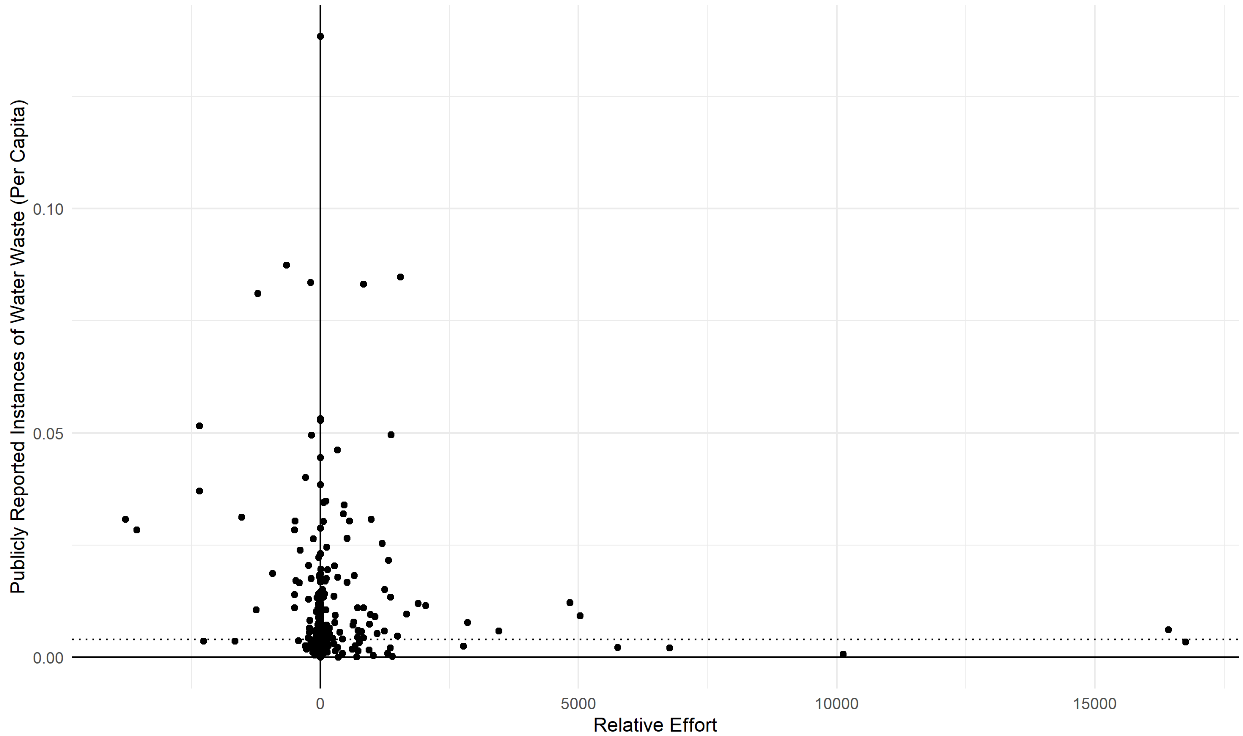
and *rate penalties*.[21] Namely, several definitions of *rate penalties* emerged. Some utilities defined these as surcharges associated with usage in higher tiered rates, hence as temporary per-unit charges that effectively act as price increases. Others issued rate penalties for exceeding a usage target or water budget allowance, overlapping in definition with *penalties*.[22] Others noted that they did not "issue fines or penalties in the legal sense of those terms," but functionally did the same by charging a drought surcharge. Moreover, there are inconsistencies in which field this information was recorded in month-to-month; the same water utility would often switch fields *penalties* and *rate penalties* were recorded in. Similarly, some water utilities defined *warnings* in ways that overlapped with *follow-ups* or with *penalties*.

Given the issues in measuring the number of *warnings* and *penalties*, I define effort in terms of the number of *follow-ups*. Though Zhang and Teodoro (2018) argue that it reflects the degree to which water utilities conveyed information about their policies, I argue that it also reflects the degree to which water utilities exert effort as it is captures instances in which water utilities actively seek out cases of water waste. Assuming the number of public complaints is a lower-bound for the number of instances of water waste, water utilities taking a more passive approach might only rely on public complaints of water waste or might not follow-up on all the cases that were reported by the public. Water utilities taking a more active role towards enforcement would theoretically follow-up on more cases than were reported. I construct a measure of relative effort, identifying a water utility as exerting *High* effort if the difference between *follow-ups* and *complaints received* is positive and *Low* effort

[21] Water utilities often neglected to record information in certain months and provided information along with subsequent months.

[22] In an interview, representatives of San Jose Water described their use of rate penalties as not being "a rate increase, but a penalty program to encourage conservation" (Rogers, 2017).

Figure 3.3.4: Number of complaints received per capita and the number of cases followed up by water utilities



otherwise. In Figure 3.3.4, I plot the relationship between complaints received per capita relative to the number of cases followed up on by water utilities.

3.3.2 Urban Water Supply Plans

I supplement the SWRCB dataset with information from each water utility's urban water management plans submitted to California's Department of Water Resources (CA DWR) in 2015 to capture water utility characteristics that may influence water utilities' incentive to pursue conservation. These factors include their primary water source, exposure to severe drought conditions, and factors associated with taking on political risk. To do so, I first obtain spatial boundaries for each water utility in the SWRCB dataset by joining them to a map of all California water utilities obtained from CA DWR.

3.3.2.1 Residential Gallons Per Capita Per Day

The SWRCB's assigned conservation targets based on R-GPCD. This assignment rule assumes that water utilities with similar R-GPCDs are similar. It may be possible, however, for two water utilities with similar R-GPCD's to differ in the proportion of water that is used by their single family customers versus multifamily residential customers. This difference would impact ability to conserve. In comparing usage characteristics by sector (single family residential, multi-family residential, commercial, other) for five water utilities subject to EO B-29-15, Gaur, Smith and Kostiuk (2019) find that usage among single family households generally reduced while water usage in other sectors (including multifamily residential water usage) remained generally uniform. I use information from each water utility's urban water management plans submitted to the DWR in 2015 to calculate the percentage of residential water usage that is single family. I also calculate the percentage of water that water utilities budget for commercial and landscaping purposes.

3.3.2.2 Groundwater Source

Water utilities differ in where they obtain their water sources from. The natural resources management literature would suggest that water utilities that are more dependent on ground water sources would have less incentive to conserve (Madani and Dinar, 2012). Groundwater is cheap to extract. There is very little amount of information on the amount of groundwater that is available. Additionally, drought plans generally give limited attention to long-term management of groundwater sources (Langridge et al., 2018). In California, legislation for groundwater management was signed in 2014. Most of the implementation deadlines, however, went into effect after EO B-29-15. I obtain information on water utilities' primary water source from U.S. Environmental Protection Agency's Safe Drinking Water Information System.

3.3.2.3 Investor-Owned Water Utilities

Lastly, the propensity for local agencies to take on political risk depends on local sociopolitical context (West, Lee and Feiock, 1992). Notably, the ownership structure of the water utility may influence its decisions to take on political risk. For instance, investor owned-utilities may be more sensitive to lost revenue than a public water utility. Investor-owned water utilities, however, are regulated by California's Public Utilities Commission (CPUC) and have decoupled rates. This mechanism enables them to recover any forgone revenue due to conservation. Teodoro, Zhang and Switzer (2018) further argue that regulation via the CPUC provides a type of political decoupling, insulating investor-owned utilities from some of the political pressures that public utilities may face as a result of being directly accountable to voters. Also using data on EO B-29-15, Teodoro, Zhang and Switzer (2018) find evidence that investor-owned water utilities were more likely to reduce water production more than public water utilities during the mandate. I identify investor-owned water utilities using a list of the water utilities regulated by California's Public Utilities Commission (CPUC).

3.3.2.4 Regional Planning

Higher-level governments often encourage horizontal coordination among local agencies to promote regional collaboration (Burby et al., 1997). Horizontal coordination is meant to improve resource planning by increasing local capacity and by aligning incentives among neighboring agencies that share resources. In the context of water management, horizontal coordination could also be a tool to mitigate over-withdrawing shared water supplies. Though horizontal coordination was not mandated as part of EO B 29-15, water utilities are encouraged to collaborate with "other water suppliers that share a common [water] source, water management agencies, and relevant public agencies, to the extent practicable" (DWR, 2015).

3.3.3 Drought Conditions

Drought conditions vary by geography. Some water utility service areas may have experienced severe drought conditions for longer periods of time than other service areas with the same assigned conservation target. To account for this potential difference, I further supplement the SWRCB dataset with information on drought conditions using data obtained from the National Oceanic and Atmospheric Administration (NOAA). Drought severity is measured using Palmer Drought Severity Index (PSDI), a measure of relative dryness based on a physical water-balance model.

3.4 Estimation

I examine the effectiveness of the assigned conservation targets on production savings using a regression discontinuity design. This approach estimates the effect produced solely by the assigned target by exploiting discontinuities in cutoffs used to assign treatment.[23] A key feature of regression discontinuity design is the existence of a score that determines treatment assignment for each unit in the sample given a cutoff score.[24] Units with scores above the cutoff score are considered "treated," while units whose score is below the cutoff are not. As discussed in Section 2.1, the SWRCB assigned conservation targets using an assignment rule based on R-GPCD during the summer of 2014. This rule can be expressed by the following piecewise function, $S(d_i)$, where variable d_i represents water utility i's GPCD in the summer of 2014 and c_i represents the nearest cutoff:

[23] Regression discontinuity design was first used Thistlethwaite and Campbell (1960) as an alternative method for evaluating social programs. See Jacob et al. (2012) for a review.

[24] A score is sometimes referred to as an index or a running variable.

$$S(d_i) = \begin{cases} 8\%, & 0 < d_i < 65, \\ 12\%, & 65 \leq d_i < 80, \\ 16\%, & 80 \leq d_i < 95, \\ 20\%, & 95 \leq d_i < 110, \\ 24\%, & 110 \leq d_i < 130, \\ 28\%, & 130 \leq d_i < 170, \\ 32\%, & 170 \leq d_i < 215, \\ 36\%, & 215 \leq d_i \end{cases}$$

An important feature of the assignment mechanism used by the SWRCB is that it essentially generates a random assignment of the treatment among utilities around the cutoffs. From the perspective of the SWRCB, the choice to assign two water utilities with near identical R-GPCD different conservation targets is arbitrary.

A potential threat to validity would arise if water utilities were able to self-select into particular cutoffs by manipulating their July-August 2014 R-GPCD. This is unlikely to have been the case for two inter-related reasons. First, EO-29-15 is the first mandate in California's history and its structure is different from mandates used in other states to manage drought. Therefore, it is unlikely that water utility in 2014 knew that a mandate would be issued in 2015 or how it would be designed. Second, cutoffs based on 2014 R-GPCD were devised after the announcement of the mandate in 2015.[25] Water utilities, therefore, could not have influenced their R-GPCD during July-August 2014 in direct anticipation of the mandate. Even if water utilities had some influence over the assignment variable, their inability to precisely manipulate it is sufficient to assume that variation in treatment near the threshold is random (Lee and Lemieux, 2010).

