DISSERTATION

HUMAN BEHAVIOR IN THE CONTEXT OF WATER SCARCITY

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ABSTRACT

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This dissertation in comprised of three chapters which use microeconomic principles and empirics to examine human behavior in the face of water scarcity. Chapter one uses an experiment to investigate the effect of threshold uncertainty on common pool resource (CPR) consumption decisions. Chapter two uses latent class analysis to endogenously identify unique household classes with respect to their water use decisions under various price and weather scenarios. Chapter three directly compares the residential water consumption decisions of households motivated primarily by social and environmental outcomes with households primarily motivated by cost and convenience. The overall goal of my work is to elucidate the behavior and motivation that leads to particular consumption decisions in the presence of water scarcity.

Chapter one explicitly models a CPR in which uncertainty around a tipping point—stock level below which the resource is destroyed—can engender two distinct Nash Equilibria (NE), both of which lead to a Tragedy of the Commons. We theoretically and empirically test how differing levels of uncertainty around the location of this tipping point affects individual and group consumption choices. Our results suggest that the presence of uncertainty increases the likelihood that individuals choose the NE consistent with resource destruction (even though it is an inferior NE) and to ignore potential impacts on resource stocks. However, conditional on choosing the superior NE, increased uncertainty does not affect consumption rates in the experiment. In addition, we introduce tax and fine policies and find that they reduce overall consumption rates and the probability that individuals choose to destroy the resource.

Chapter 2 and 3, do not explicitly model scarcity, but they examine household water consumption in the arid southwest where water scarcity is a pervasive concern. Both chapters two and three use data from Fort Collins Utilities to investigate household heterogeneity and water consumption decisions. Chapter 2 uses a finite mixture model to endogenously identify distinct water use patterns. Estimated price elasticities are consistent with previous literature and range from -0.1 in the spring for the unresponsive class to -0.8 in the summer for the responsive class. We find significant evidence that households classes exist and can generally be broken into high responsive and low responsive classes. Our results also suggest that changes in precipitation will have little effect on demand, but a 2 degree temperature increase will increase residential water demand throughout the city by approximately 5%. Lastly, chapter two investigates the burden of price increases and weather shocks across household class and income level. We find that the vast majority of water reductions due to price increases come from middle and high income homes.

Chapter three is similar to chapter two in motivation, but distinct in methodology. Chapter 3 poses and attempts to answer a simple question: do households primarily motivated by environmental and social (E&S) consideration consume water differently than households motivated primarily by cost and convenience (C&C)? Results strongly indicate that E&S consumers use less water than (C&C) consumers. Results also suggest that E&S motivated households consume significantly more water as temperatures rise. However, there is no statistical difference between E&S and C&C consumers in their responses to changing price and precipitation.

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CHAPTER 1. COMMON POOL RESOURCE DESTRUCTION IN THE PRESENCE OF UNCERTAIN TIPPING POINTS

Highlights:

- CPR social dilemmas are the result of two distinct underlying motivations
- Environmental uncertainty can induce individuals to destroy common pool resources
- Tax and fine policies significantly improve outcomes and social welfare

Introduction

Allocating scarce resources in the absence of clearly defined property rights can be a contentious and complicated process, particularly when those resources are depletable or destructible. Consequently, common pool resources (CPR's) are a well-documented source of significant social and political turmoil (Adams, Brockington, Dyson, & Vira, 2003) as well as economic inefficiency (Gordon, 1954). Despite an increasing understanding of CPR's and the science around them, humans continue to substantially overfish major parts of the ocean, deforestation continues at an annual rate of 5.2 million hectares per year (FAO, 2010), pumping continues to deplete aquifers throughout the world, and greenhouse gases are emitted at an alarming rate. Additional complications arise when the resource threshold—the stock level below which the resource is permanently damaged or destroyed—is uncertain.

This paper extends the existing literature on CPR's by examining the impact of such uncertain resource thresholds on resource consumption decisions. Our contribution is both theoretical and empirical. We investigate the effect of uncertainty on both a discrete and continuous choice consistent with the choices available to most resource constituents. Through a better understanding of resource constituents' incentive structure, it is possible to design more effective policies and solutions.

CPR's are non-excludable but rivalrous goods, where individuals acting in their own self-interest often overconsume the resource, leading to inefficiency, degradation, and, in extreme cases, destruction. Such resources often have a tipping point, beyond which their destruction is inevitable; however, the specific locations of these thresholds are rarely known with certainty. For example, fishermen and scientists may agree that sufficiently depleting fish stocks will lead to the collapse of a fishery, but the exact stock at which the population crashes is largely unknown (Botsford, Castilla, & Peterson, 1997). This paper develops a theoretical model and uses an economic experiment to determine how resource consumption decisions change with differing levels of environmental uncertainty, represented by an unknown threshold. Laboratory experiments have traditionally been used to investigate the effect of environmental uncertainty on consumption, because finding natural experiments with exogenously determined environmental uncertainty shocks and policies is difficult (Ostrom, 2006). Therefore, we choose to conduct a laboratory experiment to disentangle the behavioral responses of CPR users to varying levels of uncertainty.

While many experimental studies have found a significant relationship between overconsumption and environmental uncertainty in experimental settings (Biel & Gärling, 1995; Gärling, Biel, & Gustafsson, 1998; Rapoport, Budescu, Suleiman, & Weg, 1992), many of these experiments do not focus on a key feature of real-world CPR settings—the existence of two Nash Equilibria (NE) that are both suboptimal solutions from the perspective of the social planner. We posit that resource extraction decisions can suffer from two types of Tragedy of the Commons (TOC): one in which marginal over-consumption occurs and dissipates rents, which may or may not destroy the resource, and one in which individuals behave as if the resource will be destroyed with certainty because they anticipate others doing the same. For example, fishermen in a given fishery may harvest at levels that keep the fish stock healthy, even if the stock is below the level of maximum economic yield. This strategy reflects some amount of rent dissipation or risk of resource collapse since the stock is marginally overfished. However, as uncertainty—about both the ecosystem and the consumption rates of others—increases, fishermen may be more likely to catch as much as possible because they anticipate that fishery collapse is inevitable. For clarity, we will refer to the first NE as the *partially defect* NE—where *defect* refers to a deviation from the socially optimal solution and *partially* refers to the fact that the resource may survive. The second NE will be referred to as the *fully defect* NE*,* because individuals do not coordinate on either the *partially defect* NE nor on the socially optimal outcome (which is not an equilibrium) and thus end up with a lower expected payout because the resource is destroyed with certainty. Note that both NE are inferior to the socially optimal consumption rates, which will be referred to as the *coordinate solution*. The presence of both NE captures an important feature of many CPR systems in practice. Yet most investigations of environmental uncertainty using single-period experiments do not possess both NE (for example, Aflaki, 2013; Budescu, Rapoport, & Suleiman, 1990; Rapoport et al., 1992; Wit, van Dijk, Wilke, & Groenenboom, 2004). [1]

To better understand the underlying social dilemma associated with real-world renewable resources, it is necessary to differentiate between these two equilibria and elucidate the effect of uncertainty on which NE individuals choose, in addition to the quantity they withdraw from the

[1] A notable exception is the public good experiments performed by Barrett and Dannenberg (2012) and Dannenberg et al. (2011)

CPR. To accomplish this task we develop a CPR model featuring both NEs and implement the model using a laboratory experiment to answer the following questions:

1) Does environmental uncertainty exacerbate overconsumption by increasing the probability that resource users choose to *fully defect*?
2) When individuals do not *fully defect*, how does uncertainty affect resource consumption, and how does this consumption compare to the socially optimal solution?
3) How effective are tax and fine policies at improving efficiency in a CPR setting with environmental and social uncertainty?

Our experiment systematically manipulates the size of environmental uncertainty in the context of a CPR and tests how these changes affect individual and group consumption decisions. Individuals are randomly assigned heterogeneous payout and damage functions, placed in four-person groups, and tasked with requesting tokens from a group account. If the sum of the group's consumption is greater than the number of tokens available, each player suffers a substantial loss. Their consumption decisions are observed under three treatments (Certainty, Low Uncertainty, and High Uncertainty) and three policy settings (no regulation, excise taxes, and a fine).

Our findings are consistent with previous results showing that increased environmental uncertainty leads to increased consumption, but our contribution is to demonstrate that this phenomenon occurs because some individuals give up on saving the resource entirely (*fully defect*). We find that, *ceteris paribus*, environmental uncertainty has little effect on the request rates of individuals who choose the *partially defect NE*; it significantly increases the probability, however, that individuals *fully defect* and ignore impacts on the resource. This finding suggests that a key reason for over-extraction in the presence of uncertainty may not be the omission of external costs in the individual's extraction decision, but rather a discrete shift where each resource user defects from the better equilibrium to minimize the possible damage to himself caused by the myopic decisions of others.

Our results further suggest that accurately identifying resource tipping points can significantly reduce the chances that individuals deliberately destroy the resource, and that when such scientific knowledge is unavailable, it may be valuable to introduce policies that discourage defecting. For this experiment we introduce a tax and a fine, and conclude that both significantly increase economic efficiency.

This paper is composed of six sections. The next section provides context and highlights the research on which our experiment is based. Section 3 outlines our theoretical model, section 4 details the experiment, section 5 reports our results, and section 6 concludes.

Background

To understand how uncertainty affects the consumption decisions of individuals in the context of a common pool resource, we first identify the characteristics of CPR's and highlight the cause of the associated social dilemma. The social dilemma caused by CPR's was introduced by Hardin (1968) and formally characterized by Dawes (1980) as having two major components: 1) the payout to each individual acting in her self-interest is higher than the payout for acting in the interest of the group, and 2) all individuals receive a lower payout when everyone acts in their own monetary self-interest. The model used in this experiment is consistent with Dawes's definition, but it distinguishes two underlying causes of over-extraction: 1) the classic Prisoner's Dilemma in which marginal overextraction occurs because individuals do not account for the external costs imposed on others (*partially defect*), and 2) a deliberate exhaustion in which a coordination problem can lead to the suboptimal NE and resource collapse (*fully defect*). At both NEs individuals overconsume compared to the socially optimal solution. This basic overconsumption phenomenon has been observed in CPR's all over the world and has been the focus of considerable experimental literature (Ostrom, 2006).

Uncertainty has been introduced in the CPR setting in many contexts, including the standard rent dissipation problem (Walker, Gardner, & Ostrom, 1990), probabilistic degradation or destruction (Blanco, Lopez, & Walker, 2015; Walker & Gardner, 1992), nonpoint source pollution (Poe, Schulze, Segerson, Suter, & Vossler, 2004), varying degrees of externalities (Suter, Duke, Messer, & Michael, 2012), and unknown thresholds or tipping points (Budescu et al., 1990). Overconsumption was present in each of these experiments and was generally exacerbated by uncertainty. In addition to the social dilemmas caused by common CPR settings, uncertainty induces people to over consume even when there is no practical reason to do so. A number of explanations have been presented for this phenomenon, including an optimism or egoism bias (De Vries & Wilke, 1992; Gustafsson, Biel, & Gärling, 2000; Olsen, 1997). In our experiment, one NE is always theoretically superior to the other, but it is possible that a behavioral response may cause individuals to choose the inferior NE as uncertainty increases—this phenomenon will be tested and confirmed.

While our model is primarily consistent with CPR work, it is worth mentioning that this research has corollaries in public good experiments such as that in Barrett and Dannenberg (2012) or Dannenberg et al. (2011). In a similar context, they find that varying uncertainty levels can affect cooperation and NE choice. Barrett and Dannenberg's model is particularly relevant to our setup because it creates a very similar incentive structure in which both an inferior NE and superior NE exist, but neither equilibrium is located at the socially optimal solution. They find that catastrophe can be avoided through public good contributions in the certainty case, but not when the threshold is uncertain. They reject the hypothesis that individuals would contribute zero under uncertainty treatments—which corresponds to our *fully defect* choice to consume without consideration for impacts on the resource stock. However, we find significant evidence that subjects make this choice in the presence of uncertainty. This choice results in assured resource destruction, and is thus an indication of a very different underlying motivation.

Our model is an extension of work first proposed in the 1980's (Messick, Allison, & Samuelson, 1988). Messick et al. (1988) developed a simplified setup to investigate the fundamental CPR inefficiencies created by social and environmental uncertainty. Their setup is a single-stage, noncooperative game in which individuals extract from a common pool with an unknown threshold. Individuals receive the number of tokens they requested only if the total number requested by the group remains below the threshold. Players receive nothing if the sum of requests exceeds the threshold.

This model was further developed in Budescu et al. (1990), Budescu, Rapoport, & Suleiman (1995), and Aflaki (2013). While their experiment provides insight into the nature of uncertainty in a CPR, their setup eliminates the motivation of individuals to request if they expect the threshold to be exceeded (*fully defect*), because the payout for requesting 0 and the payout for requesting as much as possible are equivalent. Their model essentially creates a coordination game (and corresponding NEs) in which once the optimal solution is reached, no single player would deviate from that NE. Such a setup is incongruous with many real-world CPR settings. More recently, Botelho et al. (2014) used a similar setup in a dynamic setting and found that increased levels of uncertainty may lead to quicker depletion of a resource stock, but players may also adopt strategy paths that guarantee the unknown threshold will not be exceeded. Our setup uses a single-period model but allows for choices similar to those of the dynamic game. Constituents make a single extraction decision corresponding to an easily identifiable NE akin to more complex dynamic models. Two symmetric NE are created, one in which individuals *partially defect* from the *coordinate solution* and one in which they *fully defect* and destroy the resource with certainty. The decision to *partially defect* from the *coordinate solution* is akin to the defect strategy in a Prisoner's Dilemma game, whereas the choice between *partially* and *fully* defecting is one of coordination. An in-depth discussion of our model and its solutions are presented in the next section.

CPR Model and Predictions

We use a single-period, non-cooperative, *n*-person model similar to the one developed by Budescu, Rapoport, and Suleiman (1990 & 1995). We alter their model in three significant ways in order to capture key features of many CPR settings: we 1) introduce a lump-sum damage amount to reflect resource collapse, 2) incorporate decreasing returns to individual payout functions, and 3) utilize a two-step optimization framework to analyze individual behavior. These modifications create significant changes in the incentive structure of resource constituents and provide insight into the possible motivations underlying overconsumption decisions in a CPR setting.

Basic Setup

Each individual j $(j = 1,2, \dots, n)$ requests a specific number of tokens and receives a payout based on the amount they request as well as the actions of others. Individual j receives $b_j(r_j)$ dollars for requesting r_j tokens. For the general theoretical model we assume that $b_j(r_j)$ is twice differentiable and concave.

If the total group request exceeds the threshold of available tokens, an individual's total payout is reduced by D_j. The total number of tokens requested by the group is denoted $R = \sum_{j=1}^{n} r_j$, while the total number of tokens requested by other individuals is $R_{-j} = R - r_j$. The threshold under which the group must stay in order to avoid incurring the lump sum cost is a random variable $(\tilde{X})$, uniformly distributed between a lower (α) and upper (β) bound.