I examine the effect of receiving a higher conservation target using a pooled regression discontinuity approach, comparing water utilities with a higher target to similar water utilities that received lower targets. Formally, this implies that the average effect of treatment does not vary with the running variable. Treatment status can formally be defined as

$$\hat{\tau} = \lim_{x \downarrow 0} E[Y_i | x_i = \xi] - \lim_{x \uparrow 0} E[Y_i | x_i = \xi]$$

where $\hat{\tau}$, represents a "weighted average across cutoffs of the local average treatment effects across all units facing each particular cutoff value" (Bertanha, 2019).

I estimate the local average treatment effect (LATE) for this sharp discontinuity using ordinary least squares (OLS), given by (3.2):

$$Y_i = D_i \hat{\tau} + \beta X_i + \epsilon_i, \tag{3.2}$$

where D_i denotes treatment status. Following Calonico et al. (2019), I include additional covariates, represented by X_i, to account for differences among utilities with similar GPCDs

[25] Following the proclamation of EO-29-15 in April, 2015, there were several weeks of public comments. These comments were used by the SWRCB in formulating the regulations that were officially adopted at the SWRCB's May 5th meeting.

using a simple covariate-adjusted estimator.[26] First, I control for cumulative percent reduction that water utilities achieved in the year prior to the mandate to account for the possibility that past ability to conserve may be a predictor of future conservation results. A concern among utilities is that past efforts to achieve conservation make it harder to achieve conservation in the future (referred to in the literature as demand hardening). Second, I control for the number of months that a water utility received warnings from the SWRCB for falling behind their objective. Third, I control for water utility characteristics, including the percentage of residential water usage that is single family, an indicator variable for whether or not the utility is regulated by public utility commission, and an indicator variable to indicate if groundwater is the primary source of water. Following the SWRCB's methodology, I identify the months in which water utilities received warnings from the SWRCB and control for the number of letters water utilities received. Lastly, I include fixed effects for district market areas to control for media-related spillover effects that would have affected awareness levels across service areas.

I start by estimating (3.2) using the percentage cumulative water production savings achieved by utilities during the mandatory conservation period relative to their 2013 production levels as the outcome of interest, Y_i. I provide estimates of (3.2) for key coefficients in Table 3.4.3. I provide results for several different distance bandwidths to serve as a sensitivity check; narrowing the bandwidth ensures increased similarly in terms of R-GPCD at the expense of fewer observations. Starting with the estimated coefficients for the effect of receiving a higher conservation target, the results show that the differential incentives provided by the mandate likely had little effect. The coefficients are generally small, statistically

[26] This estimate is consistent under the assumption that the treatment has no mean effect on the covariates at the cutoffs.

insignificant, and negative for most specifications, meaning that water utilities with higher conservation targets generally did not save more as their counterparts with lower targets.

Turning to the effects of water utility effort and public involvement in enforcement, the results suggest that the effect of public involvement was significant. All else equal, water utilities with high effort and high complaints received conserved at least 2.1% more than water utilities with low effort and low complaints. Water utilities with high effort and low complaints conserved at least 1.7% less than water utilities with low effort and low complaints.

I re-estimate (3.2) using the difference between the cumulative savings achieved during the mandate relative to the assigned conservation target as the dependent variable. Positive differences indicate water production savings that exceed assigned conservation targets whereas negative differences indicate water production savings less than assigned conservation targets. Consistent with Figure 3.3.3, the results in Table 3.4.4 indicate that higher conservation targets were less able to meet their assigned conservation target. The results are negative, albeit statistically insignificant.

With respect to water utility effort and public involvement in enforcement, higher levels of citizen involvement in enforcement has a statistically significant effect on water utilities' ability to meet their target. As shown in Table 3.4.4, water utilities that exerted high effort and had a high amount of reported instances of "water waste" met their target by approximately 2% more than water utilities exerting low effort and low amounts of reported instances of "water waste." Water utilities with high effort but low reported instances of "water waste" were not statistically different from water utilities with low effort and low reported instances of "water waste."

3.5 Conclusion

The trend of higher-level government institutions using mandates as emergency measures as means of imposing safeguards and mitigating the consequences of droughts can be expected to continue. It is therefore important to draw lessons from previous experiences to inform future policy. In this paper, I use data on California water utilities subjected to a year-long conservation mandate. I exploit the mandate's multi-tier approach to assigning conservation targets to estimate the extent to which water utilities conserved water due to the mandate itself.

I find that mandates don't necessarily solve the principal-agent problem that state regulators often face. My results indicate that water utilities did not strongly respond to the incentive to conserve generated by the assigned cutoffs. Part of this can be explained by the two-part nature of the problem. Throughout the drought, media campaigns were used to encourage private citizens to anonymously identify and complain about other users that used water in ways deemed "wasteful." Notably the results of this study also suggest that private citizen activism appears to be an overlooked aspect of local agency compliance. Water utilities with customers that actively complained about "water waste" were not only able to conserve more but also more easily meet their assigned target. Furthermore, aggressive effort in the absence of public support may not yield desired objectives. Notably, water utilities exerting high effort but low reported instances of "water waste" were not statistically different from water utilities exerting low effort and low reported instances of "water waste."

This study also highlights the need for improving reporting standards. The data reporting requirements of the SWRCB are laudable in that it improves transparency of information. Yet, there were substantial inconsistencies regarding how water utilities reported data on warnings, penalties, and rate penalties that likely stemmed from confusion over definitions.

Table 3.4.3: Results for Cumulative Production Savings

	Bandwidth			
VARIABLES	Distance<4	Distance<5	Distance<6	Distance<7
Higher conservation target	1.108	1.113	-0.385	-0.465
	(1.780)	(1.510)	(1.513)	(1.397)
Distance from target	-0.433	-0.447*	-0.0140	-0.0133
	(0.383)	(0.252)	(0.220)	(0.178)
High complaints, low effort	3.284**	2.282**	2.035*	1.953*
	(1.417)	(1.147)	(1.165)	(1.113)
Low complaints, high effort	-0.935	-0.429	-0.462	-0.511
	(1.123)	(1.012)	(0.979)	(0.925)
High complaints, high effort	3.395***	3.582***	3.390***	3.190***
	(1.228)	(1.119)	(1.100)	(1.056)
Number of SWRCB letters received	-0.215**	-0.194**	-0.190*	-0.153*
	(0.107)	(0.0964)	(0.0969)	(0.0910)
Number of months in severe drought	0.0748	0.0392	0.162	0.181
	(0.161)	(0.123)	(0.127)	(0.126)
Regulated by CPUC	3.935**	2.869**	1.899	1.585
	(1.557)	(1.239)	(1.231)	(1.188)
Percent commercial	1.671	1.972	0.446	0.230
	(1.746)	(1.607)	(1.626)	(1.631)
Primarily supplied by groundwater	-1.103	-1.264	0.156	0.180
	(1.147)	(0.980)	(0.953)	(0.898)
Landscape	-0.519	-0.152	0.442	-0.0331
	(1.060)	(0.966)	(0.922)	(0.825)
Regional urban management plan	-0.0612	-0.0423	-0.0388	-0.0297
	(0.0616)	(0.0476)	(0.0400)	(0.0393)
Percent residential single family	7.368**	7.304**	9.144***	9.365***
	(3.378)	(2.931)	(2.801)	(2.635)
Cumulative savings year prior	0.441***	0.479***	0.548***	0.584***
	(0.0941)	(0.0822)	(0.0802)	(0.0784)
Constant	11.55***	11.14***	8.398***	8.189***
	(3.855)	(3.211)	(3.119)	(2.853)
Observations	111	145	169	192
R^2	0.666	0.665	0.616	0.624

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.4.4: Results for Production Savings Relative to Assigned Conservation Target

	Bandwidth			
VARIABLES	Distance<4	Distance<5	Distance<6	Distance<7
Higher conservation target	-0.281	-0.278	-0.968	-1.066
	(1.812)	(1.561)	(1.479)	(1.383)
Distance from target	-0.345	-0.294	-0.119	-0.0673
	(0.390)	(0.260)	(0.215)	(0.176)
High complaints, low effort	2.053	2.701**	1.901*	1.398
	(1.442)	(1.186)	(1.139)	(1.102)
Low complaints, high effort	0.963	1.431	1.293	1.208
	(1.143)	(1.047)	(0.957)	(0.916)
High complaints, high effort	3.560***	2.941**	2.774**	1.791*
	(1.249)	(1.157)	(1.075)	(1.046)
Number of SWRCB letters received	-0.840***	-0.806***	-0.812***	-0.845***
	(0.109)	(0.0997)	(0.0947)	(0.0901)
Number of months in severe drought	0.0429	0.0324	0.104	0.0818
	(0.164)	(0.127)	(0.124)	(0.124)
Regulated by CPUC	3.030*	1.849	1.219	0.906
	(1.584)	(1.281)	(1.203)	(1.176)
Percent commercial	-2.835	-3.234*	-4.282***	-3.891**
	(1.776)	(1.662)	(1.589)	(1.615)
Primarily supplied by groundwater	-0.820	-1.333	-0.232	-0.0256
	(1.167)	(1.013)	(0.931)	(0.889)
Landscape	-0.211	-0.433	-0.0703	0.168
	(1.078)	(0.999)	(0.901)	(0.817)
Regional urban management plan	-0.0562	-0.0795	-0.0330	-0.0357
	(0.0627)	(0.0492)	(0.0391)	(0.0389)
Percent residential single family	-4.750	-3.021	-2.868	-2.443
	(3.437)	(3.030)	(2.738)	(2.609)
Cumulative savings year prior	0.202**	0.266***	0.344***	0.353***
	(0.0958)	(0.0850)	(0.0783)	(0.0776)
Constant	7.810**	6.379*	4.613	4.801*
	(3.923)	(3.320)	(3.048)	(2.825)
Observations	111	145	169	192
R^2	0.731	0.708	0.674	0.666

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 1.1 Innovation Results

The results from estimating (1.7) are in Appendix Table 1.1.1:

Appendix Table 1.1.1: Main Results

	Water-Related Technologies			
	All	Conservation	Supply	Quality
Cluster in MSA	49.969***	37.762***	6.474***	10.114***
	(13.913)	(11.871)	(1.412)	(1.875)
Cluster within 50mi	21.537***	17.092***	1.916***	3.756***
	(3.581)	(3.256)	(0.245)	(0.353)
Cluster within 100mi	−1.900	−0.509	−0.617***	−1.092***
	(1.440)	(1.301)	(0.123)	(0.190)
Cluster within 150mi	0.273	−0.040	0.041	0.275
	(1.465)	(1.344)	(0.124)	(0.182)
Cluster within 200mi	−11.337***	−9.511***	−0.609***	−1.583***
	(1.845)	(1.697)	(0.123)	(0.187)
Carcinogens (lbs)	1.065***	0.743***	0.126***	0.281***
	(0.088)	(0.077)	(0.011)	(0.017)
Patenting activity in MSA	29.076***	26.783***	1.082***	1.766***
	(5.368)	(4.950)	(0.266)	(0.371)
Water patenting foreign	0.004***	0.004***	0.0004***	0.0004***
	(0.001)	(0.0005)	(0.00005)	(0.0001)
Control fun	−15.583***	−13.870***	−0.396*	−1.714***
	(3.814)	(3.609)	(0.221)	(0.382)
CEE	14.157***	9.681**	2.179***	3.709***
	(4.767)	(4.455)	(0.325)	(0.511)
MSA-EPA dist	−0.00001**	−0.00001*	−0.00000***	−0.00000***
	(0.00001)	(0.00001)	(0.00000)	(0.00000)
Northest	−4.527**	−3.978**	−0.345**	−0.486**
	(2.153)	(1.962)	(0.145)	(0.244)
Midwest	7.718*	5.803	0.767**	1.502***
	(4.056)	(3.640)	(0.301)	(0.418)
South	−6.862***	−5.999***	−0.410***	−0.721***
	(1.650)	(1.442)	(0.137)	(0.225)
Constant	33.239***	29.438***	0.223	4.128***
	(9.515)	(8.948)	(0.608)	(1.053)

Note: Effect of water technology cluster is allowed to vary by distance. Time means of the instruments omitted. HAC standard errors are reported.

As a robustness check, I also estimate a version of (1.7) restricting the effect of technology clusters to the MSA in which they are located. These results are in Appendix Table 1.1.2:

Appendix Table 1.1.2: Main Results without spillover effects

	Water-Related Technologies			
	All	Conservation	Supply	Quality
Cluster in MSA	53.739***	40.851***	6.664***	10.698***
	(14.235)	(12.141)	(1.437)	(1.911)
Carcinogens (lbs)	1.083***	0.756***	0.128***	0.284***
	(0.091)	(0.080)	(0.011)	(0.017)
Patenting activity in MSA	29.923***	27.449***	1.176***	1.913***
	(5.549)	(5.106)	(0.275)	(0.388)
Water patenting foreign	0.005***	0.004***	0.0004***	0.0004***
	(0.001)	(0.001)	(0.0001)	(0.0001)
Control fun	−16.972***	−14.985***	−0.509**	−1.944***
	(3.778)	(3.579)	(0.218)	(0.383)
CEE	14.678***	10.205**	2.159***	3.716***
	(4.830)	(4.498)	(0.330)	(0.526)
MSA-EPA dist	−0.00001	−0.00000	−0.00000***	−0.00000*
	(0.00001)	(0.00001)	(0.00000)	(0.00000)
Northest	−3.351	−3.002	−0.278*	−0.312
	(2.119)	(1.927)	(0.145)	(0.247)
Midwest	4.609	3.216	0.568*	1.059**
	(4.213)	(3.786)	(0.301)	(0.425)
South	−6.731***	−6.003***	−0.365***	−0.617***
	(1.591)	(1.402)	(0.130)	(0.208)
Constant	30.382***	27.121***	0.033	3.694***
	(9.564)	(8.983)	(0.603)	(1.051)

Note: Effect of water technology cluster limited to the MSA in which it is located. Time means of the instruments omitted. HAC standard errors are reported.

Appendix 1.2 Control Function Exclusion Restrictions

In this section, I discuss the choice of exclusion restrictions used in the selection equation and the rationale behind the identification assumption (i.e., why the variables impact selection but not the main equation of interest).

Distance to the nearest regional EPA Office

Water technology clusters that are part of the Water Technology Cluster Initiative acquire recognition from the EPA. Consistent with the regional economic framework adopted in this paper, I posit that proximity to a regional EPA office would presumably be correlated with the location of a water technology cluster. Moreover, proximity to a regional EPA office would only be associated with water-related patenting activity through it's association with water technology clusters.

Presence of a Civil and Environmental Engineering Department

Universities are a key industry-related institution in the innovative process, creating, diffusin, and deploying new knowledge in economically useful ways (Feldman et al., 2002). The location of universities Civil Engineering programs is used as a proxy for universities that focus on water-related issues. A list of these universities, provided in Appendix Appendix 1.5, is obtained from Shanghai Ranking and geocoded. Of the 200 universities listed, 48 were in the United States.

Drought history

Water technology clusters may differ in the nature of the technologies they work on, depending on the region's particular needs and strengths. I control for the propensity to work on water scarcity issues by controlling for each location's propensity to experience drought using the total number of drought episodes from 1930 through time $t-1$.

Expenditure on water and sewer infrastructure

Water innovators are interested in key aspects of water utility operations, most notably water treatment. For instance, water treatment is energy intensive. Additionally, waste-water contains valuable materials that can be extracted and re-purposed (Monteith et al., 2008). Water utilities in their capacity to finance (construct, maintain, operate) facilities necessary for those purposes due to limited resources. I proxy for water utility's capacity to collaborate using MSA-level on expenditures for facility operation, maintenance, and construction.

Appendix 1.3 Patent Codes

In this section, I provide the lists of IPC and CPC codes for water-related technologies in Appendix Table 1.3.1, Appendix Table 1.3.2, and Appendix Table 1.3.3 from Haščič and Migotto (2015). I supplement this list for desalination technologies using codes identified by van der Vegt et al. (2011). The main advantage of using these codes to identify particular types of innovations is that they are heavily reliant on the detailed knowledge of patent examiners (Haščič and Migotto, 2015; van der Vegt et al., 2011). Furthermore, this approach is useful as it captures many of the recent water-related technologies that have been driven by advances in digital technologies that has cross-over applications in the water sector. Alternative approaches to identifying patents involves the use of keywords (e.g. Ajami, Thompson and Victor, 2014). Using keywords, however, can be a costly strategy as the search outcome will be highly sensitive to the set of keywords used. This method would likely underestimate of innovation in the water sector.

Appendix Table 1.3.1: IPC and CPC Codes for Technologies Aimed at Water Pollution Abatement

Category	***IPC Codes***	***Description***
Water and Waste Water Treatment	B63J4	Arrangements of installations for treating water or sewage
	C02F	Treatment of water, waste water, sewage, or sludge
	C09K3/32	Methods for treating liquid pollutants
	E03C1/12	Plumbing installations for waste water
	E03F	Sewers-cesspools
Fertilizer from wastewater	C05F 7/00	Fertilizers from water, sewage sludge, sea slime, ooze or similar masses
Oil Spill Cleanup Related	E02B15/04-10	Devices for cleaning the surface of open water from oil or like floating materials by separating or removing these materials
	B63B35/32	Vessels adapted for collecting pollution from open water
	C09K 3/32	Materials for treating liquid pollutants, e.g. oil, gasoline, or fat

Appendix Table 1.3.2: IPC and CPC Codes for Technologies Aimed at Water Supply Augmentation

Category	***IPC Codes***	***Description***
Water Collection	E03B 5	Use of pumping plants
	E03B 3/06-26	Ways to collect drinking water or tap water from underground
	E03B 9	Methods for drawing off water
	E03B 3/04, 28-38	Ways to collect drinking water or tap water from surface water
	E03B 3/03	Ways to collect drinking water or tap water from rainwater
	E03B 3/02	Vessels for collecting or storing rainwater for use in household
	E03B 3/00, E03B 3/40	Ways to collect drinking water or tap water from surface water, underground, or rainwater
Water Storage	E03B 11	Arrangements or adaptations of tanks for water supply
Desalination	B01D	Physical or chemical processes or apparatus in general: separation
	F24J	Production or use of heat not otherwise provided
	F03G	Spring, weight, inertia, or like motors; mechanical-power-producing devices or mechanisms, not otherwise provided for or using energy sources not otherwise provided for
	F01K	Steam engine plants; steam accumulators; engine plants not otherwise provided for; engines using special working fluids or cycles
	H01L	Semiconductor devices; electric solid-state devices not otherwise provided for
	A01G	Horticulture; cultivation of vegetables, flowers, rice, fruit, vines, hops, or seaweed; forestry; watering
	F03D	Wind motors
	F04B	Positive displacement machines for liquid pumps
	F03B	Machines or engines for liquids
	B63B	Ships or other waterborne vessels; equipment for shipping

Appendix Table 1.3.3: IPC and CPC Codes for Technologies Aimed at Water Conservation

Category	***Codes***	***Description***
Indoor water conservation	F16K21/06-12	Self-closing valves, i.e. closing automatically after operation, either retarded or immediately after opening
	F16K 21/16-20	Self-closing valves, i.e. closing automatically after operation, closing after a predetermined quantity of fluid has been delivered
	F16L 55/07	Arrangement or mounting of devices, e.g. valves for venting or aerating or draining
	E03C 1/084	Jet regulators with aerating means
	E03D 3/12	Flushing devices discharging variable quantities of water
	E03D 1/14	Cisterns discharging variable quantities of water
	A47K 11/12	Urinals without flushing
	A47K 11/02	Dry closets
	E03D13/007	Waterless or low-flush urinals
	E03D5/016	Special constructions of flushing devices with recirculation of bowl-cleaning fluid
	E03B1/041	Greywater supply systems
	Y02B 40/46	Optimization of water quantity (for dishwashers)
	Y02B 40/56	Optimization of water quantity (for washing machines)

Continued on next page

Appendix Table 1.3.3 – *Continued from previous page*

Category	***Codes***	***Description***
Irrigation	A01G 25/02	Watering arrangements located above the soil which makes use of perforated pipe-lines or pip-lines with dispensing fittings, e.g. for drip irrigation
	A01G 25/06	Watering arrangements making use of perforated pipe-lines located in the soil
	A01G 25/16	Control of watering
	C12N15/8273	Mutation or genetic engineering: DNA or RNA, concerning genetic engineering, vectors, e.g. plasmids, or their isolation, preparation or purification for drought, cold, salt resistance
Power Production	F01K 23/08-10	Combustion heat from one cycle heating the fluid in another
	F01D 11	Non-positive displacement machines or engines, e.g. steam turbines/Preventing or minimizing internal leakage of working fluid
Water Distribution	F17D5/02 & E03	Pipe-line systems/Preventing, monitoring, or locating loss
	F16L55/16 & E03	Devices for covering leaks in pipes or hoses
	G01M 3/08, G01M 3/14, G01M 3/18, G01M 3/22, G01M 3/28 & E03	Investigating fluid tightness of structures, by detecting the presence of fluid at leaking point

Appendix 1.4 Water Technology Clusters Locations and Establishment Dates

Appendix Table 1.4.1: Water Technology Clusters Supported by *Water Technology Cluster Initiative*

Cluster Name	Location	Year Est.	Focus
	MIDWEST		
Current	Chicago, IL	2016	Technology testing
Michigan Water Technology Initiative	Lansing, MI	2009	Technology testing
Cleveland Water Alliance	Cleveland, OH	2014	Technology testing
Confluence Water Technology Innovation Cluster	Cincinnati, OH	2010	Treatment
Akron Global Water Alliance	Akron, OH	2014	Treatment
The Water Council	Milwaukee, WI	2007	Technology testing
	NORTHEAST		
NorthEast Water Innovation Network	Boston, MA	2011	Technology testing
Water Technology Innovation Ecosystem	Philadelphia, PA	2011	Treatment
	SOUTH		
Accelerate H20	San Antonio, TX	2010	Water and energy
H2OTECH	Atlanta, GA	2015	Human health
	WEST		
University of Arizona Water & Energy Sustainable Technology Center	Tucson, AZ	2013	Technology testing
Maritime Alliance*	San Diego, CA	2007	Maritime technology
Los Angeles Cleantech Incubator	Burbank, CA	2011	
BlueTech Valley	Fresno, CA	2011	Commercialization services, technology testing
Colorado Water Innovation Cluster	Fort Collins, CO	2010	Agriculture, efficiency, water filtration
WaterStart	Las Vegas, NV	2012	Conservation, storage, treatment
Oregon Water Tech Innovators	Portland, OR	2014	Storage, treatment, stormwater management
PureBlue	Seattle, WA	2016	

Source: Water Environment Federation (n.d.). Maritime Alliance was formerly known as TMA BlueTech.