Each individual's total payout function is:

$$\pi_j(r_j; R_{-j}) = \begin{cases} b_j(r_j) \; if \; R \leq \tilde{X} \\ b_j(r_j) \; - D_j \; if \; R > \tilde{X} \end{cases} \tag{1}$$

Individual's Problem

We assume that each of the n individuals maximizes his total expected payout given uncertainty about the threshold and assuming the actions of others are exogenous. Note, however, that because of the piecewise nature of the uniform distribution function, the expected payoff function is discontinuous across three segments, or

$$E[\pi_j(r_j; R_{-j})] = \begin{cases} b_j(r_j) & if \; r_j \leq \alpha - R_{-j} \\ b_j(r_j) - \frac{D_j(R_{-j}+r_j-\alpha)}{\beta-\alpha} & if \; \alpha - R_{-j} < r_j < \beta - R_{-j} \\ b_j(r_j) - D_j & if \; r_j \geq \beta - R_{-j} \end{cases} \tag{2}$$

Similar to a model in Hanemann (1984) we take advantage of this discontinuity and model the individual's choice of r_j utilizing a two-stage maximization framework. In the first stage, we consider the optimal request of each individual, conditional on being constrained to one of three subsets of possible requests:

$$\begin{aligned} P_{k=1} &= \{r_j \in \mathbb{R}^+ : r_j \leq \alpha - R_{-j}\} \\ P_{k=2} &= \{r_j \in \mathbb{R}^+ : \alpha < r_j + R_{-j} \leq \beta\} \\ P_{k=3} &= \{r_j \in \mathbb{R}^+ : r_j > \beta - R_{-j}\} \end{aligned} \tag{3}$$

For expositional purposes we refer to $P_{k=1}$ as the "safe range," $P_{k=2}$ as the "uncertain range," and $P_{k=3}$ as the "destruction range."

In the second stage we consider each individual's "discrete choice" of which "zone" is optimal for them to select. This two-stage approach allows us to distinguish between the underlying motivations of resource constituents. Specifically, it allows us to separately identify the standard overconsumption problem from one created by individuals' strategic behavior to exhaust the resource.

Along these lines, the individual's optimal request level, conditional on being restricted to subset P_k, is the solution to the following problem:

$$\max_{r_j} E\left[\pi_j\left(r_j; R_{-j}\right)\right] \; s.t. \; r_j \in P_k \tag{4}$$

Let $\bar{r}_{j,k}$ denote the optimal request conditional on being restricted to subset P_k. A solution exists for all P_k that are not empty. For $k = 1$, the solution is characterized by setting the marginal benefit of an additional unit equal to zero, $b_j'\left(\bar{r}_{j,k=1},; R_{-j}\right) = 0$, if there exists an $r_j \in P_1$ that satisfies that condition, otherwise $\bar{r}_{j,k=1} = \alpha - R_{-j}$. For $k = 2$, the solution is characterized by

$b_j'(\bar{r}_{j,k=2}; R_{-j}) = \frac{D_j}{\beta-\alpha}$ if such an $\bar{r}_{j,k=2}$ exists.[2] For $k = 3$, the solution is characterized by $b_j'(\bar{r}_{j,k=3}; R_{-j}) = 0$.

The second stage of the optimization problem for each individual involves deciding which zone to choose. Denote $\bar{\pi}_{j,k}(R_{-j})$ as the maximum level of profit the individual can achieve conditional on the requests of others and being restricted to subset P_k, then the individual's second-stage problem can be written as:

$$\max_{\gamma_{j,k}} \sum_k \gamma_{j,k} \bar{\pi}_{j,k}(R_{-j}) \tag{5}$$

where $\gamma_{j,k} \in \{0,1\}$ and $\sum_k \gamma_{j,k} = 1$.[3] $\gamma_{j,k}$ represents the discrete choice made by each individual.

The solution to this problem is a set of γ_k such that:

$$\gamma_{j,\tilde{k}} = \begin{cases} 1 \; if \; \bar{\pi}_{j,\tilde{k}}(R_{-j}) \geq \bar{\pi}_{j,k}(R_{-j}) \; \forall \; k \neq \tilde{k} \\ 0 \; otherwise \end{cases} \tag{6}$$

A NE exists if every player cannot improve their payout unilaterally by changing r_j or γ_j. The model is parameterized for the experiment such that two such NE exist in each uncertainty (and certainty) treatment.

Social Planner's Problem

The social planner's problem is similar to the individual's problem in that she faces the same environmental uncertainty, represented by $\tilde{X} \sim U(\alpha, \beta)$. In calculating her solution, she accounts

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[2] $\frac{D_j}{\beta-\alpha}$ represents the expected marginal cost associated with increasing r_j. Note that this is constant because of the assumption of a uniform distribution.

[3] Note that $\sum_k \gamma_k$ can be greater than one if two $\bar{\pi}_k$ are equal. However, we ignore this special case given that it isn't a possibility for the parameters/functions chosen for this experiment.

for the total damage incurred by the group, while the individual is only concerned with the damage he incurs. Thus the social planner's problem can be represented as:

$$E\left[\pi\left(r_{1,2\ldots n}\right)\right] = \begin{cases} \sum_{j=1}^{n} b_j(r_j) & if\ R \le \alpha \\ \sum_{j=1}^{n} b_j(r_j) - \frac{\left(\sum_{j=1}^{n} D_j\right)(R-\alpha)}{\beta-\alpha} & if\ \alpha < R < \beta \\ \sum_{j=1}^{n} b_j(r_j) - \sum_{j=1}^{n} D_j & if\ R \ge \beta \end{cases} \tag{7}$$

The social planner's continuous solution conditional on discrete choices are as follows. For $k = 1$, the social planer's solution is characterized by setting the marginal benefit of an additional unit equal to zero for all users, $b_j'\left(\bar{r}^{sp}{}_{j,k=1}\right) = 0\ \forall\, j$, if there exists an $r_{1,\ldots,n} \in P_1$ that satisfies that condition, otherwise $b_j'\left(\bar{r}^{sp}{}_{j,k=1}\right) = b_{-j}'\left(\bar{r}^{sp}{}_{-j,k=1}\right)\ \forall\, j$ and $R = \alpha$. For $k = 2$, the solution is characterized by $b_j'\left(\bar{r}^{sp}{}_{j,k=2}\right) = b_{-j}'\left(\bar{r}^{sp}{}_{-j,k=2}\right) = \frac{\sum_{i=1}^{n} D_i}{\beta-\alpha}\ \forall\, j$. For $k = 3$, the solution is characterized by $b_j'\left(\bar{r}^{sp}{}_{j,k=3}\right) = 0\ \forall\, j$. Comparing the social planner's solution to the NE, it is possible to show that the social planner's total request, R^{sp},will never be larger than the sum of individual requests at the NE. While this result is generally true, the proceeding exposition focuses only on the cases relevant to our experiment.

The second stage optimization problem and its solution are similar to above, such that the discrete choice social planner solution is characterized by:

$$\gamma_{\tilde{k}} = \begin{cases} 1\ if\ \bar{\pi}^{sp}{}_{\tilde{k}} \ge \bar{\pi}^{sp}{}_{k}\ \forall\, k \ne \tilde{k} \\ 0\ otherwise \end{cases} \tag{8}$$

In the general formulation of this problem it is unclear how uncertainty affects the socially optimal solution and individual NE. A list of possible general-form solutions can be made available upon request, but for the sake of this experiment and our desire to formulate a model consistent with CPR settings, we limit the general problem to specific cases for which our experiment is parameterized.

Specific Model Solutions

Many possible cases exist in the general formulation of this problem and it can easily be shown that the effect of uncertainty under the general formulation is ambiguous.[4] We focus on specific cases that possess characteristics consistent with CPR settings. These cases have two NE and are defined by the following features: 1) there exists one symmetric NE in the uncertain range (the *partially defect* NE,) 2) there exists one symmetric NE in the destruction range (the *fully defect* NE), 3) both NE have lower expected payouts than the social planner's solution,[5] 4) the *fully defect* NE is inferior to the *partially defect* NE, and 5) conditional on others *fully defecting*, no individual who *fully defects* would unilaterally change to *partial defect* and vice versa. Within this subset of the general problem, we identify one case where the social planner's discrete solution is characterized by $\gamma_1 = 1$ such that the continuous choice solution is characterized by $b_j'(\bar{r}_{j,k=2}) = b_{-j}'(\bar{r}_{-j,k=2})\ \forall\, j$ and $R^{sp} = \alpha$ (the low-uncertainty treatment), and one case where $\gamma_2 = 1$ such that the optimal continuous-choice solution is characterized by $b_j'(r_{j,k=2}) = b_{-j}'(r_{-j,k=2}) = \frac{\sum_{i=1}^{n} D_i}{\beta-\alpha}\ \forall\, j$ and $\alpha < R^{sp} \leq \beta$ (the high-uncertainty treatment). These results imply that the social planner will not accept any probability of destroying the resource in the low-uncertainty case, but will accept some risk in the high-uncertainty case. We refer to the social planner outcome as the *coordinate solution*.

[4] See Appendix (A.2) for a simple example.

[5] Note that under the certainty treatment, the coordinate solution is one of the possible Nash Equilibria.

These cases were chosen because they correspond to many CPR settings and allow for meaningful analysis. For example, it is reasonable that the social planner would ensure resource survival, or that she is willing to accept some probability of destruction. However, if the socially optimal solution is to exhaust the resource ($\gamma_3 = 1$), there would be no social dilemma. We also acknowledge that under the general set-up, it is possible that no NE exist, but these cases would not allow for meaningful analysis. The cases of interest also implicitly assume that individuals have the ability to destroy the resource (β is sufficiently small) and that resource survival creates more value than destruction—both assumptions are consistent with most CPR settings. Limiting our analysis to only these cases of interest, it is possible to investigate how uncertainty affects both the discrete and continuous choice, and how NEs compare to the socially optimal solution. First, we examine the effect of uncertainty on token requests.

Because this analysis is limited to cases where two NE exist, we cannot theoretically identify the effect of increasing uncertainty on individuals' discrete choices. The *partially defect* NE is superior to the *fully defect* NE in every treatment, but the nature of the coordination game does not allow us to determine which NE will be reached *ex ante*. Therefore, picking one discrete-choice NE over the other is a behavioral question and will be tested in the experimental section of this paper. However, this ambiguity does not exist for the continuous choice given a particular discrete choice. For example, conditional on ($\gamma_2 = 1$), individuals will request such that $b_j'\left(\bar{r}_{j,k=1}^{NE}\right) = \frac{D_j}{\beta-\alpha}$. Because damage is constant, increasing $\beta - \alpha$ decreases the RHS of the equation.[6] Given the concavity of $b_j(r_j)$, requests must increase to satisfy the equality. Thus, conditional on the discrete choice to

[6] A graphical representation of these cases is provided in the appendix (A.3).

partially defect, increasing uncertainty increases consumption. These theoretical results are empirically tested across the low- and high-uncertainty treatments.

It is also possible to compare individual NE solutions to that of the social planner and show that, for the cases of interest, individuals have an incentive to overconsume. To compare the social planner and individual decisions, note that if both solutions are in the uncertain zone ($\gamma_2 = 1$) the individual's request solution is characterized by $b_j'\left(\bar{r}_{j,k=2}^{NE}\right) = \frac{D_j}{\beta-\alpha}$, whereas the social planner's solution is characterized by $b_j'\left(\bar{r}_{j,k=2}^{sp}\right) = \frac{\sum_j D_j}{\beta-\alpha}$. This implies that, $b_j'\left(\bar{r}_{j,k=2}^{sp}\right) > b_j'\left(\bar{r}_{j,k=2}^{NE}\right)$. Given the concavity of the payout function, it follows that $\bar{r}_{j,k=2}^{NE} > \bar{r}_{j,k=2}^{sp}$ and a social dilemma exists if individuals pick the *partially defect NE.* Moreover, this disparity in perceived marginal cost between the individual and social planner makes it possible that the social planner solution is to remain in the safe zone $\gamma_1 = 1$ when the NE discrete solution is $\gamma_2 = 1$. This describes the classic Prisoner's Dilemma, and occurs if $\bar{\pi}_{j,2}(R_{-j}^{sp}) \geq \bar{\pi}_{j,1}(R_{-j}^{sp})$ for any individual.

Given these results, policies may enhance the value derived from the resource. We consider two potential policies, including both a constant tax per unit requested as well as a fee paid by all if *R* exceeds the threshold, $\tilde{X}$. The optimal policy to address this CPR dilemma requires two things. It must induce individuals to pick the correct discrete choice, γ_k, and given that choice, it must also induce individuals to request the same amount as the social planner in discrete, $\bar{r}_{j,k}^{NE} = \bar{r}_{j,k}^{sp}\ \forall\ j$. If the social planner's discrete solution is $\gamma_1 = 1$, then the solution is characterized by $R^{sp} = \alpha$ and $b_j'\left(\bar{r}_{j,k=1}\right) = b_{-j}'\left(\bar{r}_{-j,k=1}\right) \forall\ j$. To ensure a solution, a policy must dictate $\bar{\pi}_{j,1} > \ \bar{\pi}_{j,2}\ , \bar{\pi}_{j,3}$ for all players in addition to ensuring that $\bar{r}_{j,k=1}^{NE} = \bar{r}_{j,k=1}^{SP} \forall\ j$. If instead the social planner's solution is γ_2=1, then the solution is characterized by $\alpha < R^{sp} < \beta$ and $b_j'\left(r_j\right) = \frac{\sum_{i=1}^{n} D_j}{\beta-\alpha}$ for all players. To ensure this solution, a policy must dictate $\bar{\pi}_{j,2} > \bar{\pi}_{j,1}, \bar{\pi}_{j,3}$ for all players. We ignore the case where the social planner's solution is γ_3, since this solution would denote the absence of any social dilemma. Importantly, while a tax is charged per unit extracted, the fine is a lump-sum charge.

The optimal tax in this setup depends on the specific equilibrium locations. In the simplest case, where the individual and the social planner problems both have solutions in the uncertain range (the high uncertainty treatment), taxes are set such that $tax = [\frac{\sum_{j=1}^{n} D_{-j}}{\beta-\alpha}]$. When the social planner solution is below the uncertain range (the low uncertainty treatment), the tax must be set differently since the social planner solution in this case is $b_j'(\bar{r}_{j,k=1}^{sp}) < \frac{\sum D_j}{\beta-\alpha}$. If the tax were set at the previous level, $[\frac{\sum_{j=1}^{n} D_{-j}}{\beta-\alpha}]$, individuals would be over taxed. The optimal tax in this case is $b_j'(\bar{r}_{j,k=1}^{sp}) - \frac{D_j}{\beta-\alpha} = tax$. In either case, an excise tax increases the marginal cost of extraction regardless of discrete choice, and it therefore effectively eliminates the *fully defect* NE and moves the *partially defect* NE to coincide with the *coordinate solution* under both uncertainty treatments. The fine also shifts the *partially defect* NE to coincide with the *coordinate solution*; however, it does not eliminate the *fully defect* NE since it only increases expected marginal value in the uncertain range. Theoretically, the fine is equivalent to increasing the size of D_j to $\sum_{j=1}^{n} D_j$, and thus is set as $fine = \sum_{j=1}^{n} D_{-j}$. Because taxes increase marginal cost regardless of discrete choices, we expect their presence to increase $b_j'(\bar{r}_{j,k}^{NE})$ and thus reduce total consumption. Fines, by comparison, only affect marginal cost in the uncertain zone, and may not induce efficient discrete choices.