Appendix Table 1.4.2: Other Water Technology Clusters Not Supported by *Water Technology Cluster Initiative*

Cluster	**Location**	**Year Est.**	**Focus**
NorTech	Cleveland, OH	2011	Technology testing
Louisiana Water Network		2015	
Global Water Alliance (GWA)	Philadelphia, PA	2006	Safe drinking water and sanitation/hygiene services
Pittsburg Water Economy Network	Pittsburg, PA	2012	Industrial Water Retention and Storage, Water Reuse and Treatment
Surge Accelator*	Houston, TX	2011	Energy efficiency, oil and gas
Urban Clean Water Technology Zone	Tacoma, WA	2014	Stormwater treatment

Notes: These technologies clusters are discussed in Picou (2014). Of these, Surge Accelator filed for bankruptcy in 2016.

Appendix 1.5 Engineering Departments with a Water Specialization

Appendix Table 1.5.1: List of US Universities with Environmental Engineering Department with a Water Specialization

Texas A&M University	University of North Carolina at Chapel Hill
University of California, Davis	Columbia University
University of Illinois at Urbana-Champaign	Georgia Institute of Technology
University of California, Berkeley	North Carolina State University - Raleigh
Colorado School of Mines	Portland State University
Stanford University	University of California, Riverside
University of Colorado at Boulder	University of Iowa
Oregon State University	Yale University
University of California, Irvine	Florida International University
Pennsylvania State University - University Park	Johns Hopkins University
Colorado State University	University of Connecticut
Duke University	University of Massachusetts Amherst
California Institute of Technology	University of Michigan-Ann Arbor
Cornell University	University of Nevada-Las Vegas
Princeton University	University of Utah
University of Florida	University of California, Los Angeles
University of Washington	University of California, Santa Barbara
Virginia Polytechnic Institute and State University	Arizona State University
Massachusetts Institute of Technology (MIT)	The Ohio State University - Columbus
Michigan State University	Utah State University
Purdue University - West Lafayette	University of Idaho
University of Maryland, College Park	University of Oklahoma - Norman
University of Minnesota, Twin Cities	University of Arizona
University of Nebraska - Lincoln	The University of Texas at Austin

Appendix 1.6 Robustness Check: Effect of Water Technology Clusters on Innovative Activity

In this section, I use a Bayesian Structural Time-Series (BSTS) approach is used as an alternative method to quantify the causal impact of water technology clusters on patenting activity (a robustness check on the estimates presented in Section 1.4). The BSTS approach consists of constructing counterfactuals, referred to as synthetic controls, to represent the scenario where no technology cluster was established. The synthetic control is constructed using using a matching algorithm that identifies a pool of MSAs without clusters with similar patenting trends to MSAs that establish clusters prior to treatment. The difference between post-treatment predictions for the synthetic control and the observed outcomes observed for the treated MSAs is considered the impact of establishing a water technology cluster.

The BSTS approach is implemented in three steps (Brodersen et al., 2015; Schmitt et al., 2018).[27] First, Each MSA $i \in 1, ..., N$ with a water technology cluster is matched with a set of control MSA's $C_k = c_k, k \in 1, ..., K$ that does not have a cluster. The set of control MSAs are chosen based on the similarities in patenting activity prior to the establishment of the water technology cluster. In the second step, predicted levels of innovation for the synthetic control are subtracted from the observed levels of innovation in the treated MSAs to obtain a measure of increased patenting levels due to the water technology cluster for each treated MSA i in each post-intervention year, s.

[27] The methodology was developed to assess the the impact of marketing campaigns. The BSTS methodology was implemented using the R package *CausalImpact* provided by Google (Brodersen et al., 2015) via the *MarketMatching* wrapper written to simplify implementation. "CausalImpact 1.2.1, Brodersen et al., Annals of Applied Statistics (2015). http://google.github.io/CausalImpact/"

$$\phi_{is}^{(\tau)} = y_{is} - \tilde{y}_{is}^{(\tau)} \quad \text{(Appendix 1.6.1)}$$

The cumulative impact of water technology clusters in each treated MSA i is then calculated as the sum of the impact in post-intervention years.

$$\phi_{i}^{(\tau)} = \sum_{s=1}^{T} \phi_{is}^{(\tau)} \quad \text{(Appendix 1.6.2)}$$

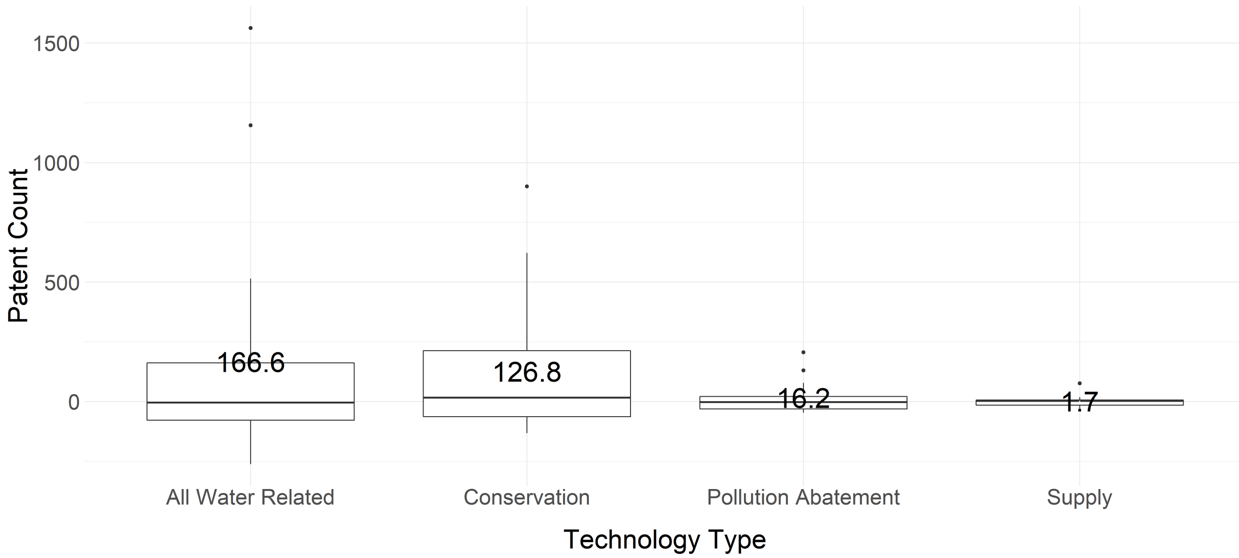
The average impact of water technology clusters is the average of these effects across treated MSAs:

$$\bar{\phi}^{(\tau)} = \sum_{i=1}^{N} \frac{\phi_{i}^{(\tau)}}{N} \quad \text{(Appendix 1.6.3)}$$

As in Section 3.4, the impact of water technology clusters is estimated using a 0mi, 50mi and 100mi radii. Results for the average effect of water technology clusters on patenting activity, $\bar{\phi}^{(\tau)}$, by technology type are provided in Appendix Figure 1.6.1- Appendix Figure 1.6.3. In Appendix Figure 1.6.1, the effect of water technology clusters is limited to the MSA in which it is located. The results indicate that the establishment of water technology clusters, on average, has no effect on patenting activity.

In Appendix Figure 1.6.2, the effect of water technology clusters is extended to MSAs within a 50mi radius of a water technology cluster. The results indicate that the establishment

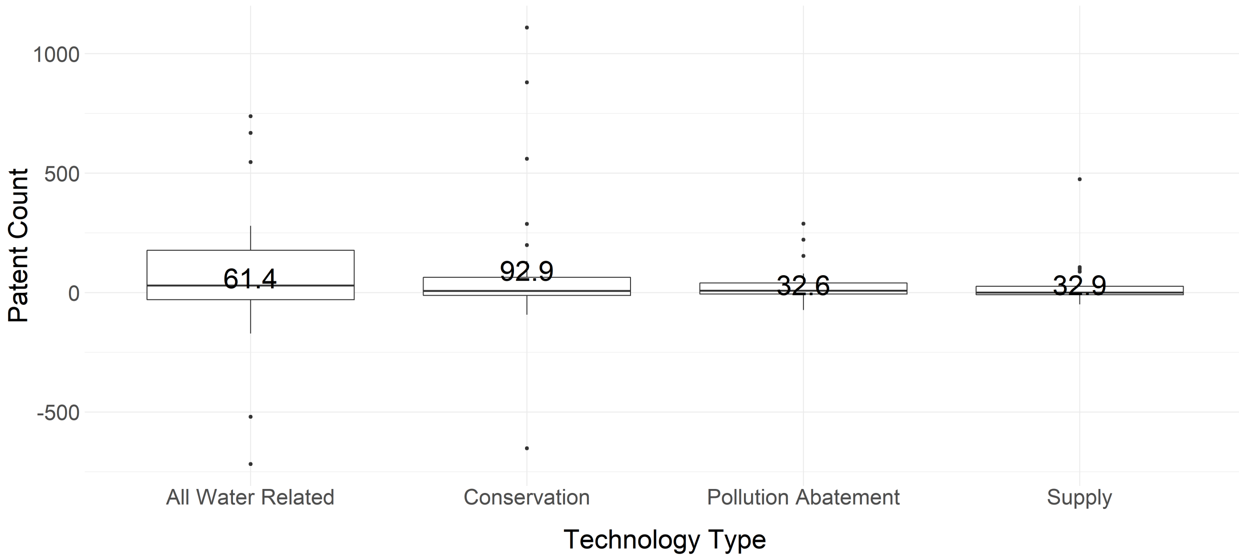
Appendix Figure 1.6.1: Impact of Water Technology Clusters on Patenting Activity



Note: The boxplot shows the average effect of water technology clusters on patenting activity by technology type. Effect of technology cluster limited to the MSA in which it is located.