To test these theoretical predictions, an experiment was used in which policies and resource threshold uncertainty could be exogenously introduced and varied.

Experimental Setup

The experiment attracted 96 undergraduate students from Colorado State University, who received an average payment of $27. It was conducted in the spring and fall semesters of 2015 in a computer lab using z-Tree (Fischbacher 2007). The experiment was conducted over six sessions, one session of 20 students, four with 16, and one with 12.

Experimental Design and Procedures

In each session, individuals participated in 12 rounds made up of 8 static periods.[7] The 9 rounds of interest in this analysis differed by policy and uncertainty treatment, while the 8 periods within a round remained identical to one other. By introducing three uncertainty treatment levels and three policies, we can compare the instances of defecting under each permutation of policy and uncertainty level. Uncertainty treatments included: 1) Certainty, 2) Low Uncertainty, and 3) High Uncertainty. The ordering of each treatment varied across sessions to control for possible ordering effects.

At the start of each round, participants were informed of the uncertainty and policy treatment for that round. Then players independently requested specific numbers of tokens. After each player made a request, a payout screen was displayed with key information from the period.[8] This screen informed participants of how much they requested (not the requests of others), if the group

[7] While students participated in 12 rounds, only 9 are used in this paper. The rounds with the Certainty-varying treatment were used to answer a different question and will be analyzed in a future paper.

[8] Note that to help ensure independent rounds, the total payout of participants was determined by a randomly selected period such that no wealth or cumulative effect would affect later rounds.

exceeded the threshold, the total money paid for potential damage and policy payments, and their payout for the period. While groups were always comprised of four players, the individual make-up of each group was pseudo-randomly assigned each period.

At the beginning of the experiment, individuals were provided with a table showing their actual payout per token as well as the damage amount they would incur if the sum of requests surpassed the threshold. Half of the players in each group were assigned a low-productivity payout schedule, in which the payout per token was less than that of high-productivity participants (parameterization described in the following section). Individuals did not know others' true payouts, only that they were heterogeneous and that individuals who receive higher payouts per token also suffer larger damages when the threshold is exceeded.

This experimental design allows us to systematically examine the relationship between environmental uncertainty and resource constituents' equilibrium choices and consumption. Participants face the simple choice of requesting a specific token amount and should be able to easily identify the *fully defect* choice since it corresponds to the token amount at which marginal benefit equals zero on their payout table.

We chose to avoid revealing the requests of other individuals in a group, and instead elected to only inform individuals if their group stayed below or exceeded the threshold. This decision was made to reflect reality, in which resource users are unlikely to observe the exact consumption of other individuals. It also helps us avoid a tit-for-tat strategy, which is necessary to assume the independence of periods.

Model Parameterization for the Experiment

For the experiment, a group size of four is used to allow for symmetry and to create group dynamics that may not be present in a bi-lateral game. D_j and $b_j(r_j)$ are unchanged for each participant across each treatment to help with understanding. Thus, the only parameters that change across treatments are those associated with the uncertainty range (α and β), although $E[\tilde{X}]$ remains constant throughout the experiment. α and β were chosen to reflect three uncertainty treatments: certainty, low uncertainty, and high uncertainty. The specific uncertainty parameterization of each treatment is presented in Table 1. In the certainty case, $\alpha = \beta = 18$.

Table 1.1. Uncertainty Range by Treatment

	$\boldsymbol{\alpha}$	$\boldsymbol{\beta}$	**Uncertainty Range**
Certainty	18	18	0
Low Uncertainty	12	24	12
High Uncertainty	8	28	20

The payoff functions for the experiment participants were parameterized to introduce heterogeneity in user type to represent more and less productive resource extractors. Table 2 presents the payouts associated with different levels of requests made by each user type. Notice that the high productivity user has a higher payout associated with each level of request and faces a larger damage penalty if the group exceeds the resource threshold, reflecting larger losses to higher productivity users from resource collapse.

Table 1.2. Payout Schedule and Damage Amount for Each User

Marginal Payout per Token											
Tokens Requested	0	1	2	3	4	5	6	7	8	9	10
Low Productivity	-	$11.00	$7.50	$4.50	$2.80	$1.75	$0.90	$0.10	-$0.50	-$1.20	-$1.75
High Productivity	-	$13.00	$9.50	$6.50	$4.80	$3.75	$2.90	$2.10	$1.40	$0.80	$0.25
Damage	Low productivity: $16					High productivity: $30					

The model was parameterized such that both the *partially* and *fully defect* NE exist in both uncertainty treatments. The individual *partially defect* NE is in the uncertainty zone under both low and high uncertainty, and the payout from that equilibrium is always higher than that of the *fully defect* NE. The numeric solutions under each treatment are summarized in Table 3.

Table 1.3. Individual & Social Planner Solutions and Corresponding Total Expected Value

	Partially Defect NE				
	Token Requests		Expected Payout		
Productivity type	Low	High	Low	High	Total
Certainty	many NE	many NE	many	many	many
Low Uncertainty	5	6	14.2	15.5	59.3
High Uncertainty	6	7	14.4	15.6	59.2
	Fully Defect NE				
	Token Requests		Expected Payout		
Productivity type	Low	High	Low	High	Total
Certainty	7	10	12.55	15.0	55.1
Low Uncertainty	7	10	12.55	15.0	55.1
High Uncertainty	7	10	12.55	15.0	55.1
	Coordinate Solution				
	Token Requests		Expected Payout		
Productivity type	Low	High	Low	High	Total
Certainty	3	6	23.0	40.5	127
Low Uncertainty	2	4	18.5	33.8	105
High Uncertainty	2	4	18.5	27.8	86.2

Policy Parameterization

Each of the three uncertainty treatments will be investigated under two policies in addition to the base case—a per-unit tax on extraction, and a fine for exceeding the threshold. The optimal tax in the high uncertainty treatment is set such that $tax = [\frac{\sum_{j=1}^{n} D_{-j}}{\beta-\alpha}]$, or \$4.67 for low productivity users and \$1.78 for high productivity users. In the low uncertainty treatment, the tax is set to $tax = b_j'\left(\bar{r}_{j,k=1}^{sp}\right) - \frac{D_j}{\beta-\alpha}$, or \$3.80 for low productivity users and \$3.10 for high productivity users. The fine is set as the total damage others would incur if the threshold is exceeded. Numerically, this results in a \$76 fine for low productivity users and \$62 fine for high productivity users. Under this parameterization, conditional on other group members *fully defecting* and pushing the group into the destruction range, no single individual can unilaterally improve expected payout by decreasing requests. In fact, if an individual chooses to *partially defect* when others in the group chose to *fully defect*, that individual would suffer substantial losses because he would incur both the damage and the fine without gaining the extra benefit from extracting $\bar{r}_{j,k=3}^{NE}$. Therefore, the fine policy does not eliminate the *fully defect* NE.

Experimental Results

To better understand the impact of uncertainty on an un-regulated CPR, we begin by restricting our analysis to just those periods where no policies are in place. Tables 4a-c, below, contain summary statistics characterizing the token requests, frequency the threshold was crossed, and percent of times the fully defect strategy was adopted across each of the different uncertainty treatments for these rounds.

Without a policy, the threshold was exceeded 37.5% of the time under the known threshold, 58.9% in the low uncertainty treatment, and 52.1% of the time in the high uncertainty treatment.

Table 1.4a. Summary Statistics: % of Periods the Threshold was Exceeded

	No Policy	Tax	Fine
Certain	37.5%	6.8%	8.3%
Low Uncertainty	58.9%	14.6%	27.6%
High Uncertainty	52.1%	29.2%	28.1%

Individuals chose to *fully defect* 5.6% of the time under the certainty treatment, 16.0% of the time under the low uncertainty treatment, and 15.5% of the time under the high uncertainty treatment (Table 4b).

Table 1.4b. Summary Statistics: % of Requests to Fully Defect by Treatment

	No Policy	Tax	Fine
Certain	5.60%	0.26%	0.78%
Low Uncertainty	16.0%	0.39%	1.82%
High Uncertainty	15.4%	0.65%	1.43%

The *fully defect* choice is defined with a binary variable that takes the value of 1 if participants request the amount of tokens such that $b_j' = 0$, and 0 otherwise. Average token requests by treatment and user type are also reported in Table 4c.

Table 1.4c. Summary Statistics: Request Means by Treatment and Use Type

	Whole Sample						Coordinate Only					
	No Policy		Tax		Fine		No Policy		Tax		Fine	
Productivity	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High
Certainty	4.49	4.75	3.44	4.34	4.11	4.12	4.38	4.34	3.43	4.31	4.07	4.12
	(0.99)	(1.75)	(0.93)	(1.05)	(0.93)	(1.02)	(0.87)	(1.01)	(0.92)	(1.01)	(0.85)	(1.01)
Low Uncertainty	4.64	5.51	2.65	4.58	3.58	3.71	4.33	4.36	2.63	4.55	3.45	3.70
	(1.57)	(2.67)	(1.17)	(1.65)	(1.18)	(1.24)	(1.39)	(1.58)	(1.15)	(1.61)	(1.00)	(1.24)
High Uncertainty	4.78	5.42	2.96	3.47	3.50	3.37	4.41	4.50	2.93	3.43	3.44	3.30
	(1.83)	(2.74)	(1.00)	(1.54)	(1.34)	(1.73)	(1.71)	(1.99)	(0.95)	(1.47)	(1.27)	(1.60)

Standard deviation is reported in parentheses

While it is clear that some individuals choose the *fully defect* equilibrium in the presence of environmental uncertainty, it is less clear that they successfully identify the *partially defect* NE. If we count observations within 1 token of NE requests, we can calculate the proportion of individual requests that are consistent with NE results. For low productivity users, 41.0% of all observed requests in the low uncertainty case are within 1 token of the *partially defect* NE. High productivity users are less consistent; only 30.5% of observed requests fall in this range in the same information treatment, although this result is partially driven by the fact that high productivity users more frequently *fully defect*. Under high uncertainty these percentages decrease substantially to 24.7% for low productivity users and 14.2% for high productivity users. Risk preferences may explain some of these deviations, since the NE calculations assume risk neutrality in payouts.[9]

[9] Participants were generally risk averse—identified with a Holt-Laury test (Holt & Laury, 2002). After the CPR experiment was conducted, participants were given a Holt-Laury test. Results are reported on a score of 1 to 10, where 1 represents extreme risk loving and 10 represents extreme risk aversion. The average risk score for participants was 6.3, suggesting that participants in the sample were, on average, mildly risk averse. Mild risk aversion would lower the tolerance individuals have for risk and either cause a lower request rate than the partially defect NE, or if risk aversion is significantly large, it may induce individuals to fully defect under uncertainty.

To answer the research questions posed at the beginning of this paper a number of empirical model specifications are estimated using data from the experiment. The dependent variable in each of these models is either the number of tokens requested or a binary variable meant to represent the choice to *fully defect*. We model the number of tokens or the discrete choice as a function of several independent variables. First, x_{itcs} is a vector of dummy variables for each policy treatment observed for individual i in period t, round c, and session s of the experiment. Tax and fine dummy variables take a value of 1 if that policy is in place and 0 otherwise. w_{itcs} is a vector of dummy variables indicating the uncertainty treatment, ρ_{itcs} is a vector of policy-uncertainty interaction dummies and z_i is a dummy variable for risk aversion where $z = 1$ if an individual is risk averse and $z = 0$ otherwise. If ϵ_{itcs} is an idiosyncratic error term, our econometric models can be written as:

$$y_{itcs} = f(\beta_0 + x'_{itcs}\beta_1 + w'_{itcs}\beta_2 + \rho'_{itcs}\beta_3 + z_i'^{\beta_4} + \epsilon_{itcs}) \tag{9}$$

The coefficients of interest include β_1 and β_2 where the vector β_1 represents the impact of policies on either the quantity of tokens requested or on the discrete decision to *fully defect*. β_2 is the effect of uncertainty on each dependent variable. The above equation was estimated for the discrete decision under three model specifications, logit random effects (logit-RE), logit, and fixed-effects linear probability. The logit random-effects models is the preferred model for estimating the impacts of policy and uncertainty, while the other two were included for robustness. Results are qualitatively and quantitatively consistent across all specifications. For models including the quantity of tokens requested, we estimate linear models both pooled and with individual fixed effects. We now present empirical model results and use them to elucidate the role of uncertainty in CPR consumption decisions, including both continuous quantity decisions and the discrete decision to *fully defect.*

Environmental uncertainty and the discrete choice

First, we investigate if uncertainty affects request rates by increasing the probability that individuals choose the discrete choice to *fully defect*. In this case, y indicates if individuals *fully defect* (y = 1) or they do not (y = 0). We examine the individuals' discrete choice by estimating equation 9 using logit-RE, logit, and OLS-FE specifications (Table 5). Positive and significant coefficients on the uncertainty treatments indicate that the decision to *fully defect* is consistently influenced by the presence of environmental uncertainty; however, the probability is not significantly different across low- and high-uncertainty treatments. The logit-RE model indicates that the probability an individual fully defects increases by 4.7% when moving from a world of certainty to one in which uncertainty exists around the resource threshold. The effect is qualitatively similar under the other model specifications, but larger in magnitude.

Table 1.5. Binary Decision to Fully Defect

VARIABLES	(1) LOGIT-RE	(2) LOGIT	(1) OLS-FE
Low Uncertainty	0.0471***	0.124***	0.103***
	(0.0080)	(0.0197)	(0.0091)
High Uncertainty	0.0453***	0.120***	0.100***
	(0.0080)	(0.0198)	(0.0091)
Fine	-0.0713***	-0.214***	-0.0482***
	(0.0164)	(0.0493)	(0.0099)
Tax	-0.108***	-0.331***	-0.0534***
	(0.0265)	(0.0800)	(0.0010)
Tax Interaction	-0.0229***	-0.0481	-0.0990***
	(0.0271)	(0.0859)	(0.0122)
Fine Interaction	-0.020***	-0.041	-0.093***
	(0.0166)	(0.0517)	(0.0122)
Risk Aversion		0.0223	
		(0.0145)	
Constant			0.056***
			(0.0070)
Observations	6,912	6,912	6,912
R-squared			0.090
Number of subjects	96		96

Standard errors in parentheses
Logit models are reported as average marginal effects
*** p<0.01, ** p<0.05, * p<0.1

Uncertainty and Resource Consumption

While uncertainty induces some individuals to *fully defect* and exhaust the resource, we are also interested in how uncertainty affects the request rates of individuals who choose to *partially defect*. Table 6 presents the results of equation 9 when y_{itcs} is the request rate of individual i. In columns 1 and 3, only observations for subjects that did not *fully defect* are included and it becomes clear that, conditional on not fully defecting, uncertainty has a very small or insignificant effect on the number of tokens requested. On the other hand, when including the whole sample, uncertainty significantly increases the number of tokens requested (columns 2 and 4). The result that the presence of uncertainty exacerbates overconsumption is consistent with what others have found (Budescu et al., 1995; Rapoport et al., 1992; Walker & Gardner, 1992), but here this is largely the result of a change in the discrete resource use decision.