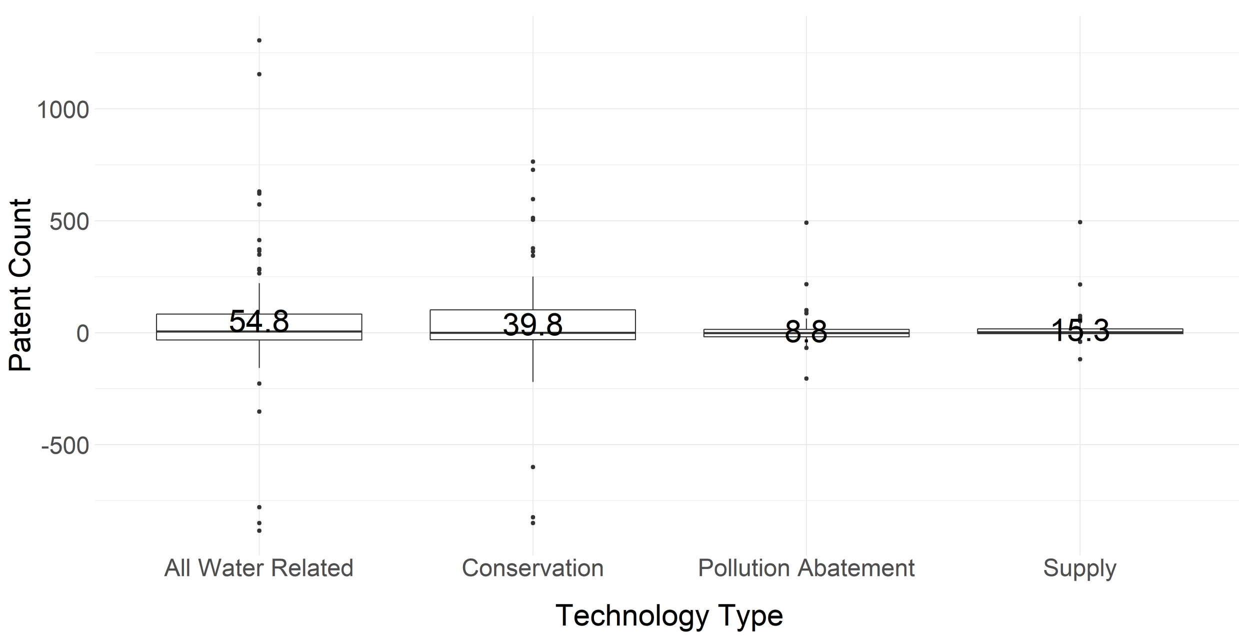
of water technology clusters, on average, increases patenting activity for technologies that augment water supply and those that abate water pollution.

Appendix Figure 1.6.2: Impact of Water Technology Clusters on Patenting Activity: 50mi radius



Note: The boxplot shows the average effect of water technology clusters on patenting activity by technology type. Effect of technology cluster extented to MSAs within a 50mi radius. The algorithm could not find adequate matches for three MSAs.

Appendix Figure 1.6.3: Impact of Water Technology Clusters on Patenting Activity: 100mi radius



Note: The boxplot shows the average effect of water technology clusters on patenting activity by technology type. Effect of technology cluster extented to MSAs within a 100mi radius. The algorithm could not find adequate matches for three MSAs.

Appendix 2.1 Deriving the Water Stress Index

Previous studies of water demand have taken a variety of approaches in modeling relevant environmental factors. The most common controls used are measures of precipitation (Moncur, 1987; Renwick and Archibald, 1998; Martínez-Espiñeira and Nauges, 2004; Roseta-Palma et al., 2013) or a combination of precipitation and temperature measures (Lyman, 1992; Agthe and Billings, 1997; Pint, 1999; Martínez-Espiñeira, 2003; Taylor, McKean and Young, 2004; Gaudin, 2006; Wichman, 2017). Some studies have instead relied on measures of evapotranspiration (Billings and Agthe, 1980; Nieswiadomy and Molina, 1988; Hewitt and Hanemann, 1995; Dandy, Nguyen and Davies, 1997; Olmstead, Hanemann and Stavins, 2005). Many additional measures – such as wind speed, minutes of sunshine, and temperature differences relative to some threshold – have also been used.[28] Some recent demand estimation studies in western states have made use of satellite imagery data to calculate a Normalized Difference Vegetation Index (NDVI), a measure of landscape "greenness" to represent demand (Wentz and Gober, 2007; Balling, Gober and Jones, 2008; Harlan et al., 2009; Halper et al., 2015; Wolak, 2016; Clarke, Colby and Thompson, 2017; Brent, 2016).

In contrast to these approaches, we create a water stress index using the RHESSys model.[29] The advantage of this model is that it uses elements of ecosystem models (e.g. BIOME-BGC (Running and Hunt Jr, 1993) and CENTURY (Parton et al., 1987)) to model

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[28] Though typically weather variables are included as linear terms, Maidment and Miaou (1986) argue that the effects of weather may be nonlinear, as the effects of rainfall, for example, diminish over time. Martínez-Espiñeira (2002) argues that the number of rainy days can have a psychological impact therefore can have a greater impact on water demand.

[29] RHESSys has been widely used to model spatially distributed soil moisture, evapotranspiration, surface and subsurface runoff, carbon and nitrogen cycling in different biomes and under different climate and land use change scenarios (Band et al., 1993; Bart, Tague and Moritz, 2016; Gao et al., 2018; Garcia, Tague and Choate, 2016; Hanan, Tague and Schimel, 2017; Hwang, Band and Hales, 2009; Lin, 2013; Lin et al., 2015, 2019; Miles and Band, 2015).

spatial and temporal dynamics of soil moisture available to lawns (the top 20 cm of soil). To do this, we first provide the RHESSys model with highly detailed spatial information to partition the landscape into forest, roads, rooftops, impervious surfaces, wetlands, pasture/agriculture lands, and lawns.[30] We then model surface and subsurface water flowpaths over the watershed. Outputs of RHESSys relevant to this study includes catchment-scaled streamflow, patch-scaled (30 m) soil moisture, and patch-scaled vegetation water demand and evapotranspiration.

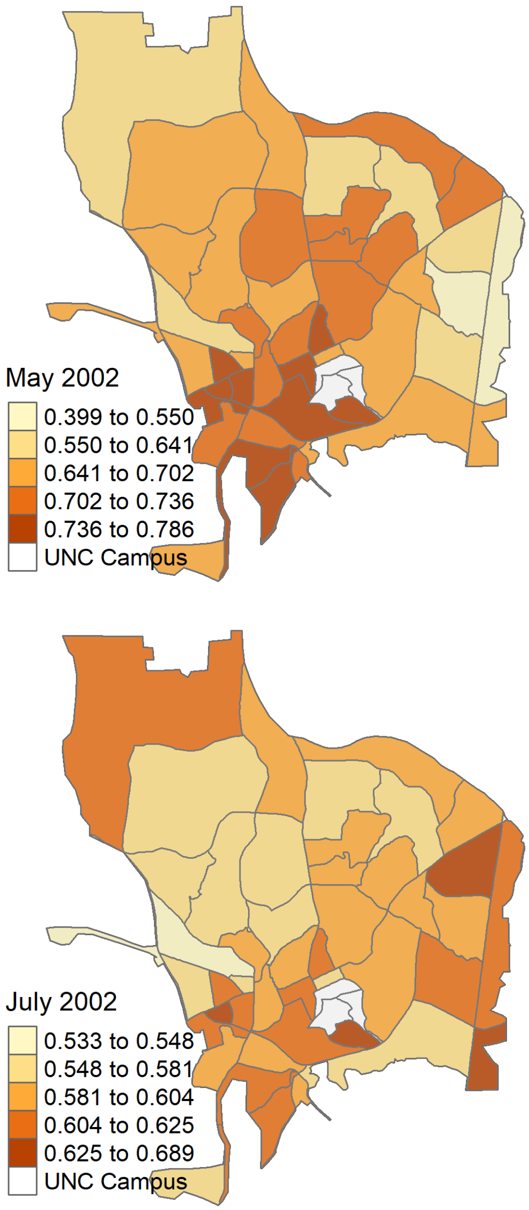
Using data from USGS gauges in the OWASA service area, we calibrate parameters related to hydrologic conductivity (water transport rate in soil columns) in our model using information for 2000-2004 and validate the model using information for 2007-2009.[31] We conduct Monte Carlo simulations to generate five-thousand predictions of streamflow/catchment runoff using these parameters. These predictions are then compared to the observed streamflow in order to find the set of conductivity parameters that best represents the area under study. Model fit is evaluated using the weekly Nash–Sutcliffe model efficiency coefficient (NSE), both logged and in levels.[32] We rank all simulations by their NSE coefficients and select the top-two-hundred for our study. For each of these simulations, we summarize model outputs as an index, given by $WS_r = 1 - \xi^a/\xi^p$, that captures the lack of moisture available to lawns. In this equation, ξ^a represents actual evapotranspiration and ξ^p represents potential

[30] We use land use landcover information at a resolution of 1 meter from the Environmental Protection Agency's EnviroAtlas (Pickard et al., 2015).

[31] We calibrate the model using low streamflow conditions due to drought conditions during 2001-02 and high streamflow that resulted from the extreme wet event in the latter part of 2002. Other time periods provide information on "normal" streamflow conditions. We validate the hydrological model using 2007-2009, a time period in which another drought occurred.

[32] Comparisons of predicted to observed streamflow require consideration of how predictions perform under various flow events (high vs. low). The NSE coefficient in levels provides information on model fitness for high flow events whereas the log transformed NSE coefficient provides information on model fitness for low flow events. High weekly and log-weekly NSE values are desired.

Appendix Figure 2.1.1: Water Stress During the 2002 Drought



evapotranspiration. We create two versions of the variable at different spatial scales: a Census Block Group specific measure (used in the main analysis) and another at the watershed level. Appendix Figure 2.1.1 graphically represents the spatial and temporal variation in the water stress index in the study area during the onset of the 2002 drought.

Appendix 2.2 Demand Estimation Results

Main Specification

The results from estimating (2.1) are in Appendix Table 2.2.1.

Appendix Table 2.2.1: Main Results

	Usage Profile					
	Low		***Moderate***		***Heavy***	
	Wealth Level					
	High	***Low***	***High***	***Low***	***High***	***Low***
Price	-0.0629	-0.0455	-0.0816	-0.0666	-0.1037	-0.134
	(0.0238)	(0.0149)	(0.0138)	(0.0161)	(0.0233)	(0.0375)
Stage 1	0.000400	-0.0011	-0.0016	-0.0028	-0.004	-0.0056
	(0.0004)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0006)
Stage 2	-0.0009	-0.0023	-0.0027	-0.0038	-0.004	-0.0051
	(0.0007)	(0.0005)	(0.0004)	(0.0005)	(0.0007)	(0.0013)
Emergency	-0.0057	-0.0071	-0.0114	-0.0106	-0.0199	-0.0119
	(0.0008)	(0.0005)	(0.0005)	(0.0005)	(0.0008)	(0.0013)
Water stress	0.0491	0.0327	0.0673	0.0467	0.0851	0.0477
	(0.0032)	(0.0022)	(0.0018)	(0.0022)	(0.003)	(0.0053)
Temperature	0.0134	0.0102	0.0461	0.0233	0.121	0.0436
	(0.0045)	(0.0028)	(0.0027)	(0.003)	(0.0045)	(0.0072)
Year trend	-0.0416	-0.0168	-0.03	-0.0284	-0.0197	-0.0149
	(0.0037)	(0.0026)	(0.0022)	(0.0027)	(0.0036)	(0.0064)
Cons. req.	-0.1488	-0.0373	-0.1706	-0.1347	-0.2257	-0.0867
	(0.026)	(0.0181)	(0.0152)	(0.0188)	(0.025)	(0.0441)
Cons. req. x Year trend	0.0441	0.00480	0.0245	0.0111	0.00580	-0.0265
	(0.0059)	(0.0041)	(0.0034)	(0.0042)	(0.0056)	(0.0099)

Note: *Cons. req.* is the year conservation requirement OWASA passed following the 2002 drought. Regressors not shown: read days, and intra-year time trend. Standard errors are in parentheses.