Table 1.6. Token Requests without Policies

VARIABLES	(1) OLS Omitting Fully Defect	(2) OLS Whole Sample	(3) FE Omitting Fully Defect	(4) FE Whole Sample
Low Uncertainty	-0.017	0.456***	0.056	0.456***
	(0.0786)	(0.1040)	(0.0607)	(0.0786)
High Uncertainty	0.098	0.480***	0.129**	0.480***
	(0.0785)	(0.1041)	(0.0604)	(0.0786)
Risk Aversion	-0.309***	-0.298***		
	(0.0716)	(0.0947)		
Constant	4.581***	4.833***	4.327***	4.618***
	(0.0742)	(0.100)	(0.0414)	(0.0556)
Observations	2,019	2,304	2,019	2,304
R-squared	0.010	0.016	0.002	0.021
Number of subjects			96	96

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

This distinction is important because it highlights an erroneous conclusion that can be made if one simply looks at the average effect of uncertainty. The increase in average request under uncertainty obfuscates the real mechanism behind the exacerbated CPR dilemma: Individuals are more likely to *fully defect* and ignore the role of the environmental threshold in the presence environmental uncertainty. Viewing the social dilemma as a discrete shift rather than a simple rent dissipation problem has significant implications for the cause and solution to the CPR problem.

Interestingly, risk aversion appears to have little effect on the decision to *fully defect* (Table 5), even though theory suggests that extreme risk aversion should induce individuals to do so.[10] In general, extremely risk averse participants may choose to request fewer tokens to decrease the probability of incurring a loss, but they may also *fully defect* in order to prevent the severe personal loss that would occur if they coordinate but the resource is destroyed anyway. When the *partially defect* NE creates an outcome in which the resource has some probability of destruction, resource constituents with strong risk aversion may intentionally destroy the resource to eliminate uncertainty. We find no evidence that risk averse players *fully defect* more frequently. However, conditional on not *fully defecting,* risk aversion decreases the requests made by individuals (Table 6), consistent with a desire to avoid exceeding the threshold.

Policy Impacts with Threshold Uncertainty

Our results strongly suggest that uncertainty leads to overconsumption relative to the social optimum both because individuals choose to *fully defect* and because they don't account for the damage additional token requests imposes on others by increasing the probability of resource destruction. Thus, it is worth evaluating how effective different policies are at reducing consumption to more efficient levels.

Theoretically, the fine, unlike the tax, does not eliminate the *fully defect* NE. To empirically test if tax and fine policies prevent the *fully defect* equilibrium, equation 9, we examine the coefficient estimates on the policy variables. We estimate the coefficients on the dummy variables for the tax and fine policy as well as interaction terms between these policies and the presence of uncertainty.

[10] See appendix for this theoretical result.

First, we investigate policy impacts on the binary variable indicating the discrete choice to *fully defect*. Table 5 shows that both policies are effective at eliminating the choice to *fully defect* and coefficients do not differ significantly across the policies. This suggests that while theoretically different, both policies are qualitatively similar in practice.

It is clear that CPR dilemmas in the presence of an unknown tipping point are at least partially caused by the decision to *fully defect*. However, the more common explanation is also observed, since individuals do not properly account for the increased probability of damage imposed on others. Accordingly, we test for the effect of policies on individuals' request rates to see if policies can achieve efficient outcomes. We find that both fine and tax policies successfully reduce consumption by as much as 1.7 tokens (Table 7), however this reduction is less than the amount necessary to attain the efficient outcome.

Table 1.7. Token Requests Including Policies (Whole Sample)

VARIABLES	OLS-FE
Low Uncertainty	0.566***
	(0.0634)
High Uncertainty	0.371***
	(0.0634)
Tax	-0.737***
	(0.0694)
Fine	-0.497***
	(0.0694)
Tax-Uncertainty Interaction	-0.936***
	(0.0851)
Fine-Uncertainty Interaction	-1.05***
	(0.0851)
Constant	4.618***
	(0.0491)
Observations	6,912
R-squared	0.191
Number of subjects	96

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

It is worth noting that while both policies are equally effective at reducing the instances of defecting and reducing overall consumption, the fine policy is empirically less efficient because it does not create the efficient differentiation in request rates between low and high productivity users. The fine causes low and high efficiency users to cut back equally, while the tax causes the low productivity users to cut back comparatively more. While the cause of this result is unclear, it may come from the certainty differences across policies. The tax is charged with certainty for each token requested whereas the fine only increases the expected cost to an individual. Nevertheless, both incentivize CPR users to extract less of the resource and increase efficiency.

Conclusion and Discussion

The theoretical and empirical results presented here suggest that the destruction of CPRs may result from a discrete choice to exhaust the resource and not simply a failure to internalize the full costs of resource extraction. When uncertainty around a resource's ecological or physical tipping point exists, individuals are more likely to ignore potential resource degradation even when the corresponding consumption decisions lead to inferior outcomes and assured resource destruction. We find that while uncertainty induces some individuals to knowingly damage the resource by ignoring potential impacts on the resource, it has little effect on those individuals who do not intentionally *fully defect*. In addition, taxes and fines for resource extraction decrease the probability that individuals choose to destroy the resource under the assumption that destruction is inevitable.

Previous studies have found that environmental uncertainty leads to increased consumption. Our results do not contradict these findings, but they suggest that increased CPR consumption may be the result of a distinct change in resource constituents' underlying choice to ignore impacts on resource stocks in anticipation that others will do the same. Our main contribution is to distinguish CPR over-use incentives in a context of threshold uncertainty—a distinction which is important from a behavioral and policy perspective. If little is known about a resource, users may take the mindset that it is likely to be destroyed regardless of their choices. In this context, the rational way to use the resource is to myopically maximize net value, ignoring any true impact on the resource. In this way, CPR dilemmas in the presence of tipping points create both a Prisoner's Dilemma and a coordination problem.

This research has several policy-relevant implications. First, regulation of CPR's with uncertain tipping points through taxes and fines has the potential to improve efficiency. This improvement comes through both marginal decreases in extraction as well as deterring individuals from choosing to deliberately destroy the resource. When strict tax and fine policies are politically infeasible, there may still be significant gains from interventions that eliminate the ability (or desire) of resource constituents to *fully defect.*

In settings where outside policies are unlikely to be adopted and local institutions do not exist or lack the capacity to design and implement conservation policies, better information about the resource may provide an opportunity to improve the sustainability of that resource over time and increase the value obtained from scarce natural resources, even if the first-best solution cannot be reached. Reducing or re-characterizing uncertainty to affect public perception (and actions) has been explored in the field of climate science, where "identifying and reducing scientific uncertainty about climate change is a dominant theme of many scientific assessment[s]" (Shackley & Wynne, 1996). Climate scientists have chosen to largely focus public information campaigns on exact thresholds (350.org or 2^{o}) because such precise goals can encourage coordination. As with greenhouse gas emissions, decreasing scientific uncertainty may change resource extraction behavior even without implementing additional policies. In this way, improving the physical understanding of vulnerable CPR systems can avoid resource exhaustion and enhance the livelihoods of people who depend on the resource.

While there are some shortcomings associated with condensing a time-dependent CPR scenario into a single-period experiment, our setup maintains much of the incentive structure present in dynamic games. The single-period game allows for many more independent observations, and can be a tool when time and money constraints are binding. Moreover, setting up this repeated static game allows us to easily differentiate between discrete choices in the presence of environmental uncertainty. Given the strong effect of threshold uncertainty on fully defecting, our results suggest the need to consider this feature in CPR modeling whenever such uncertainty exists.

Future work in this area will include evaluating the interaction of social and environmental uncertainty within this framework, the introduction of other types of policies such as communication, a more formal investigation of risk preferences, and most importantly, an attempt to identify why the same uncertainty has heterogeneous effects on individuals' discrete resource consumption choices. Overall, we demonstrate that resource threshold uncertainty can affect both marginal extraction decisions and the willingness of extractors to consider impacts on resource stocks.

REFERENCES

Adams, W. M., Brockington, D., Dyson, J., & Vira, B. (2003). Managing tragedies: understanding conflict over common pool resources. *Science*, *302*(5652), 1915–1916.

Aflaki, S. (2013). The effect of environmental uncertainty on the tragedy of the commons. *Games and Economic Behavior*, *82*, 240–253.

Barrett, S., & Dannenberg, A. (2012). Climate negotiations under scientific uncertainty. *Proceedings of the National Academy of Sciences of the United States of America*, *109*(43), 17372–6

Biel, A., & Gärling, T. (1995). The role of uncertainty in resource dilemmas. *Journal of Environmental Psychology*, *15*(3), 221–233.

Blanco, E., Lopez, M., & Walker, J. (2015). The Opportunity Costs of Conservation with Deterministic and Probabilistic Degradation Externalities. *Environmental and Resource Economics*, 1–19. http://doi.org/10.1007/s10640-014-9868-7

Botsford, L. W., Castilla, J. C., & Peterson, C. H. (1997). The management of fisheries and marine ecosystems. *Science*, *277*(5325), 509–515.

Budescu, D. V., Rapoport, A., & Suleiman, R. (1995). Common Pool Resource Dilemmas under Uncertainty: Qualitative Tests of Equilibrium Solutions. *Games and Economic Behavior*, *10*(1), 171–201. http://doi.org/10.1006/game.1995.1029

Budescu, D. V, Rapoport, A., & Suleiman, R. (1990). Resource dilemmas with environmental uncertainty and asymmetric players. *European Journal of Social Psychology*, *20*(6), 475–

487. http://doi.org/10.1002/ejsp.2420200603

Dannenberg, A., Löschel, A., Paolacci, G., Reif, C., & Tavoni, A. (2011). Coordination under threshold uncertainty in a public goods game. *ZEW-Centre for European Economic Research Discussion Paper*, (11-065).

Dawes, R. M. (1980). Social dilemmas. *Annual Review of Psychology*, *31*(1), 169–193.

De Vries, S., & Wilke, H. A. M. (1992). Constrained egoism and resource management under uncertainty.

FAO. (2010). *Managing Forests for the Future*. Rome, Italy. Retrieved from http://www.fao.org/docrep/014/am859e/am859e08.pdf

Gärling, T., Biel, A., & Gustafsson, M. (1998). Different kinds and roles of environmental uncertainty. *Journal of Environmental Psychology*, *18*(1), 75–83.

Gordon, H. S. (1954). The Economic Theory of a Common-Property Resource: The Fishery. *Journal of Political Economy*, *62*(2), 124–142 CR – Copyright © 1954 The University. http://doi.org/10.2307/1825571

Greene, W. (2004). The behaviour of the maximum likelihood estimator of limited dependent variable models in the presence of fixed effects. *The Econometrics Journal*, *7*(1), 98–119.

Gustafsson, M., Biel, A., & Gärling, T. (2000). Egoism bias in social dilemmas with resource uncertainty. *Group Processes & Intergroup Relations*, *3*(4), 351–365.

Hardin, G. (1968). The Tragedy of the Commons. *Science* , *162* (3859), 1243–1248. Retrieved from http://www.sciencemag.org/content/162/3859/1243.abstract

Holt, C. A., & Laury, S. K. (2002). Risk aversion and incentive effects. *American Economic Review*, *92*(5), 1644–1655.

Messick, D. M., Allison, S. T., & Samuelson, C. D. (1988). Framing and communication effects on group members' responses to environmental and social uncertainty. *Applied Behavioral Economics*, *2*, 677–700.

Olsen, R. A. (1997). Desirability bias among professional investment managers: Some evidence from experts. *Journal of Behavioral Decision Making*.

Ostrom, E. (2006). The value-added of laboratory experiments for the study of institutions and common-pool resources. *Journal of Economic Behavior & Organization*, *61*(2), 149–163. http://doi.org/10.1016/j.jebo.2005.02.008

Poe, G. L., Schulze, W. D., Segerson, K., Suter, J. F., & Vossler, C. A. (2004). Exploring the Performance of Ambient-Based Policy Instruments When Nonpoint Source Polluters Can Cooperate. *American Journal of Agricultural Economics* , *86* (5), 1203–1210. http://doi.org/10.1111/j.0002-9092.2004.00665.x

Rapoport, A., Budescu, D. V, Suleiman, R., & Weg, E. (1992). Social dilemmas with uniformly distributed resources.

Shackley, S., & Wynne, B. (1996). Representing uncertainty in global climate change science and policy: Boundary-ordering devices and authority. *Science, Technology & Human Values*, *21*(3), 275–302.

Suter, J. F., Duke, J. M., Messer, K. D., & Michael, H. A. (2012). Behavior in a Spatially Explicit Groundwater Resource: Evidence from the Lab. *American Journal of Agricultural Economics* . http://doi.org/10.1093/ajae/aas058

Walker, J. M., & Gardner, R. (1992). Probabilistic Destruction of Common-pool Resources: Experimental Evidence. *The Economic Journal*, *102*(414), 1149–1161 CR – Copyright

© 1992 Royal Econom. http://doi.org/10.2307/2234382

Walker, J. M., Gardner, R., & Ostrom, E. (1990). Rent dissipation in a limited-access common-pool resource: Experimental evidence. *Journal of Environmental Economics and Management*, *19*(3), 203–211. http://doi.org/10.1016/0095-0696(90)90069-B

Wit, A., van Dijk, E., Wilke, H., & Groenenboom, A. (2004). The interplay between environmental and social uncertainty in social dilemmas. *Contemporary Psychological Research on Social Dilemmas*, 376–398.

CHAPTER 2. EVALUATING THE EFFECT OF CONSERVATION AND COST MOTIVATIONS ON WATER DEMAND

Highlights

- Households primarily motivated by environmental and social considerations consume less water than households primarily motivated by cost and convenience.
- Price and weather shocks induce identical water consumption responses from consumers regardless of their underlying motivations for conservation.

Introduction

As natural resources such as water become increasingly scarce, managers often seek policies to reduce demand (Geick 2000). In urban water systems, individual household characteristics strongly influence the effectiveness of demand-side management strategies (DSM) as well as the additional demands induced by hot and dry weather events (Kenney et al. 2008; Nieswiadomy 1992; Schleich and Hillenbrand 2009; Billings and Day 1989). Yet, little is known about the relationship between household conservation attitudes and realized consumption. Municipal water providers must anticipate changes in household consumption patterns driven by changes in price or drought conditions to effectively plan supply and distribution systems. Understanding how customer motivations translate to consumption responses will help inform this task. Recent studies have attempted to better understand household water consumption decisions either through the creation of household classes or by including household characteristics directly into the demand equations, but these studies have traditionally focused on the effect of observable household characteristics such as house size. Few studies of US water consumers have used stated preference methods to evaluate the effect of underlying beliefs and attitudes on revealed residential water use and conservation.

Utilities and water suppliers in the southwestern United States have introduced a number of education and conservation programs over the past two decades in an attempt to address increasing water scarcity. While programs differ from city to city, they are generally designed for the representative customer in a service region. However, Willis et al. (2011) opine that "[d]etermining motives for saving water are key when designing educational urban water saving strategies; hence at the outset, an understanding of consumption and attitudes towards water is vital." Moreover, convenience, cost, social pressure, and environmental attitudes have all been shown to be motivating factors in conservation (Olmstead et al. 2007; Olmstead and Stavins 2009; Arbués et al. 2016; Trumbo and O'Keefe 2001). Thus, understanding the relative effects of each motivation on water consumption has implications for designing programs and policies. This paper investigates the relationship between underlying motivations of conservation and water consumption decisions by using household level utility data and telephone surveys.

Economic theory and previous research suggest that individual consumers will decrease water use when the price of water increases (Espey et al.1997; Dalhuisen et al. 2003). It also suggests that if precipitation and temperature are intermediary goods in the creation of a good or service—a green lawn or garden for example—municipal water and precipitation are likely substitutes such that increased rain should decrease municipal water consumption. Indeed, these results have been found in numerous settings (Arbués et al. 2003; Worthington and Hoffman 2008).Standard economic theory, however, does little to help us understand how stated environmental and cost attitudes interact with weather and price shocks with respect to consumption behavior. Thus, we propose and test a series of hypotheses to empirically elucidate how consumer stated preferences influence responses to prices and the weather.

Hypothesis 1

Households primarily motivated by environmental and social (E&S) outcomes consume less total water than consumers primarily motivated by cost and convenience (C&C).

Hypothesis 2

E&S consumers respond less to changes in price than C&C consumers. *Ceteris paribus*, we hypothesize customers concerned with cost will have more elastic demand with respect to price.

Hypothesis 3

E&S consumers and C&C consumers will respond identically to changes in monthly precipitation and temperature.

These questions are of particular interest because they provide direction for water suppliers' future education and conservation programs. Moreover, they must be answered empirically because theory does little to guide our hypotheses. Our results reveal that E&S consumers use less water on average but both consumer groups respond identically to variation in price and weather. This result has important implications for water and other resource managers because it suggests that heterogeneity in consumer type may not always lead to expected variation in responses to conservation policies.

The remainder of this paper is comprised of four sections: in the next section we briefly summarize the existing water demand and environmental psychology literature. Section three outlines our methodology and data, section four presents our results, and section five concludes.

Background

Considerable research has been dedicated to the relationship between household characteristics and water consumption behavior; we return to this area for two reasons. First, only a few studies focus on the effect of underlying attitudes and beliefs on water consumption, the majority of which are specific to Australia. Randolph and Troy (2008) find that attitudes and culture significantly affect water use, and for this reason estimates in one city may not be externally valid for another. Accordingly, previous qualitative results may or may not be replicable in new geographic areas (Willis et al. 2013). As such, our analysis is similar to investigation of water use in Eastern Australia, but applied to a representative city in the southwestern United States. The second goal of this study is to add another data point to the debate over environmental attitudes and actions, which has substantial implications for how to efficiently incentivize resource conservation.

Research has linked environmental attitudes and beliefs to a host of environmental conscientious actions such as recycling, composting, efficient appliance installation, and conservation (Cialdini et al. 1990; Taylor and Todd 1997; Millock and Nauges 2010). In the specific context of water, a number of underlying motivations have been linked to lower consumption levels, including reducing costs (Olmstead and Stavins 2009; Arbués et al. 2003), normative social pressure (Trumbo and O'Keefe 2001; Víctor Corral-Verdugo and Frías-Armenta 2006), responding to possible punishment (Agras, Jacob, and Lebedeck 1980), and pro-environmental attitudes (Corral-

Verdugo et al. 2003). While the majority of findings suggest that environmental attitudes are linked to pro-environmental actions, these results are far from unanimous. A particular schism can be observed between the environmental psychology literature—which contains a number of studies with inconsistent results linking attitudes to actions—and the resource economics literature—which generally finds that attitudes lead to actions.

In the environmental psychology literature, research on environmental behavior is extensive, but results explicitly linking psychological factors and motivations to conservation behavior are mixed and considered inconclusive (Gregory and Leo 2003; Tuan 1968). In many of these studies, environmental attitudes have been shown to insufficiently explain pro-environmental behavior (Kollmuss and Agyeman 2002; Poortinga et al. 2004). Since social scientists often assume that people live according to their values and stated preferences, this phenomenon has received significant attention in the field of environmental psychology (Diekmann and Preisendörfer 1998; Diekmann and Preisendörfer 2003; Whitmarsh and O'Neill 2010). To address this discrepancy, a number of theories have been proposed, with the Minimum Cost Theory garnering the most attention and support. Diekmann and Preisendörfer (1998) suggest that environmetnal conciousness will translate into behavior only when the monetary and/or non-monetary cost is sufficiently low. Thus, understanding how customers' motivations around cost and convenience lead to consumption and conservation decisions is a necessary step in creating effective conservation policies. This finding is particularly relevent for water suppliers who sponsor education and conservation programs, and suggests that convenience may be a strong driver in encouraging conservation.

Results from the field of applied economics have been slightly more encouraging. Educational campaigns have been a common practice for most utilities, and evidence suggests that they are an effective conservation tool (Michelsen et al. 1999; Nieswiadomy 1992). However, it is worth noting that water education programs have historically been introduced simultaneously with other DSM strategies, making it difficult to identify the sole effect of education. Moreover, it is difficult to determine if education programs simply provide knowledge—a prerequisite in changing behavior (Hungerford and Volk 1990)—which allows people to make more efficient decisions, or if education campaigns engender a sense of environmental stewardship which in turn increases the personal "value" of conservation.[11] It remains unknown if education programs work because they reduce cost and increase convenience, or if they work because people feel good about conserving. Here, we begin to investigate this difference by measuring if the consumption decisions of households who claim to be motivated by cost and convenience differ from those motivated by social and environmental concerns.

Individuals motivated by environmental and social outcomes are of particular interest because there is evidence that education campaigns focused on simply fostering environmental education can lead to long-term pro-environmental attitudes (Ballantyne and Packer 2005; Farmer et al. 2007). If E&S motivated consumers use less (or respond differently) than their C&C motivated counterparts, then education programs designed to shift attitudes may be an effective way to reduce water consumption. Indeed, there is some evidence that environmental education campaigns reduce consumption for this reason (Zsóka et al. 2013).

Lastly, research suggests that stated primary motives, "such as altruistic and social values, are often covered up by the more immediate, selective motives, which evolve around one's own needs

[11] Blake (1999) highlighted a framework in which to view environmental attitudes and actions and noticed a Value-Action Gap. Simply put, people have environmental values and perform environmental actions, but in many cases actions do not line up to attitudes, such that the "Gap" exists either because the values were not sufficiently large or the costs of the action were not sufficiently small.

(e.g. being comfortable, saving money and time)" (Kollmuss and Agyeman 2002). Thus, even if households are environmentally and socially motivated, these attitudes may not translate into actions if significant barriers to conservation exist. Combining what we already know about cost, convenience, and environmental attitudes with the results from this paper, it is clear that well-designed conservation programs must be tailored to the underlying motivations and characteristics of consumers.

Methods

To properly test the hypotheses of interest and to ensure robustness, we estimate two regression models as well as statistical hypothesis testing. To answer hypothesis one, we first use a t-test across consumer preference types to test if unconditional water use is significantly different across E&S and C&C customers. Next, we use Model 1 (described below) where a dummy variable for E&S customer type is included and the associated coefficient is tested for significance. While Model 1 provides a conditional mean that may isolate the effects of motivations from other household characteristics, it may also suffer from endogeneity. Thus, to test hypotheses 2 and 3 we use Model 2, which controls for unobserved, time-invariant household characteristics (described below).

Hypothesis 2 and 3 refer to household consumption responses to external shocks, such that fixed effect (FE) models allow us to examine the coefficients of interest and average out any household specific characteristics that may cause biasness in the estimation. Using the regression specification from Model 2, we test the interaction coefficients for significance to determine if the marginal responses to weather and price differ across customer types.

Model Selection

Attempting to identify causal relationships between household characteristics and water demand has been historically difficult. For example, Arbues et al. (2016) attempt to identify household factors that influence water saving behaviors. While such questions have numerous relevant applications for city planning and resource management, these analyses often lack a clear strategy for identifying causal impacts. Identification and endogeneity concerns arise from a number of sources that have been identified in the literature, where the chief issues are omitted variable bias and simultaneity (i.e., reverse causation).

The simultaneity concern arises because—by definition—price is a function of water use under increasing block rate price structures. Under such pricing, reverse causality is assured. Fortunately, this concern is solved indirectly by addressing another issue typically associated with estimating residential water demand, the lack of an immediate price signal. Consumers do not generally have real-time price information when making water consumption decision. Thus, researchers have largely agreed that the price signal to which households respond is that of last month's bill (Espey et al. 1997). Using last month's bill solves the simultaneity problem, but it is still possible that the price on last month's bill is correlated to the error term of this month's demand (for example, a broken pipe last month may affect water use decisions this month). Accordingly, we perform a Hausman test and find no evidence of endogeneity in the price variable (Wu-Hausman Statistic=0.346).

The more serious concern is the possibility of unobserved variable bias or spurious correlations with variables omitted from the model. The crux of the issue is the possible correlation between explanatory variables and error due to unobserved or confounding variables, although the richness of our data and overall fit of our model is encouraging. For instance, three variables that are often unobserved and possibly correlated to explanatory variables in previous studies are conservation attitudes, environmental attitudes, and the area of irrigated turf. We have information on all three typically unobserved variables. Including these factors reduces, but does not eliminate concerns related to biased estimates produced from an ordinary least squares (OLS) model. Accordingly, one must be very specific in model selection and the inference that can be made from each statistical test.

While many of the issues associated with estimating household water demand can be alleviated with a fixed effects model, doing so necessitates the omission of time invariant factors, which may be useful in predicting and understanding demand. Accordingly, we use two model specifications, consistent with previous work (Kenney 2008; Espey et al. 2003; Schleich and Hillenbrand 2009): a pooled OLS where E&S households are indicated with a dummy variable and a fixed effects model with interaction dummies for E&S households.

While the standard OLS model (Model 1) may suffer from endogeneity issues, our coefficient estimates are qualitatively consistent across models (although price elasticities are lower in the FE specification) and the inclusion of attitude and turf variables leads to a significantly better fit than many previous attempts in the literature. Both of these points increase confidence in our results. The fixed effects interaction model (Model 2) is used to reduce the possibility of unobserved heterogeneity and the risk of biased estimates. It does not, however, allow for the examination of time invariant information, and thus, does not provide insight into the relationship between many household characteristics and water use that may be of interest. We include the OLS model to provide insight into the relationship between time invariant household characteristics and water demand, but a Hausman test suggests fixed effects are required ($\chi = 42.1$). Accordingly, the specific models used in our estimation are consistent with previous literature and described below (Kenney et al. 2008; Espey, et al. 1997; Arbués et al. 2016; Willis et al. 2013; Willis et al. 2011).

Model 1: Pooled OLS with E&S dummy

$$y_{it} = x_{it}\beta + h_i\gamma + d_i\rho + \epsilon_{it} \tag{1}$$

where y_{it} is the amount of water consumed by household i in time period t. x_{it} is a vector of time-varying explanatory variables including price, average daily temperature, and precipitation. h_i is a vector of time invariant household characteristics. d_i is a dummy variable that takes a value of 1 if consumer i is identified as E&S motivated and 0 if a consumer is C&C motivated. β, γ and ρ are coefficients to be estimated and ϵ_{it} is an error term with a mean of zero. The Appendix (A1) contains a list of all variables used in the estimation of both models.

Model 2: OLS fixed effects with interactions

$$\tilde{y}_{it} = \tilde{x}_{it}\beta + d_i\tilde{x}_{it}\gamma + \alpha_i + \epsilon_{it} \tag{2}$$

where $\tilde{y}_{it}$ is the demeaned amount of water consumed by household i in time period t. $\tilde{x}_{it}$ is a demeaned vector of explanatory variables, and α_i is a household specific intercept term.

We test for heteroscedasticity in the OLS model with a standard Breusch-Pagan (B-P) test. For the FE model we use the modified test suggested by Greene (2000) and operationalized by Baum (2001). Heteroscedasticity is present in both models ($\chi = 42.1$ and $\chi = 4330.3$).

We also test for autocorrelation in both models with a Breusch-Godfrey and the modified Breusch-Godfrey suggested by Woolridge (2002) and find no evidence that such a pattern exists. Due the presence of heteroscedasticity, we adjust our standard error estimates in Model 1 with White's correction and use robust standard error estimates clustered at the household level in Model 2.

Data and Household Characteristics

The attitudinal data used in our analysis comes from a survey conducted in a representative city in Colorado, where the primary utility company has employed a mixture of DSM strategies over the last 15 years. A severe drought in 2002 and 2003 alerted the Colorado Water Conservation Board (CWCB) to the importance of promoting water conservation and efficiency throughout the state. Among other tactics, the CWCB promoted policies that require all major municipal water suppliers to design and implement efficiency plans to manage water and plan for future water scarcity. Primary utility providers have since adopted a suite of price and non-price DSM strategies, including education programs, sprinkler audits, rebates, and increasing block rate (IBR) pricing structures. IBR's are designed to discourage use by increasing the marginal price of water as individual household demand enters higher tiers and is often the most cost effective tool with which to manage demand (Olmstead and Stavins 2009; Arbués et al. 2003). However, the effectiveness of price as a conservation tool largely depends on the ability and desire of customers to cut back on their water use. Naturally, we anticipate that customers concerned primarily with cost may respond differently to price increases than those concerned with environmental or social issues.

In 2014 the city used a consulting service to author a customer segmentation study. While these questions were not designed to specifically answer our research questions, there are a number of questions embedded in the survey that elicit customer attitudes and beliefs. We therefore match survey responses to specific household billing data (for the years 2009-2014) in order to evaluate the relationship between stated attitudes and observed consumption behavior. In the parlance of Environmental Psychology literature, we compare survey responses to billing data in order to investigate the "Value-Action Gap" and identify how heterogeneous motivations affect water consumption and responses to price and weather.

We focused on a subset of questions in the survey that directly elicit participant environmental, social, and personal motivations for conservation. Survey respondents were asked to rate their effort in reducing water consumption for everyday activities on a scale from 0 (never try) to 9 (always try). Participants also indicated if their interest in reducing consumption was attributable to any of the following considerations: impact to the environment, impact on the community, cost to the household, and comfort and convenience. These questions were also answered on a scale from 0 (completely disagree) to 9 (completely agree). The specific questions used in our analysis are the following:

1) Please rate your level of effort to reduce or minimize the amount of water and electricity that you use.
2) When considering whether to use water or electricity, I consider the environmental impact that my household's water and electricity use will have on the community.
3) When considering whether to use water or electricity, I consider the economic impact that my household's water and electric use will have on the community.

4) When considering whether to use water or electricity, I consider how much it will cost my household to use those services.
5) When considering whether to use water or electricity, I consider the comfort and convenience of those in my household.

Households were classified as E&S motivated if the sum of questions two and three was greater than the sum of questions four and five. If the opposite was true, households were labeled as C&C motivated. Households where the sums were equal across question groups are excluded from the analysis since their primary stated motivation cannot be identified. Note that this classification does not mean that E&S households do not consider cost or convenience; it means simply that they are motivated to a greater extent by environmental and social concerns. The inverse is true for C&C consumers. To ensure robustness, consumers were grouped using a range of criteria. Results, presented in the Appendix (A3), are qualitatively similar across each classification method.