Ignoring Heterogeneous Impact of Environmental Factors

If we do not allow the impact of environmental factors to vary by wealth and usage profiles, we may fail to capture cross-household preference differences for outdoor water usage. This yields very different conclusions regarding price sensitivity. To see this, we run a series of alternative specifications that reduce heterogeneity in various ways. First, we estimate a model in which the impact of environmental factors varies by usage profiles but not by wealth:

$$q_{it} = \sum_u \sum_w \tau_{uw} \beta_{uw} p_t + \sum_u \sum_w \sum_k \tau_{uw} X_{it} \phi_{uwk} + \sum_u \tau_u Z_{it} \theta_u + \eta_i + \epsilon_{it}. \qquad \text{(Appendix 2.2.1)}$$

The results from estimating (Appendix 2.2.1) are in Appendix Table 2.2.2. Comparing the results to Appendix Table 2.2.1, elasticity estimates for high-wealth household are smaller, while those for low-wealth households are larger. The effect is particularly strong among households with *Moderate* and *Heavy* usage profiles.

Appendix Table 2.2.2: Main results allowing environmental controls to vary by usage profile but not by wealth

	Usage Profile					
	Low		***Moderate***		***Heavy***	
	Wealth Level					
	High	***Low***	***High***	***Low***	***High***	***Low***
Price	-0.0439	-0.0541	-0.055	-0.1071	-0.0573	-0.2708
	(0.0227)	(0.0145)	(0.0134)	(0.0153)	(0.0229)	(0.0354)
Stage 1	-0.0002	-0.0008	-0.0021	-0.002	-0.0046	-0.0036
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0006)
Stage 2	-0.0017	-0.0019	-0.0033	-0.0029	-0.0047	-0.0032
	(0.0007)	(0.0005)	(0.0004)	(0.0005)	(0.0007)	(0.0012)
Emergency	-0.0061	-0.0068	-0.0115	-0.0104	-0.0198	-0.012
	(0.0008)	(0.0005)	(0.0004)	(0.0005)	(0.0007)	(0.0013)
Water stress*	0.0677	0.0402	0.0677	0.0402	0.0677	0.0402
	(0.0014)	(0.0015)	(0.0014)	(0.0015)	(0.0014)	(0.0015)
Temperature*	0.0550	0.0184	0.0550	0.0184	0.0550	0.0184
	(0.0021)	(0.002)	(0.0021)	(0.002)	(0.0021)	(0.002)
Year trend	-0.0376	-0.019	-0.0277	-0.0325	-0.0177	-0.0226
	(0.0036)	(0.0026)	(0.0021)	(0.0026)	(0.0036)	(0.0061)
Cons. req.	-0.1604	-0.0311	-0.1753	-0.1244	-0.2267	-0.0732
	(0.0258)	(0.018)	(0.0151)	(0.0186)	(0.025)	(0.0435)
Cons. req. x Year trend	0.0427	0.00550	0.0229	0.0131	0.00350	-0.0203
	(0.0058)	(0.0041)	(0.0034)	(0.0042)	(0.0056)	(0.0099)

Note: *Cons. req.* is the year conservation requirement OWASA passed following the 2002 drought. Regressors not shown: read days, and intra-year time trend. Standard errors are in parentheses.

Second, we estimate a model in which the impact of environmental factors varies by wealth but not by usage profiles:

$$q_{it} = \sum_u \sum_w \tau_{uw}\beta_{uw}p_t + \sum_u \sum_w \sum_k \tau_{uw}X_{it}\phi_{uwk} + \sum_w \tau_w Z_{it}\theta_w + \eta_i + \epsilon_{it}. \qquad \text{(Appendix 2.2.2)}$$

The results from estimating (Appendix 2.2.2) are in Appendix Table 2.2.3. Compared to Appendix Table 2.2.2, elasticity estimates for high wealth household are smaller while those for low-wealth households are larger among households with *Heavy* usage profiles. Note that this results in positive elasticity estimates for high wealth households with *Heavy* usage profiles.

Appendix Table 2.2.3: Main results allowing environmental controls to vary by wealth but not by usage profile

	Usage Profile					
	Low		***Moderate***		***Heavy***	
	Wealth Level					
	High	***Low***	***High***	***Low***	***High***	***Low***
Price	-0.1615	-0.07	-0.0968	-0.0496	0.0292	-0.0801
	(0.0226)	(0.0143)	(0.0134)	(0.0154)	(0.0221)	(0.0349)
Stage 1	0.00170	-0.0007	-0.0015	-0.0032	-0.0054	-0.0062
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0005)
Stage 2	0.000500	-0.0018	-0.0027	-0.0043	-0.0054	-0.0055
	(0.0007)	(0.0005)	(0.0004)	(0.0005)	(0.0007)	(0.0012)
Emergency	-0.006	-0.0069	-0.0116	-0.0107	-0.019	-0.0116
	(0.0008)	(0.0005)	(0.0004)	(0.0005)	(0.0007)	(0.0013)
Water stress*	0.0677	0.0402	0.0677	0.0402	0.0677	0.0402
	(0.0014)	(0.0015)	(0.0014)	(0.0015)	(0.0014)	(0.0015)
Temperature*	0.0550	0.0184	0.0550	0.0184	0.0550	0.0184
	(0.0021)	(0.002)	(0.0021)	(0.002)	(0.0021)	(0.002)
Year trend	-0.046	-0.0191	-0.0297	-0.0263	-0.0167	-0.0138
	(0.0036)	(0.0026)	(0.0021)	(0.0026)	(0.0034)	(0.006)
Cons. req.	-0.146	-0.0321	-0.1741	-0.1409	-0.2188	-0.0852
	(0.0258)	(0.018)	(0.0151)	(0.0186)	(0.0248)	(0.0434)
Cons. req. x Year trend	0.0491	0.00620	0.0252	0.0102	-0.0006	-0.0288
	(0.0058)	(0.0041)	(0.0034)	(0.0042)	(0.0056)	(0.0099)

Note: *Cons. req.* is the year conservation requirement OWASA passed following the 2002 drought. Regressors not shown: read days, and intra-year time trend. Standard errors are in parentheses.

Next, we estimate a model in which the impact of environmental factors is not allowed to vary by either wealth or usage profiles:

$$q_{it} = \sum_u \sum_w \tau_{uw}\beta_{uw}p_t + \sum_u \sum_w \sum_k \tau_{uw}X_{it}\phi_{uwk} + \tau_u Z_{it}\theta + \eta_i + \epsilon_{it}. \qquad \text{(Appendix 2.2.3)}$$

The results from estimating (Appendix 2.2.3) are in Appendix Table 2.2.4. Compared to Appendix Table 2.2.2, elasticity estimates for high-wealth household are smaller while those for low-wealth households are larger for households with *Moderate* and *Heavy* usage profiles. We obtain positive elasticity estimates for high wealth households with *Heavy* usage profiles. Elasticity estimates under this specification are larger for both high- and low-wealth households with *Light* usage profiles.

Appendix Table 2.2.4: Main results not allowing environmental controls to vary by wealth or usage profile

	Usage Profile					
	Low		***Moderate***		***Heavy***	
	Wealth Level					
	High	***Low***	***High***	***Low***	***High***	***Low***
Price	-0.1128	-0.123	-0.05	-0.1028	0.0764	-0.132
	(0.0224)	(0.014)	(0.0132)	(0.0151)	(0.022)	(0.0348)
Stage 1	0.000900	0.000300	-0.0023	-0.0022	-0.0061	-0.0052
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0005)
Stage 2	-0.0004	-0.0008	-0.0036	-0.0032	-0.0064	-0.0045
	(0.0007)	(0.0005)	(0.0004)	(0.0005)	(0.0007)	(0.0012)
Emergency	-0.0061	-0.0067	-0.0117	-0.0106	-0.019	-0.0114
	(0.0008)	(0.0005)	(0.0004)	(0.0005)	(0.0007)	(0.0013)
Water stress*	0.0677	0.0402	0.0677	0.0402	0.0677	0.0402
	(0.0014)	(0.0015)	(0.0014)	(0.0015)	(0.0014)	(0.0015)
Temperature*	0.0550	0.0184	0.0550	0.0184	0.0550	0.0184
	(0.0021)	(0.002)	(0.0021)	(0.002)	(0.0021)	(0.002)
Year trend	-0.0427	-0.0238	-0.0263	-0.0309	-0.0131	-0.0188
	(0.0036)	(0.0025)	(0.0021)	(0.0026)	(0.0034)	(0.006)
Cons. req.	-0.1518	-0.0223	-0.1798	-0.1299	-0.226	-0.0728
	(0.0257)	(0.0179)	(0.0151)	(0.0186)	(0.0248)	(0.0434)
Cons. req. x Year trend	0.0465	0.00910	0.0225	0.0128	-0.0031	-0.0262
	(0.0058)	(0.0041)	(0.0034)	(0.0042)	(0.0056)	(0.0099)

Note: *Cons. req.* is the year conservation requirement OWASA passed following the 2002 drought. Regressors not shown: read days, and intra-year time trend. Standard errors are in parentheses.

Finally, we analyze a model without any heterogeneous effects:

$$q_{it} = \beta_j p_t + \sum_k X_{it}\phi_{kj} + Z_{it}\theta_j + \eta_i + \epsilon_{it}. \qquad \text{(Appendix 2.2.4)}$$

The results from estimating (Appendix 2.2.4) are in Appendix Table 2.2.5.

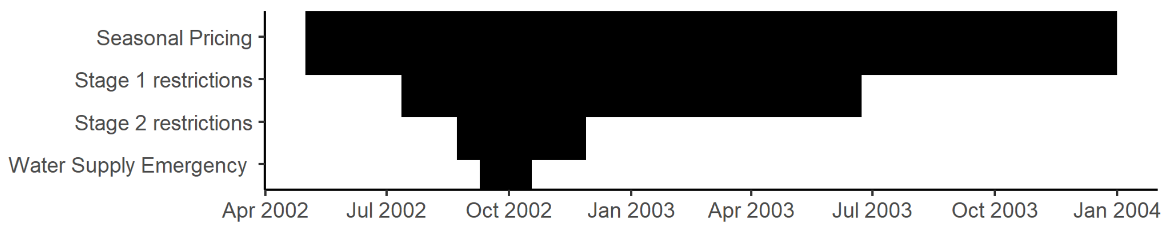
Appendix Table 2.2.5: Main Results No Heterogeneity

	All Households
Price	-0.0811
	(.0075)
Stage 1	-0.00230
	(.0001)
Stage 2	-0.00310
	(.0002)
Emergency	-0.0109
	(.0003)
Water stress	0.0553
	(.001)
Temperature	0.0377
	(.0014)
Year trend	-0.0211
	(.0011)
Cons. req.	-0.0724
	(.004)
Cons. req. x Year trend	0.0331
	(.0001)

Note: *Cons. req.* is the year conservation requirement OWASA passed following the 2002 drought. Regressors not shown: read days, and intra-year time trend. Standard errors are in parentheses.