Other data sources

Billing data were matched to survey data and the county assessor's database to obtain specific physical information about each household. Consistent with previous literature, we include age of home and size of home as explanatory variables. In addition to the assessor's data, we matched households to a parcel-specific LiDAR (Light Detection and Ranging) analysis, which provides a grass area estimate for each household in the sample. Demographic information was collected during the utility-sponsored survey. Lastly, weather observations recorded by CoAgMet stations were matched to specific billing cycles to provide average daily temperature and precipitation estimates corresponding to each bill.

Due to the wide range of data sources, a substantial portion of the households originally surveyed was dropped to ensure each observation had complete data. Additionally, obvious outliers were omitted from the analysis (a complete explanation of the data cleaning process is provided in the Appendix (A2)). After matching household survey responses across the different datasets, 6,760 observations for 119 distinct surveyed households remain. Although the sample is small, there is no identifiable reason to suggest that missing households are systematically related and would lead to biased sampling. Summary statistics describing households in the sample are reported in Table 1. Use and weather summary statistics are reported in Table 2.

Table 2.1. Summary Statistics: Household Characteristics

(n=119)	Mean	Std. Dev.	Min	Max
Single family homes	0.97	0.18	0	1
# persons/ household	2.56	1.30	1	8
Grass area (acres)	0.011	0.006	0	0.032
House size (sf)	1566.04	476.00	780	2745
Conserve (Q1)	6.90	1.79	0	9
Environmental (Q2)	5.95	2.56	0	9
Social (Q2)	5.01	2.76	0	9
Cost (Q3)	6.53	2.42	0	9
Convenience (Q4)	7.05	1.83	0	9

Table 2.2. Summary Statistics: Monthly Variables

(n=6,759)	Mean	Std. Dev.	Min	Max
Water Use (gal)	7835.12	6884.08	600	62400
Price/1,000 (gal)	2.53	0.41	0.41	6.18
Precipitation (mm)	28.93	31.65	0.00	173.23
Temperature (^{o}C)	9.72	8.85	-5.77	24.61

Results

Tables 1 and 2 provide summary statistics for the entire sample, but it is worth comparing consumer types across a range of household characteristics. Accordingly, Table 3 provides summary statistics of explanatory variables grouped by motivation type. E&S and C&C households are significantly different across a number of characteristics, including household size, number of persons per household, and their effort to reduce water consumption as elicited by the survey. Low-income households are more likely to be E&S motivated, although there is no statistical difference for middle and high income groups. There is also no significant difference in grass area between household types, which is surprising given the environmental cost of turf lawns.

Table 2.3. Household Characteristics by Consumer type

	C&C	E&S	
Water Use (gal)	8358.6	6899.9	***
	(109.0)	(126.3)	
Grass Area (acres)	0.011	0.011	
	(0.00068)	(0.0011)	
House size (sf)	1611	1481	*
	(57.23)	(65.25)	
# Persons	2.733	2.256	**
	(0.161)	(0.163)	
Conserve (0-9)	6.55	7.512	***
	(0.198)	(0.267)	
Low Income (count)	5	9	**
High Income (count)	29	19	
Obs.	76	43	

* denotes significant difference across groups
*** p<0.01, ** p<0.05, * p<0.1

Although our dataset is richer than those used in some previous studies, the following regression results must still be interpreted carefully. Specifically, we can identify the effect of environmental attitudes and household characteristics separately, thus reducing the spurious correlation that would likely exist without attitudinal variables. However, we cannot confidently preclude the existence of other underlying unobservable variables driving both explanatory factors and water consumption. Nevertheless, the inclusion of variables traditionally omitted from water demand estimation make some headway on the possible unobserved variable bias and endogeneity concerns of previous studies. Coefficient estimates for Model 1 and Model 2 are presented in Table 4 and are largely consistent with previous findings. As expected, water consumption increases with the number of occupants, income, grass area, and the size of a home. These relationships between household physical characteristics and water use have been well established in the literature. The hypotheses posed at the beginning of this article are intended to investigate similar relationships for household motivations; we return to them now.

Hypothesis 1 states that consumers who are environmentally and socially motivated (E&S consumers) use less water than consumers who are motivated by personal cost and convenience (C&C consumers). We performed three tests to evaluate this proposition, the simplest of which is a t-test[12], which yielded a t-statistic of 10.26. Thus, the unconditional mean of water consumption is significantly different across E&S and C&C consumers. While the unconditional mean is useful, it does not allow us to separate the effect of motivation from underlying characteristics that may be correlated with motivation. To investigate the conditional mean, we examine the results in Table 4 (column 1), where E&S motivated consumers are represented with a dummy variable. The E&S dummy variable in Table 4 (column 1) is statistically significant and negative, suggesting that E&S

[12] Given the skewness of the distribution of monthly water consumption, data were log transformed to more closely fit a normal distribution.

motivated consumers use significantly less water than those motivated by C&C conditional on weather and household characteristics. These results allow us to conclude that the E&S consumers use less water than their C&C counterparts.

Table 2.4. Model 1 and 2 Regression Results

VARIABLES	OLS Pooled	FE Interactions
Ln(Price)	-0.409***	-0.203***
	(0.0510)	(0.0892)
Bill days	0.0397***	0.0429***
	(0.00340)	(0.0024)
Precipitation	-0.00152***	-0.00155***
	(0.000254)	(0.00017)
Temperature	0.0459***	0.0442***
	(0.00132)	(0.00275)
Summer dummy	0.150***	0.135***
	(0.0262)	(0.0249)
Middle income	0.0872***	
	(0.0201)	
High income	0.206***	
	(0.0202)	
Single family home	0.879***	
	(0.0398)	
# of persons/household	0.119***	
	(0.00521)	
$d_{E\&S}$ (E&S dummy)	-0.133***	
	(0.0166)	
Grass area	1.606	
	(1.244)	
House size	0.000115***	
	(1.58e-05)	
Conservationist	-0.124***	
	(0.0189)	
Price*$d_{E\&S}$		-0.0834
		(0.134)
Precipitation*$d_{E\&S}$		-0.00034
		(0.00046)
Temperature*$d_{E\&S}$		0.0045
		(0.0045)
Bill days*$d_{E\&S}$		-0.00765***
		(0.00371)
Summer dummy*$d_{E\&S}$		0.0341
		(0.0470)
Constant	3.229***	5.594***
	(0.320)	(0.224)
Observations	6,583	6,640
R-squared	0.488	0.549
Number of households		119

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

The second hypothesis states that E&S consumers respond less to changes in price than C&C consumers, presumably because cost savings motivate C&C customers to reduce more relative to E&S customers. The most straightforward way to evaluate this hypothesis is evaluating the interaction terms in the FE-interaction model (Table 4, column 2). The price-E&S interaction term is insignificant, suggesting there is no observable difference across motivation types. Although it is statistically insignificant it is worth noting that the coefficient on the price interaction term is negative, which suggests that customers who claim to be motivated by cost (C&C) may be less responsive to price increases than E&S consumers. While this result is unexpected, it is possible that households that state a strong cost motivation for conservation are implicitly acknowledging their inelastic demand such that cost is a concern precisely because they do not have the ability to respond to price increases with reductions in quantity consumed.

Hypothesis 3 states that E&S and C&C consumers will respond equally to changes in precipitation and temperature. This claim is also tested with the FE-interaction model. As expected, both consumer types decrease consumption with precipitation and increase consumption with temperature. Results in Table 4 (column 2) support hypothesis 3 and suggest that there is no statistical difference in how C&C and E&S consumers respond to precipitation and temperature.

Discussion

Our overall results suggest that the underlying motivations of residential water consumers affect consumption but do not affect how consumers respond to exogenous weather and price shocks. Thus, this work simultaneously supports and rejects the existence of the "Value-Action Gap" (Kollmuss and Agyeman 2002). Consumers motivated by environmental preference use less, which suggests that they conserve consistent with their attitudes. However, their response to external shocks like weather and price are not statistically different from other consumers, which suggests a discontinuity between attitudes and actions.

While our results suggest that environmentally and socially motivated households use less water than those homes concerned with cost and convenience, more work is necessary to further elucidate this relationship. If environmental motivation is the true cause of conservation, significant implications exist for municipal-sponsored education and conservation programs. Moreover, because there is no difference in how consumers respond to price and weather shocks, water providers should not tailor education campaigns to the stated motivations of their customers. For example, if customers claim to be primarily motivated by cost, one might assume that campaigns focusing on increasing price structures would be an effective way to induce conservation. However, there is no differential response to price across customer types such that tailoring a campaign in this way is unlikely to increase conservation relative to the case where this policy is more widely promoted.

Conservation education is a common tool used by water suppliers, but its effectiveness is poorly understood. A key question in determining the effectiveness of conservation programs is the specific mechanism by which they work. For example, some programs may provide specific knowledge that allows individuals to conserve through new behaviors of which they may have been previously unaware. Other programs may foster pro-environmental attitudes that increase the utility consumers get from conserving. Our initial results indicate that environmental attitudes—at least stated ones—are associated with lower water consumption, which may suggest that education and conservation programs that foster social and pro-environmental attitudes may be a practical strategy to induce conservation.

Future work on this topic should help identify the specific means by which E&S consumers use less water than their C&C counterparts. Moreover, better understanding around the immediate and long-term behavioral effects of educational and conservation campaigns to engender social and environmental attitudes has significant implications for water suppliers.

REFERENCES

Agras, W Stewart, Rolf G Jacob, and Melissa Lebedeck. 1980. "The California Drought: A Quasi-experimental Analysis of Social Policy." *Journal of Applied Behavior Analysis* 13 (4). 561–70.

Arbués, Fernando, Miguel Ángel Bolsa, and Inmaculada Villanúa. 2016. "Which Factors Determine Water Saving Behaviour? Evidence from Spanish Households." *Urban Water Journal* 13 (5). 511–20.

Arbués, Fernando, Marıa Ángeles Garcıa-Valiñas, and Roberto Martınez-Espiñeira. 2003. "Estimation of Residential Water Demand: A State-of-the-Art Review." *Journal of Socio-Economics* 32 (1). 81–102.

Ballantyne, Roy, and Jan Packer. 2005. "Promoting Environmentally Sustainable Attitudes and Behaviour through Free-choice Learning Experiences: What Is the State of the Game?" *Environmental Education Research* 11 (3). 281–95.

Billings, R Bruce, and W Mark Day. 1989. "Demand Management Factors in Residential Water Use: The Southern Arizona Experience." *Journal of the American Water Works Association* 81 (3). 58–64.

Cialdini, Robert B, Raymond R Reno, and Carl A Kallgren. 1990. "A Focus Theory of Normative Conduct: Recycling the Concept of Norms to Reduce Littering in Public Places." *Journal of Personality and Social Psychology* 58 (6). American Psychological Association: 1015.

Clayton, Susan. 2007. "Domesticated Nature: Motivations for Gardening and Perceptions of Environmental Impact." *Journal of Environmental Psychology* 27 (3). Elsevier: 215–24.

Corral-Verdugo, Víctor, Robert B Bechtel, and Blanca Fraijo-Sing. 2003. “Environmental Beliefs and Water Conservation: An Empirical Study.” *Journal of Environmental Psychology* 23 (3). 247–57.

Corral-Verdugo, Víctor, and Martha Frías-Armenta. 2006. “Personal Normative Beliefs, Antisocial Behavior, and Residential Water Conservation.” *Environment and Behavior* 38 (3): 406–21.

Dalhuisen, Jasper M., Raymond JGM Florax, Henri LF De Groot, and Peter Nijkamp. "Price and income elasticities of residential water demand: a meta-analysis." *Land economics* 79, no. 2 (2003): 292-308.

Diekmann, Andreas, and Peter Preisendörfer. 1998. “Environmental Behavior Discrepancies between Aspirations and Reality.” *Rationality and Society* 10 (1). 79–102.

Diekmann, Andreas, and Peter Preisendörfer. 2003. “Green and Greenback the Behavioral Effects of Environmental Attitudes in Low-Cost and High-Cost Situations.” *Rationality and Society* 15 (4). 441–72.

Espey, Molly, James Espey, and W Douglass Shaw. 1997. “Price Elasticity of Residential Demand for Water: A Meta-Analysis.” *Water Resources Research* 33 (6). AGU AMERICAN GEOPHYSICAL UNION: 1369–74.

Farmer, James, Doug Knapp, and Gregory M Benton. 2007. “An Elementary School Environmental Education Field Trip: Long-Term Effects on Ecological and Environmental Knowledge and Attitude Development.” *Journal of Environmental Education* 38 (3). 33–42.

Gleick, P.H., 2000. A look at twenty-first century water resources development. *Water International*, *25*(1), pp.127-138.

Gilg, Andrew, and Stewart Barr. 2006. "Behavioural Attitudes towards Water Saving? Evidence from a Study of Environmental Actions." *Ecological Economics* 57 (3). Elsevier: 400–414.

Gregory, Gary D., and Michael Di Leo. 2003. "Repeated Behavior and Environmental Psychology: The Role of Personal Involvement and Habit Formation in Explaining Water Consumption." *Journal of Applied Social Psychology* 33 (6): 1261–96.

Head, Lesley, and Pat Muir. 2007. "Changing Cultures of Water in Eastern Australian Backyard Gardens." *Social & Cultural Geography* 8 (6). 889–905.

House-Peters, Lily, Bethany Pratt, and Heejun Chang. 2010. "Effects of Urban Spatial Structure, Sociodemographics, and Climate on Residential Water Consumption in Hillsboro, Oregon." *JAWRA* 46 (3). 461-472.

Hungerford, Harold R, and Trudi L Volk. 1990. "Changing Learner Behavior through Environmental Education." *Journal of Environmental Education* 21 (3). 8–21.

Kenney, Douglas S, Christopher Goemans, Roberta Klein, Jessica Lowrey, and Kevin Reidy. 2008. "Residential Water Demand Management: Lessons from Aurora, Colorado." *Journal of the American Water Resources Association* 44 (1). 192–207.

Kollmuss, Anja, and Julian Agyeman. 2002. "Mind the Gap: Why Do People Act Environmentally and What Are the Barriers to Pro-environmental Behavior?" *Environmental Education Research* 8 (3). 239–60.

Michelsen, An M, J Thomas McGuckin, and Donna Stumpf. 1999. "Nonprice Water Conservation Programs As A Demand Management Tool." *Journal of the American Water Resources Association* 35 (3). 593-602

Millock, Katrin, and Céline Nauges. 2010. "Household Adoption of Water-Efficient Equipment: The Role of Socio-Economic Factors, Environmental Attitudes and Policy." *Environmental* *and Resource Economics* 46 (4). 539–65.

Nieswiadomy, Michael L. 1992. "Estimating Urban Residential Water Demand: Effects of Price Structure, Conservation, and Education." *Water Resources Research* 28 (3). 609–15.

Olmstead, Sheila M, W Michael Hanemann, and Robert N Stavins. 2007. "Water Demand under Alternative Price Structures." *Journal of Environmental Economics and Management* 54 (2). 181–98.

Olmstead, Sheila M, and Robert N Stavins. 2009. "Comparing Price and Nonprice Approaches to Urban Water Conservation." *Water Resources Research* 45 (4). Wiley Online Library.