Appendix 2.3 Command-and-Control (CAC) Restrictions

Appendix Figure 2.3.1: Timeline of CAC Restriction Implementation



Definitions of stage restrictions provided in April 2002

- **Stage 1:** Irrigation of lawns, gardens, trees, or shrubs with OWASA-supplied potable water applied through any system or device other than a hand-held hose or watering can shall be allowed only three days out of each week.

- **Stage 2:** Irrigation of lawns, gardens, trees, or shrubs with OWASA-supplied potable water applied through any system or device other than a hand-held hose or watering can shall be allowed only one day out of each week.

- **Water Supply Emergency:** No OWASA-supplied potable water for any outdoor purposes other than emergency fire suppression or other activities necessary to maintain public health, safety, or welfare.

Modifications of CAC policies in June 2003

- **Year-Round Conservation Requirement:** Spray irrigation limited to 3 days/week. Use of reclaimed or harvested water strongly encouraged. Use of water saving fixtures strongly encouraged.

Appendix 2.4 Sensitivity Analysis: Usage Profile Assignment

In the main paper, we defined households in terms of their usage profile observed during the year prior to treatment, October 2000-September 2001. Here we consider an alternative specification in which the households are defined in terms of their usage profile observed during October 1999-September 2000. Appendix Table 2.4.1 shows the summary statistics of household characteristics.

Appendix Table 2.4.1: Usage and Parcel Characteristics, Different Reference Year

	All	***Historical Usage Profile***		
	Households	***Low & Flat***	***Moderate***	***Heavy & Seasonal***
House size (sq. ft.)	2346.29	1950.14	2427.12	2879.72
	(878.20)	(768.36)	(797.71)	(947.13)
Number of bedrooms	3.56	3.25	3.63	3.94
	(0.96)	(0.91)	(0.93)	(0.97)
Number of bathrooms	2.55	2.22	2.62	2.97
	(0.85)	(0.82)	(0.77)	(0.91)
Yard size (acres)	0.44	0.39	0.45	0.50
	(0.34)	(0.33)	(0.34)	(0.35)
Property value (1000 USD)	206.65	165.66	214.04	264.59
	(98.18)	(80.87)	(89.75)	(115.57)
Total households (N)	4455	1507	2181	767
High wealth households (N)	2375	503	1295	577

Appendix Table 2.4.2 shows the results of estimating (2.1) using the usage profiles observed during October 1999-September 2000. We find that the main estimation results are robust to which pre-treatment year is used to assign usage profiles.

Appendix Table 2.4.2: Main Results, Different Reference Year

	Usage Profile					
	Low		***Moderate***		***Heavy***	
	Wealth Level					
	High	***Low***	***High***	***Low***	***High***	***Low***
Price	-0.0727	-0.0343	-0.0818	-0.0885	-0.1111	-0.0726
	(0.0227)	(0.015)	(0.0143)	(0.0161)	(0.0219)	(0.0348)
Stage 1	-0.0017	-0.0025	-0.0015	-0.0018	-0.0024	-0.0017
	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0006)
Stage 2	-0.0026	-0.0032	-0.0027	-0.0029	-0.0027	-0.003
	(0.0007)	(0.0005)	(0.0005)	(0.0005)	(0.0007)	(0.0012)
Emergency	-0.0097	-0.0092	-0.0105	-0.0085	-0.0177	-0.0105
	(0.0008)	(0.0005)	(0.0005)	(0.0006)	(0.0007)	(0.0012)
Water stress	0.0630	0.0352	0.0602	0.0449	0.0874	0.0503
	(0.0031)	(0.0022)	(0.0019)	(0.0023)	(0.0028)	(0.0049)
Temperature	0.0312	0.0121	0.0382	0.0206	0.121	0.0372
	(0.0044)	(0.0028)	(0.0028)	(0.003)	(0.0043)	(0.0067)
Year trend	0.00530	0.00550	-0.0302	-0.04	-0.0562	-0.0936
	(0.0037)	(0.0027)	(0.0023)	(0.0028)	(0.0034)	(0.0061)
Cons. req.	-0.1004	-0.022	-0.15	-0.102	-0.3092	-0.3321
	(0.0253)	(0.018)	(0.0157)	(0.019)	(0.0234)	(0.0411)
Cons. req. x Year trend	0.00630	-0.0137	0.0200	0.0151	0.0475	0.0674
	(0.0057)	(0.0041)	(0.0035)	(0.0043)	(0.0053)	(0.0093)

Note: *Cons. req.* is the year conservation requirement OWASA passed following the 2002 drought. Regressors not shown: read days, and intra-year time trend. Standard errors are in parentheses.

Appendix Table 2.4.3 shows the year-to-year transitions starting with October 1999-September 2000. The percentages are similar to those presented in Table 2.4.3.

Appendix Table 2.4.3: Transition in Usage Profiles, Different Reference Year

Panel A	All Households *(N=4455)*								
Oct99-Sep00	*Light (N=1508)*			*Moderate (N=2181)*			*Heavy (N=766)*		
	L	*M*	*H*	*L*	*M*	*H*	*L*	*M*	*H*
Oct00-Sep01	0.81	0.19	0.00	0.11	0.82	0.07	0.01	0.31	0.68
Oct01-Sep02	0.77	0.22	0.01	0.15	0.74	0.11	0.02	0.31	0.68
Oct02-Sep03	0.88	0.12	0.00	0.35	0.62	0.03	0.09	0.57	0.33
Oct03-Sep04	0.85	0.14	0.01	0.32	0.62	0.06	0.06	0.52	0.42
Oct04-Sep05	0.83	0.16	0.01	0.32	0.63	0.05	0.08	0.51	0.42
Panel B	Lower Wealth Households *(N=2080)*								
Oct99-Sep00	*Light (N=1005)*			*Moderate (N=886)*			*Heavy (N=189)*		
Oct00-Sep01	0.86	0.13	0.00	0.15	0.80	0.05	0.03	0.37	0.60
Oct01-Sep02	0.84	0.16	0.00	0.19	0.73	0.08	0.03	0.42	0.55
Oct02-Sep03	0.90	0.10	0.00	0.39	0.59	0.02	0.13	0.58	0.29
Oct03-Sep04	0.88	0.12	0.00	0.36	0.59	0.05	0.09	0.57	0.34
Oct04-Sep05	0.87	0.12	0.00	0.36	0.60	0.03	0.15	0.57	0.28
Panel C	Higher Wealth Households *(N=2375)*								
Oct99-Sep00	*Light (N=503)*			*Moderate (N=1295)*			*Heavy (N=577)*		
Oct00-Sep01	0.70	0.30	0.00	0.09	0.83	0.08	0.01	0.29	0.71
Oct01-Sep02	0.65	0.33	0.02	0.13	0.74	0.13	0.01	0.27	0.72
Oct02-Sep03	0.84	0.16	0.00	0.32	0.64	0.04	0.08	0.57	0.35
Oct03-Sep04	0.80	0.19	0.01	0.29	0.65	0.06	0.05	0.50	0.45
Oct04-Sep05	0.76	0.23	0.01	0.29	0.65	0.06	0.05	0.49	0.46

Appendix 2.5 Water Stress vs. Traditional Environmental Controls

In this section, we assess the goodness of fit for models using different sets of environmental controls. We compare the main set of results, using a Block Group-level water stress index, to models using collections of weather variables. We obtained data for weather variables from the NC Climate Office for the Chapel Hill-Williams Airport weather station. We use the following environmental controls:

- Ad hoc collection 1: Total precipitation and average temperature
- Ad hoc collection 2: Total precipitation, lagged total precipitation, average temperature, lagged average temperature
- Ad hoc collection 3: Total precipitation, total precipitation squared, number of days with no rain, average temperature
- Water Stress at watershed level and average temperature
- Water Stress at Census Block Group level and average temperature

We do not include NDVI in our comparison models, as the area of study is not well suited for use because the coarse resolution of the satellite images (30m x 30m) is not precise enough to discern landscapes on individual parcels in the study area. Aside from typically small parcel sizes, tree cover is prevalent, and the area is relatively wet, therefore cloud cover obstruction frequently results in unusable images.[33]

[33] NDVI particular useful in areas such as the western United States, regions where parcel sizes are relatively large, climate is arid and hence experience few cloudy days, and tree cover sparse. https://earthexplorer.usgs.gov/

We assess model fit based on deviations in prediction accuracy using several model evaluation scores. We provide scores for root mean squared error (RMSE), mean absolute percentage error (MAPE), and mean absolute error (MAE) in Appendix Table 2.5.1. The errors provided in the table are based on differences between actual and predicted values and smaller errors reflect more accurate predictions. Scores differ in how large errors are treated. RMSE gives extra weight to large errors whereas MAPE and MAE give equal weight to all errors. MAPE differs from the other two metrics in that is scores are in terms of percentages and are therefore scale-independent. The results suggest that using water stress leads to minor improvements in model fit.

Appendix Table 2.5.1: Goodness of Fit Results

Environmental Model	RMSE	MAPE	MAE
Collection 1	39.452	27.641	28.702
Collection 2	39.322	26.205	28.584
Collection 3	39.145	28.265	28.492
Water Stress Regional	38.723	23.241	28.175
Water Stress Block Group	38.778	25.349	28.204

Notes: All models include average temperature. RMSE: Root mean square error, MAPE: Mean absolute percentage error, MAE: Mean absolute error

Estimation Results for Alternative Environmental Controls

Appendix Table 2.5.2 through Appendix Table 2.5.5 contain results from models with alternative environmental controls. The results are qualitatively similar to the main estimation results, with a few small differences. Specifically, the alternative environmental controls produce lower price sensitivity among wealthier households with *Moderate* and *Light* usage profiles, although the differences are smaller in the models with more complex collections of weather variables. Our findings suggest that collections of weather variables in relatively wet climate areas similar to the area of study may be used in water demand estimation studies without the introduction of too much measurement error. Future research, however, is needed to test the robustness of this measure in the context of different climates.

The most common combination of weather variables used as environmental controls is *ad hoc collection 1.* Using these measures results in price elasticity estimates that are qualitatively similar though smaller in magnitude to those found when using water stress.

Appendix Table 2.5.2: Main Results with Ad hoc Collection 1 instead of Block Group Water Stress

	Usage Profile					
	Low		***Moderate***		***Heavy***	
	Wealth Level					
	High	***Low***	***High***	***Low***	***High***	***Low***
Price	-0.0269	-0.0279	-0.0286	-0.033	-0.0295	-0.1018
	(0.0236)	(0.0148)	(0.0137)	(0.0159)	(0.0231)	(0.0372)
Stage 1	-0.0011	-0.0021	-0.0037	-0.0044	-0.0066	-0.0071
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0006)
Stage 2	-0.0023	-0.0034	-0.0049	-0.0057	-0.0067	-0.0066
	(0.0007)	(0.0005)	(0.0004)	(0.0005)	(0.0007)	(0.0012)
Emergency	-0.0068	-0.0074	-0.013	-0.0113	-0.0221	-0.0128
	(0.0008)	(0.0005)	(0.0005)	(0.0005)	(0.0007)	(0.0013)
Precipitation	-0.031	-0.0209	-0.04	-0.0255	-0.0496	-0.0291
	(0.0026)	(0.0017)	(0.0016)	(0.0018)	(0.0026)	(0.0044)
Temperature	0.0235	0.0149	0.0592	0.0294	0.138	0.0506
	(0.0045)	(0.0028)	(0.0027)	(0.003)	(0.0045)	(0.0072)
Year trend	-0.0283	-0.0076	-0.0121	-0.0143	0.00330	-0.001
	(0.0036)	(0.0026)	(0.0021)	(0.0026)	(0.0035)	(0.0062)
Cons. req.	-0.184	-0.0668	-0.222	-0.1833	-0.2987	-0.1338
	(0.0259)	(0.018)	(0.0151)	(0.0186)	(0.0249)	(0.0437)
Cons. req. x Year trend	0.0383	0.00210	0.0172	0.00760	-0.002	-0.0301
	(0.0059)	(0.0041)	(0.0034)	(0.0042)	(0.0057)	(0.0099)

Note: *Cons. req.* is the year conservation requirement OWASA passed following the 2002 drought. Regressors not shown: read days, and intra-year time trend. Standard errors are in parentheses.

When we include *ad hoc collection 2* in the model, our price elasticity become more similar to those we obtain when using water stress.

Appendix Table 2.5.3: Main Results with Ad hoc Collection 2 instead of Block Group Water Stress

	Usage Profile					
	Low		***Moderate***		***Heavy***	
	Wealth Level					
	High	***Low***	***High***	***Low***	***High***	***Low***
Price	-0.0335	-0.0327	-0.0452	-0.0412	-0.0592	-0.108
	(0.0238)	(0.0149)	(0.0138)	(0.016)	(0.0232)	(0.0374)
Stage 1	-0.0004	-0.0017	-0.0025	-0.0034	-0.0049	-0.0062
	(0.0004)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0006)
Stage 2	-0.0022	-0.0036	-0.0048	-0.0052	-0.0067	-0.006
	(0.0008)	(0.0005)	(0.0004)	(0.0005)	(0.0007)	(0.0013)
Emergency	-0.007	-0.0075	-0.0134	-0.0118	-0.0226	-0.0133
	(0.0008)	(0.0005)	(0.0005)	(0.0005)	(0.0007)	(0.0013)
Precipitation	-0.0307	-0.0219	-0.0406	-0.0259	-0.0519	-0.0283
	(0.0027)	(0.0018)	(0.0016)	(0.0019)	(0.0027)	(0.0045)
Lagged precipitation	-0.0104	-0.0039	-0.0203	-0.0176	-0.029	-0.0195
	(0.0023)	(0.0015)	(0.0014)	(0.0016)	(0.0022)	(0.0038)
Temperature	0.0178	0.00150	0.0480	0.0250	0.117	0.0516
	(0.0064)	(0.0043)	(0.0038)	(0.0046)	(0.0063)	(0.0106)
Lagged temperature	0.0134	0.0228	0.0280	0.0134	0.0499	0.00460
	(0.0081)	(0.0054)	(0.0048)	(0.0057)	(0.0079)	(0.0134)
Year trend	-0.0334	-0.011	-0.0211	-0.0224	-0.0093	-0.0095
	(0.0037)	(0.0027)	(0.0022)	(0.0027)	(0.0036)	(0.0064)
Cons. req.	-0.1883	-0.0711	-0.2293	-0.1884	-0.3091	-0.1395
	(0.0259)	(0.0179)	(0.0151)	(0.0186)	(0.0249)	(0.0436)
Cons. req. X Year trend	0.0424	0.00520	0.0244	0.0137	0.00810	-0.0238
	(0.0059)	(0.0041)	(0.0035)	(0.0043)	(0.0057)	(0.01)

Note: *Cons. req.* is the year conservation requirement OWASA passed following the 2002 drought. Regressors not shown: read days, and intra-year time trend. Standard errors are in parentheses.

Similarly, when we include *ad hoc collection 3* in the model, our price elasticity estimates become more similar to those we obtain when using water stress.

Appendix Table 2.5.4: Main Results with Ad hoc Collection 3 instead of Block Group Water Stress

	Usage Profile					
	Low		***Moderate***		***Heavy***	
	Wealth Level					
	High	***Low***	***High***	***Low***	***High***	***Low***
Price	-0.0334	-0.0304	-0.043	-0.0428	-0.0468	-0.1116
	(0.0237)	(0.0148)	(0.0137)	(0.016)	(0.0231)	(0.0373)
Stage 1	-0.0008	-0.0018	-0.0035	-0.0042	-0.0065	-0.007
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0006)
Stage 2	-0.0017	-0.003	-0.0036	-0.0046	-0.005	-0.0055
	(0.0007)	(0.0005)	(0.0004)	(0.0005)	(0.0007)	(0.0013)
Emergency	-0.0069	-0.0075	-0.0128	-0.0113	-0.0216	-0.0126
	(0.0008)	(0.0005)	(0.0005)	(0.0005)	(0.0007)	(0.0013)
Precipitation	-0.0574	-0.0436	-0.0566	-0.0346	-0.0545	-0.0304
	(0.0059)	(0.0038)	(0.0036)	(0.004)	(0.0058)	(0.0094)
Precipitation squared	0.0394	0.0265	0.0333	0.0165	0.0225	0.0107
	(0.0062)	(0.0033)	(0.0037)	(0.0035)	(0.0061)	(0.0092)
Days no rain	0.00870	-0.0016	0.0253	0.0161	0.0357	0.0213
	(0.0027)	(0.0019)	(0.0017)	(0.002)	(0.0026)	(0.0043)
Temperature	0.0232	0.0144	0.0612	0.0320	0.141	0.0540
	(0.0045)	(0.0029)	(0.0027)	(0.0031)	(0.0045)	(0.0073)
Year trend	-0.028	-0.0089	-0.0103	-0.0137	0.00550	-0.0001
	(0.0036)	(0.0026)	(0.0021)	(0.0026)	(0.0035)	(0.0062)
Cons. req.	-0.1594	-0.0551	-0.1757	-0.1505	-0.2422	-0.0991
	(0.0262)	(0.0182)	(0.0153)	(0.0189)	(0.0252)	(0.0442)
Cons. req. X Year trend	0.0348	0.00120	0.00990	0.00260	-0.0108	-0.0354
	(0.0059)	(0.0041)	(0.0034)	(0.0043)	(0.0057)	(0.01)

Note: *Cons. req.* is the year conservation requirement OWASA passed following the 2002 drought. Regressors not shown: read days, and intra-year time trend. Standard errors are in parentheses.

We obtain similar price elasticity estimates when we use watershed-level water stress measures versus the Block-Group-level water stress measures of our main analysis.

Appendix Table 2.5.5: Main Results with Regional Level Water Stress instead of Block Group Water Stress

	Usage Profile					
	Low		***Moderate***		***Heavy***	
	Wealth Level					
	High	***Low***	***High***	***Low***	***High***	***Low***
Price	-0.0655	-0.0467	-0.0869	-0.0691	-0.1095	-0.1367
	(0.0238)	(0.0149)	(0.0138)	(0.016)	(0.0232)	(0.0374)
Stage 1	0.000700	-0.0009	-0.0011	-0.0024	-0.0033	-0.0051
	(0.0004)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0006)
Stage 2	-0.0005	-0.002	-0.0022	-0.0032	-0.0031	-0.0044
	(0.0008)	(0.0005)	(0.0004)	(0.0005)	(0.0007)	(0.0013)
Emergency	-0.0057	-0.007	-0.0113	-0.0104	-0.0197	-0.0117
	(0.0008)	(0.0005)	(0.0005)	(0.0005)	(0.0008)	(0.0013)
Water stress regional	0.0473	0.0317	0.0660	0.0472	0.0857	0.0492
	(0.0029)	(0.0021)	(0.0017)	(0.0021)	(0.0028)	(0.005)
Temperature	0.0117	0.00800	0.0436	0.0202	0.118	0.0403
	(0.0045)	(0.0028)	(0.0027)	(0.003)	(0.0045)	(0.0072)
Year trend	-0.0445	-0.0191	-0.0345	-0.0319	-0.0256	-0.0189
	(0.0038)	(0.0027)	(0.0022)	(0.0028)	(0.0036)	(0.0065)
Cons. req.	-0.1257	-0.0262	-0.1373	-0.1187	-0.1857	-0.0703
	(0.0262)	(0.0182)	(0.0153)	(0.0189)	(0.0252)	(0.0442)
Cons. req. x Year trend	0.0416	0.00430	0.0211	0.0106	0.00240	-0.0266
	(0.0058)	(0.0041)	(0.0034)	(0.0042)	(0.0056)	(0.0099)

Note: *Cons. req.* is the year conservation requirement OWASA passed following the 2002 drought. Regressors not shown: read days, and intra-year time trend. Standard errors are in parentheses.

Appendix 2.6 Transitions in Usage Profiles By Wealth

In this section we provide information on the fraction of households that transition in usage profiles by household wealth. Transitions are qualitatively similar to that observed for the entire sample with the exception that significant decreases in usage in transitioning from *Heavy* to *Light* are more frequently observed among low wealth households than high wealth households.

Appendix Table 2.6.1: Transitions in Usage Profiles

Panel A	All Households *(N=4455)*								
Oct00-Sep01	*Light (N=1481)*			*Moderate (N=2301)*			*Heavy (N=673)*		
	L	*M*	*H*	*L*	*M*	*H*	*L*	*M*	*H*
Oct01-Sep02	0.82	0.17	0.00	0.12	0.76	0.11	0.01	0.24	0.75
Oct02-Sep03	0.89	0.11	0.00	0.35	0.62	0.03	0.05	0.56	0.39
Oct03-Sep04	0.86	0.13	0.01	0.31	0.63	0.06	0.04	0.49	0.46
Oct04-Sep05	0.85	0.14	0.01	0.31	0.64	0.06	0.06	0.49	0.44
Panel B	Lower Wealth Households *(N=2080)*								
Oct00-Sep01	*Light (N=1003)*			*Moderate (N=912)*			*Heavy (N=165)*		
Oct01-Sep02	0.87	0.13	0.00	0.15	0.77	0.07	0.02	0.35	0.63
Oct02-Sep03	0.90	0.10	0.00	0.40	0.57	0.02	0.06	0.60	0.34
Oct03-Sep04	0.88	0.12	0.00	0.36	0.59	0.05	0.04	0.56	0.39
Oct04-Sep05	0.88	0.12	0.00	0.36	0.61	0.03	0.10	0.57	0.33
Panel C	Higher Wealth Households *(N=2375)*								
Oct00-Sep01	*Light (N=478)*			*Moderate (N=1389)*			*Heavy (N=508)*		
Oct01-Sep02	0.74	0.26	0.01	0.10	0.76	0.14	0.00	0.20	0.79
Oct02-Sep03	0.87	0.12	0.00	0.32	0.65	0.03	0.05	0.55	0.40
Oct03-Sep04	0.82	0.17	0.01	0.28	0.65	0.07	0.05	0.47	0.48
Oct04-Sep05	0.79	0.19	0.01	0.27	0.65	0.07	0.05	0.47	0.48

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