Poortinga, Wouter, Linda Steg, and Charles Vlek. 2004. "Values, Environmental Concern, and Environmental Behavior a Study into Household Energy Use." *Environment and Behavior* 36 (1). 70–93.

Randolph, Bill, and Patrick Troy. 2008. "Attitudes to Conservation and Water Consumption." *Environmental Science & Policy* 11 (5). 441–55.

Russell, Sally, and Kelly Fielding. 2010. "Water Demand Management Research: A Psychological Perspective." *Water Resources Research* 46 (5).

Schleich, Joachim, and Thomas Hillenbrand. 2009. "Determinants of Residential Water Demand in Germany." *Ecological Economics* 68 (6). 1756–69.

Taylor, Shirley, and Peter Todd. 1997. "Understanding the Determinants of Consumer Composting behavior1." *Journal of Applied Social Psychology* 27 (7). 602–28.

Trumbo, Craig, and Garrett J O'Keefe. 2001. "Intention to Conserve Water: Environmental Values, Planned Behavior, and Information Effects. A Comparison of Three Communities Sharing a Watershed." *Society &Natural Resources* 14 (10). 889–99.

Tuan, Yi-Fu. 1968. "Discrepancies between Environmental Attitude and Behaviour: Examples from Europe and China." *The Canadian Geographer/Le Géographe Canadien* 12 (3). 176–91.

Whitmarsh, Lorraine, and Saffron O'Neill. 2010. "Green Identity, Green Living? The Role of pro-Environmental Self-Identity in Determining Consistency across Diverse pro-Environmental Behaviours." *Journal of Environmental Psychology* 30 (3). 305–14.

Willis, Rachelle M, Rodney A Stewart, Damien P Giurco, Mohammad Reza Talebpour, and Alireza Mousavinejad. 2013. "End Use Water Consumption in Households: Impact of Socio-Demographic Factors and Efficient Devices." *Journal of Cleaner Production* 60. 107–15.

Willis, Rachelle M, Rodney A Stewart, Kriengsak Panuwatwanich, Philip R Williams, and Anna L Hollingsworth. 2011. "Quantifying the Influence of Environmental and Water Conservation Attitudes on Household End Use Water Consumption." *Journal of Environmental Management* 92 (8). 1996–2009.

Worthington, Andrew C, and Mark Hoffman. 2008. "An Empirical Survey of Residential Water Demand Modelling." *Journal of Economic Surveys* 22 (5). 842–71.

Zsóka, Ágnes, Zsuzsanna Marjainé Szerényi, Anna Széchy, and Tamás Kocsis. 2013. "Greening due to Environmental Education? Environmental Knowledge, Attitudes, Consumer Behavior and Everyday pro-Environmental Activities of Hungarian High School and University Students." *Journal of Cleaner Production* 48. 126–38.

CHAPTER 3. HETEROGENEOUS WATER DEMANDS: LETTING THE DATA SPEAK FOR THEMSELVES

Highlights

- In each season (except spring) at least two classes of households exist, one responsive class and one inelastic class.
- Price increases and temperature are key drivers in water use, while precipitation has little effect.
- A 10% price increase will lead to a 5.2% reduction in residential use, with over 50% of the reduction coming from high income households; only 3% of the reduction will come from low income homes.

Introduction

Increasing populations and a changing climate have spurred many water utilities to introduce pricing and policy strategies in an attempt to ameliorate scarcity concerns. While conservation is often the stated goal of these programs, the public nature of utilities creates a normative objective in which the affordability and distributional effects of such policies are a chief concern among decision makers (Barberán and Arbués 2009). Both the effectiveness of these policies and the population on which the burden falls depends on the customers to whom municipal water is provided, how they differ from one another, and how their consumption is likely to change in the future. As previous literature has suggested (Renwick and Archibald 1998; Kenney et al. 2008;

Willis et al. 2011), we believe that customers are inherently different (in both observable and unobservable ways) in how they make water consumption decisions, and that such differences must be understood in order to design efficient and equitable water policies. Previous literature has generally assumed a single underlying data generating process for residential water use, which necessitates a model that is flexible enough to accommodate heterogeneity across customer observations. Such an assumption requires the researcher to *ex ante* know how individuals make consumption decision in order to properly specify the model. We explore an alternative approach, using a finite mixture model (FMM) which endogenously determines household class membership without imposing the assumptions of more common methodologies. This paper uses billing and weather data from a representative city in the southwestern United States to identify heterogeneous classes of households with respect to water consumption decisions. We estimate seasonal demand responses for two types of customers and use them to forecast water quantity and distributional effects associated with changes in price and weather.

There is substantial evidence that demand side management (DSM) and weather shocks significantly impact water customers' consumption decisions (Espey, Espey, and Shaw 1997; Arbués, Garcıa-Valiñas, and Martınez-Espiñeira 2003), but rigorous investigations into how these impacts vary across heterogeneous households are rare. Accordingly, this paper contextualizes residential water use in the Southwest and highlights the importance of accounting for heterogeneity in estimating the effectiveness of conservation strategies and future water demand.

A number of explanatory factors have been shown to influence water use, and thus are likely to create heterogeneity in a household's response to price and weather shocks. Some of these factors are known and can be observed—house size for example; some of these factors are known but cannot be observed—presence of efficient appliances; and some are unobserved because they are the unknown unknowns. Standard regression analysis incorporates these observed explanatory factors directly into structural demand equations which creates two significant sources of error: 1) endogeneity issues connected to omitted or unobservable variables, 2) average effects across explanatory variables may minimize error, but in the presence of heterogeneous responses, they also obfuscate the true story.

Using a finite mixture model does not eliminate the concerns associated with omitted explanatory variables, but it does allow such omissions to be partly subsumed by the “class” component of the model. [CITE]. The second concern has traditionally been addressed by splitting samples based on *a priori* beliefs about what factors influence types of classes. While separating households into groups based on average use or demographic characteristics may provide insight, marketing literature has long acknowledged that “*a priori* segmentation based on demographic and psychographic variables may be infeasible or insufficient to explain differences in consumption decisions” (Jedidi, Jagpal, and DeSarbo 1997; Moore 1980). For example, a household may appear similar in location and size, but vary greatly across unobservable characteristics such as understanding of the billing structure or the prevalence of efficient appliances.

We use a FMM to estimate price elasticity and weather response coefficeints, allowing for different marginal effects across sub-sections of the population (classes). The FMM approach allows price elasticity and weather responses to be estimated for each latent class and simultaneously estimates the probability of class membership based on concomitant, observable factors. We find significant evidence that differences in price elasticity and weather responses exist across classes, and that such heterogeneity is obfuscated when a single equation is used to estimate demand. We identify two distinct classes within each season (spring, summer, fall, winter) and use household demographic and geographic characteristics to determine the probability of class membership for each household. This approach allows us to estimate heterogeneous welfare effects associated with changes in price and weather. It also may result in more accurate demand forecasting but needs to be externally validated.

Water demand and responses to price and weather were estimated independently for each season for two reasons: 1) utilities across the Southwest are concerned with intra-annual water supplies due to the nature of snowpack and reservoir systems; 2) it provides more flexibility such that households may be responsive in some seasons and not in others. For example, houses with large lawns and efficient appliances may respond significantly to precipitation in summer months when outdoor use is high, but be relatively inelastic in winter months because indoor use is already efficient[13].

We then use these demand estimates from each season to predict future water use under possible future climate and price scenarios. Demand functions are estimated at the household level and aggregated to Census Block Groups, such that quantity and welfare effects can be calculated for different regions of the city.

This paper is broken into six sections. The next section summarizes the long history of residential water research and the benefits of using the FMM approach. Section three outlines our methodology and identifies our data sources. Section four presents econometric results and the corresponding demand predictions. Section five concludes.

[13] Including seasonal interaction terms and a series of dummy variables is an alternative, commonly utilized approach; however, this restricts the underlying data generating process to be the same across seasons, which is unlikely given that uses of water differ substantially across seasons. Estimating seasons independently also has the added advantage of shorter computation times.

Background and Motivation

Residential Water Demand

Water use is influenced by a host of explanatory factors, including: temperature, precipitation, drought, pricing structure, the presence of high efficiency devices, age of the home, income, education, number of persons per household, environmental attitudes and other demographic characteristics (Kenney et al. 2008; Arbués, Garcıa-Valiñas, and Martınez-Espiñeira 2003; Willis et al. 2013; Willis et al. 2011). Generally speaking, previous attempts to quantify water demand involve econometric models of the form $Q_d = f(P, X)$ where the quantity of water, Q_d, is a function of price, P, and a vector of other factors like household characteristics and weather.

Many papers of varying quality have been published investigating the effects of household characteristics on water consumption. These papers generally acknowledge the limitations of causal inference due to possible endogeneity and unobserved variable issues. We avoid this complication by including only exogenous factors outside the control of the household, price and weather (and using fixed effects to ensure unbiased results), in our demand function estimates. Factors that may suffer from endogeneity or other complications are included only in determining the probability that a household is a member of a certain class—which does not require a causal interpretation to be meaningful. Additionally, it can be shown that in the case of questionable identification strategies, latent class analysis prevents errors associated with spurious correlations (Hagenaars and McCutcheon 2002). To our knowledge, only one study has used a finite mixture model to estimate heterogeneous household water demands (Stone et al. 2016), and while their work strongly suggests the presence of underlying class types, the study was limited by a lack of spatially identifiable billing data (e.g. lawn size, house size, etc). We extend their work by including a more complete set of concomitant variables which determine class membership.

We focus on price as the main DSM strategy for three reasons. First, water price is “the main instrument to control demand” (Arbues 2003). Second, other conservation strategies like education campaigns and advanced metering may be financially infeasible for small service providers, but pricing options are available to all utilities and are often the most cost effective strategy (Olmstead and Stavins 2009). However, using price as a tool for conservation can have implications for geographic and socio-economic equity (Rogers, De Silva, and Bhatia 2002) as well as human rights considerations (Bluemel 2004; Hardberger 2005). Accordingly, our paper includes a brief description of distributional effects across income levels. The last reason to focus on price is a practical one. Replacing aging infrastructure is likely to increase utility prices across the United States. As such, it is imperative to develop a methodology to determine who will bear the burden of price increases, and how effective they will be at generating revenue and encouraging conservation.

While price increases could theoretically lower revenue for utilities, price elasticity estimates from the literature have been surprisingly consistent across methodologies and data sources, usually ranging between -0.4 and -1.0 (Espey, Espey, and Shaw 1997; Arbués, Garcıa-Valiñas, and Martınez-Espiñeira 2003; Scheierling, Loomis, and Young 2006). However, these elasticity estimates are usually reported as an average for entire service areas and may not be useful if a city is dynamic in its development or demographics.

Finite Mixture Model

Given the importance of heterogeneity in determining the distributional effects and efficiency of residential water policies, particularly in the context of a changing climate, surprisingly little work has rigorously tested for distinct classes beyond *a priori* dividing samples (Kenney et al. 2008; Worthington and Hoffman 2008). The benefit of using the FMM is that no assumptions are made on the grouping characteristics, rather groups are endogenously determined based on observed responses.

While clustering models are often employed for this kind of analysis, they are somewhat unsatisfactory. Most clustering techniques simply minimize Euclidean across variables believed to be important by the researcher, whereas a FMM is a statistical model postulated for the population from which the sample is taken (Hagenaars and McCutcheon 2002). Thus, the key assumption necessary to use an FMM approach is the existence of sub-populations, each of which possess a unique distribution. Such an assumption is reasonable in the context of water customers given differences in household and socio-economic characteristics. Therefore, the FMM approach is less subject to the biases and assumptions embedded in more common cluster analysis.

Figure 1 provides an illustrative example of how monthly consumption distributions differ across residential zoning types (low density compared to medium and high density). The figure confirms our expectation that low density residential users not only use more water, but also possess greater variability from household to household and month to month. This figure suggests the presence of distinct sub-population distributions that differ across characteristics associated with each zoning type—since zoning class is unlikely to directly change water use. Thus, underlying characteristics of households are included as concomitant variables used to determine class membership.

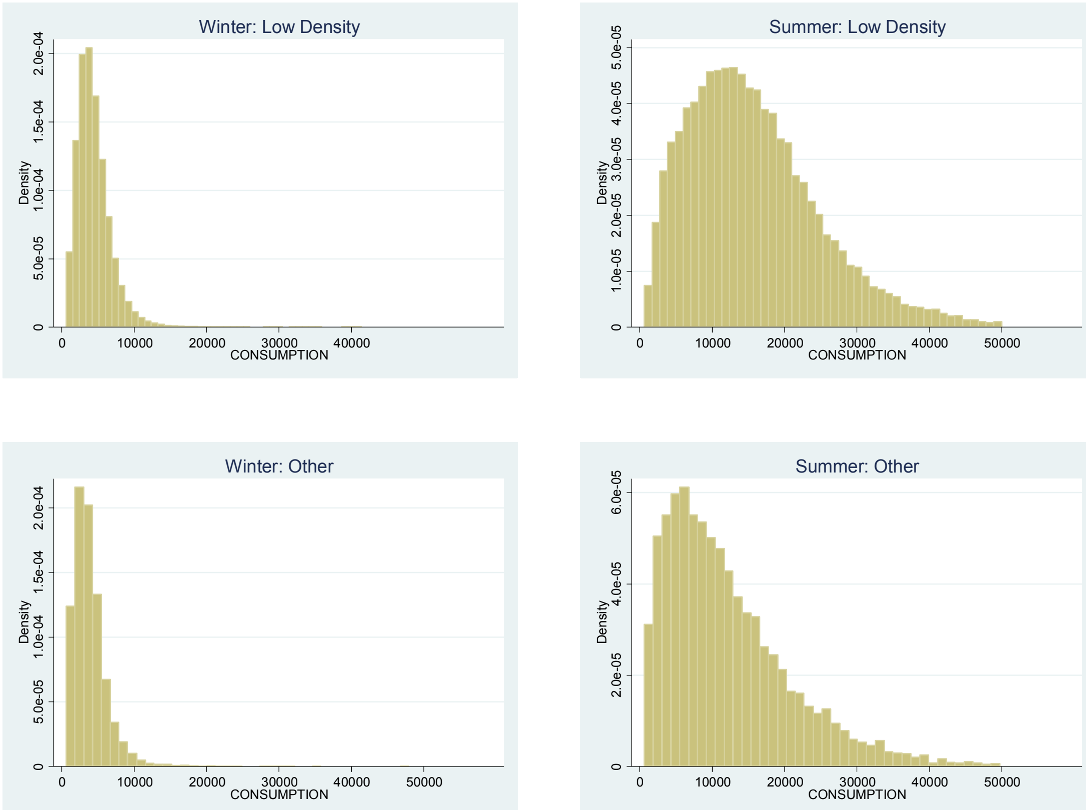

Figure 3.1. Consumption Distributions by Zoning Type and Season

The last practical advantage of FMMs over k-mean and other clustering techniques is the needlessness of scaling, which can be arbitrary in many clustering methods. By this we mean that normally distributed variables of unknown variance are often normalized such that observations can be clustered with "appropriate" weight on each factor, but *ex ante*, it is difficult to determine what constitutes appropriate weighting. The usefulness of FMM's is succinctly stated by Boxell who notes that, "The finite mixture model may have considerable relevance to decision-makers in that it permits some understanding of preference heterogeneity through incorporation of individual characteristics... and accounts for preference heterogeneity to a degree by simultaneously estimating segment specific membership and choice parameters" (Boxall 2002). The specific methodology and model is presented in the next section.

Methods

While demand estimation is common practice in applied economics, the introduction of the finite mixture model and the uniqueness of residential water complicate the analysis. The most basic component of the model is the demand function, which can be represented as:

$$w_{cit} = f_c(P_{it}, x_{it}, y_{it}, \mu_i, \epsilon_{it}) \quad (1)$$

where c indexes class, i indexes household, and t indexes time. y is a vector of weather variables, x is a vector of household specific characteristics, P represents the relative average price of water[14], and μ is a term that encapsulates individual specific characteristics that may or may not be observed. Here "class" refers to a subset of the population for which the underlying data generating process is the same.

The first complication in estimating a demand function for residential water is the obscurity of price from the perspective of the consumer. Unlike a department store, customers do not see real time price information based on their consumption. The price signal to which consumers respond under (increasing and decreasing) block rate structures has been a topic of considerable investigation (Charney and Woodard 1984; Opaluch 1984; Hewitt and Hanemann 1995; Klaiber et al. 2014; Nieswiadomy 1992) and with some exceptions, researchers generally agree that the perceived price to which consumers respond is the price experienced on last month's bill.

While there is general consensus that customers respond to a lagged price, it is less clear if customers respond to variable price, average variable price, or average total price (Ito 2012; Wichman 2014; Baerenklau, Schwabe, and Dinar 2014). Standard economic theory would suggest

[14] For theoretical consistency, we standardize income and the price of water relative to an aggregate price of all other goods (See Hanneman (1998) for a discussion on the necessity of this method for theoretical consistency), as defined by the Bureau of Labor Statistics "CPI-less shelter" estimates.

that variable price is the relevant price in consumption decisions, but uncertainty exists around both tier locations and overall billing structure such that researchers have recently argued that average price is the most acute price signal. We use average variable price (which will simply be referred to as price) in this analysis because it seems most consistent with marginal decision making processes.

Using last month's bill addresses another complication created by block rate structures, a simultaneity problem of price and quantity. Under increasing block rates (IBRs), current use dictates current marginal price. Using lagged price breaks the simultaneity concern, but it does not necessarily preclude the possibility of endogeneity. Price—even last month's price—may be endogenous. We instrument for last month's price in an attempt to minimize any correlation P_{it-1} may have with ϵ_{it} through unobserved variables or spurious correlations. Thus, for the sake of this paper, we use the instrumented average variable price of last month's bill, $\hat{P}_{i(t-1)c}$, as a proxy for the perceived price faced by utility customers in the current month[15].

Once the relevant price signal is determined, we follow standard conventions in the field and specify Equation 1 as a log function (Worthington and Hoffman 2008), such that the demand equation of interest can be written as:

$$\ln(w_{cit}) = \alpha_c + \beta_c \ln\left(\hat{P}_{i(t-1)c}\right) + \gamma_c y_{it} + \omega_c x_i + \mu_i + \epsilon_{it} \tag{2}$$

where $\beta,$ and γ are parameters to be estimated. Because μ may include individual specific unobservable variables, estimating the above equation will likely result in biased estimates. Traditionally, this issue has been addressed through fixed effects model in which individual

[15] Average price was estimated as a fixed effects regression where tilde denotes deviations from the mean and $\tilde{p}_{it} = \tilde{X}_{it}B + \tilde{Z}_{it}\eta + \epsilon_{it}$ where X is a vector of all variables included in the FMM, Z is a vector of price block data such that $Z = (price\ block\ 1\ , price\ block\ 2, bill\ days_{t-1})$, and β and η are parameters to be estimated.

specific time invariant terms are averaged out of the model. Thus, the new function to estimate can be written as:

$$(w_{itc} - \overline{w}_{ic}) = \alpha_c + \beta_c(\hat{P}_{i(t-1)c} - \hat{\bar{P}}_{ic}) + \gamma_c(y_{it} - \bar{y}_{ic}) + \omega_c(x_i - \bar{x}_i) + (\epsilon_{itc} - \bar{\epsilon}_{itc}) \qquad (3)$$

Where time invariant x variables drop out of the model and variables now represent deviations from their household mean and are denoted with tildes such that the new equation is:

$$\widetilde{w}_{itc} = \beta_c \tilde{P}_{i(t-1)c} + \gamma_c \tilde{y}_{it} + \tilde{\epsilon}_{itc} \qquad (4)$$

Consumer responses to price and temperature can be estimated as deviations from their average using the above equation, which looks identical to many econometric models of the last decade, except that it contains the subscript c such that our estimation depends on the underlying class of each observation. Because we are not *a priori* dividing the sample into classes, we need a method by which class membership is determined—enter the finite mixture model.

We hypothesize that households fundamentally differ in their water consumption decisions, thus, estimating averages across a sample may lead to consistent estimates but obfuscate important relationships and nuanced conclusions. A FMM estimates unique coefficients for each class where the response coefficients and the concomitant coefficients are estimated simultaneously to determine the response parameters of interest within a certain class as well as the probability of class membership for each observation. Moreover, household characteristics are averaged out of the traditional fixed effects model whereas they remain in the fixed effects finite model as concomitant variables that determine class membership.

Concerns with respect to unobservable characteristics are small using this approach, but to ensure unbiased results we again use a fixed effects finite mixture model such that response variables of each observation are demeaned consistent with Deb and Trivedi's (2013) proposed methodology.

We further assume that the heterogeneity of water consumption responses may change seasonally, thus the following is estimated separately for each season:

$$f(\widetilde{w}|x,\tilde{y},\delta_c,\beta_c,\sigma_c) = \sum_{c=1}^{C} \pi_c(x,\delta)\, N(\widetilde{w}_{itc}|\tilde{y},\beta_c,\sigma_c) \quad (5)$$

where a vector of observable household characteristics, x, can be used to predict the probability, π_c, that an observation belongs to class c such that the $\sum_{c=1}^{C} \pi_c = 1$. π_{cit} is estimated as a multinomial logit function consistent with most applications of the FMM (Kamakura, Kim, and Lee 1996; Kamakura and Wedel 2004). Deviations from the mean of exogenous variables to which consumers respond are contained in the $\tilde{y}$ vector. δ is a vector of coefficients determining class membership probabilities, β and is a vector of demand response coefficients, and σ is a dispersion term.

Once demand and class membership estimates are obtained, we forecast potential changes in price and weather. Quantity and distributional effects are then calculated for the increased price scenario.

Forecasting and Demand Predictions

Once model parameters are estimated, we use them to predict the likely demand responses to changes in price and weather. Where total water, $\widehat{w}_{it} = \pi_{c=1}\widehat{\widetilde{w}}_{itc=1} + \pi_{c=2}\widehat{\widetilde{w}}_{itc=2} + \overline{w}_{is}$ for each season. We estimate future water use as a percent of past use by averaging the monthly temperature, precipitation, and variable price for the five years used in the sample. These averages are then modified to create three scenarios: 1) a 2 degree increase consistent with some climate projections (EPA), 2) a 10% reduction in precipitation, and 3) a 10% increase in price. Under the price increase scenario, we also estimate welfare effects at the household level by integrating over the estimated demand function. Total welfare changes are estimated by averaging welfare estimates across households in the sample within each block group and then multiplying the average welfare estimate by to the total number of household units in the block group.

Data Sources

The data used for this analysis are particularly rich and covers a five year period from 2010 through 2014. This period was chosen in part because of the large variation in weather. 2012 was exceedingly hot and dry, 2013 was particularly wet and the remaining years fall somewhere close to average. This time period was also chosen because the American Community Survey (ACS) has a complete record for the area of interest for these years. Our sample consists of 420,766 total observations from 9,369 unique households[16].

Demand Factors

Water Consumption and Policies:

Monthly billing data were collected from the largest utility provider in the area for the years 2010 through 2014. The billing data contain monthly consumption and all necessary cost information. During the years of interest, customers experienced little variation in policies beyond changes in price. The billing data provided have the advantage of being spatially

[16] Note that these were was cleaned due to some obvious inconsistencies and outliers as well as a need to match observations to a variety of data sources. An explanation of which observations were omitted from the analysis can be provided upon request.

identified, which allows us to map households to specific Census Block Groups and other variables of interest.

Weather

Temperature and precipitation data were gathered from CoAgmet using weather Station FTC01 and FTC03. CoAgmet is a service provided by the Colorado Climate Center at Colorado State University which provides daily values of weather variables for stations across the state. These daily values were matched to billing data such that each billing period contains weather events for the days present on the bill. From these stations we create a variable for average temperature (calculated $\frac{daily\ high+daily\ low}{2}$) and a variable for cumulative precipitation over the bill period.

A dummy variable for 2012 was also included because it was an exceedingly dry year with significant wild fires that dried out the air and deposited ash across the city. Because restrictions were not in place during this period we expect to see a noticeable increase in water consumption during this period which may not be captured by just precipitation and temperature.

Class Membership Probability Factors

Demographic:

The five year summary files from the ACS were used as demographic information at the Block Group level. This aggregation may lead to some measurement error since variables at the block group level were matched to the household level and most likely bias results downward through reduced variation. Key variables obtained from the ACS include: median income and average household size.

Household Characteristics

Household sizes (reported in ft^2) were obtained from the Larimer County Assessor's office, and grass area per parcel was obtained directly from the local utility provider who commissioned a LiDAR (Light Detection and Ranging) analysis for the city in 2012.

Summary statistics for the households included in the sample are reported in Table 1. Weather and use statistics are reported for each season in Table 2.

Table 3.1. Households Summary Statistics

(n=10,602) VARIABLES	mean		min	max
House size (sf)	1,764	(544.5)	348	8,741
Grass area (acres)	0.0114	(0.007)	0	0.212
Income ($1,000)	59.71	(20.53)	11.96	105.31
# Persons/house	2.49	(0.420)	1.48	5.56
New home	0.079	(0.269)	0	1

standard errors in parentheses

Table 3.2. Seasonal Summary Statistics

(n=138,297)	Summer			
VARIABLES	mean		min	max
Water use (gal)	15,035	(9,542)	600	80,000
Bill days	30.86	(1.881)	26	36
Precipitation (mm)	39.02	(32.58)	0	159.8
Average temp (C)	21.02	(1.855)	15.65	24.61
Price ($/1,000)	2.55	(0.372)	0	75.4

(n=120,526)	Fall			
VARIABLES	mean		min	max
Water use (gal)	6,116	(4,937)	600	74,650
Bill days	30.57	(2.101)	26	36
Precipitation (mm)	21.32	(26.93)	0	173.5
Average temp (C)	6.398	(5.964)	-4.801	17.80
Price ($/1,000)	02.52	(0.433)	0.153	35.9

(n=99,290)	Winter			
VARIABLES	mean		min	max
Water use (gal)	4,475	(2,610)	600	69,400
Bill days	30.53	(1.947)	26	36
Precipitation (mm)	9.362	(9.707)	0	41.92
Average temp (C)	-0.739	(2.569)	-6.697	9.255
Price ($/1,000)	02.54	(0.471)	0.396	6.73

(n=122,916)	Spring			
VARIABLES	mean		min	max
Water use (gal)	8,087	(6,609)	600	78,900
Bill days	30.13	(2.257)	26	36
Precipitation (mm)	42.76	(34.39)	0	151.4
Average temp (C)	10.88	(4.583)	2.216	22.55
Price ($/1,000)	2.51	(0.387)	0.161	6.18

standard errors in parentheses

Demand equations for each class type in each season are estimated with the above information, and subsequently used to predict future water use under a variety of scenarios.

Results

Our results indicate that a distinct set of classes exist in each season, and that members of each class respond differently to changes in price and weather. Moreover, our results indicate that observable information can help predict class membership of particular households. We also find that with one exception, classes can generally be divided into “responsive” and “unresponsive” customers, such that if a group has larger responses to one shock, they generally have larger responses to the other shocks as well. This pattern is present in every season except spring, where for each class, the relative responsiveness to one explanatory does not translate to more responsiveness to another.

While FMMs can theoretically handle a large number of classes; estimating coefficients for multi-class models is computationally intensive. We use two classes per season in our analysis for two simple reasons. First, the criteria by which component number choice is judged, AIC and BIC, show negligible improvement moving from two components to three components. For example, using a random sample from our data, we ran the model with up to 5 components (this could not be done on the entire sample due to computation constraints), and we find that in the summer season the two component model has scores of $AIC = 5204.19$ and $BIC = 5447.33$. In the three component model there is a small improvement to $AIC = 5137.84$ and $BIC = 5357.31$ (an improvement of $\sim 1\%$), and between three and four components, there is virtually no improvement. Given the relatively small improvement from using the three component model, the two component model was used to reduce computation time[17].

[17] A similar result can be seen in winter and fall; although there may be significant gains from increasing the number of classes in the spring season. Note this result is interesting given that

Class Responses and Probabilities

The ultimate goal of this paper is to identify heterogeneous populations that can lead to better understanding of household water consumption. As hypothesized, households are clearly heterogeneous in their responses to a change in price or weather. The class response coefficients are reported for each season in Table 3 while the probability of class membership conditional on observable household characteristics is reported in Table 4. A number of key conclusions can be drawn from these results.

Our results are consistent with previous price elasticity findings; as expected, we find that some customers are considerably more responsive to external shocks than others and that households are generally more responsive to price in the fall and summer months. This result is intuitive. In winter and spring water is generally used exclusively for indoor purposes; whereas in summer and fall, households with irrigation needs have considerable opportunity to conserve their outdoor water use by changing their irrigation decisions. For the same reasons, a similar pattern exists for households' responsiveness to precipitation and average temperature (except in winter months where precipitation has no significant effect on water use). This result is expected since warm spring months may lead to earlier lawn and landscape irrigation, while warm falls may prolong it. It is worth noting that precipitation variables are very significant, but with relatively small magnitudes. This point is highlighted when we examine the forecasted climate and price scenarios, and suggests that very few households possess rain sensors or otherwise adjust much to precipitation events.

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our regression results find a significantly more responsive class across all explanatory variables in every season except spring.

With two small exceptions, our results indicate that households who are more responsive with regard to one shock are more responsive to others as well. For example, in the fall class 2 is more responsive to price, precipitation, and temperature. This result suggests that: 1) some households have attitudes and awareness that leads to this responsiveness, or 2) they have house and property characteristics that allow for such responses, or 3) both one and two are true. While distinguishing between these underlying causes is difficult, Table 4 provides some insight into which characteristics affect class membership, and thus, water use responsiveness.

Table 3.3. Response Coefficients

VARIABLES	Fall Class 1	Fall Class 2	Winter Class 1	Winter Class 2	Spring Class 1	Spring Class 2	Summer Class 1	Summer Class 2
ln(Price)	-0.329***	-0.727***	-0.482***	-0.254***	-0.104***	-0.134***	-0.873***	-0.490***
	(0.0156)	(0.0187)	(0.0406)	(0.0113)	(0.0182)	(0.0243)	(0.0411)	(0.0112)
Precipitation	-0.00702***	-0.0331***	-0.00740	0.00265	-0.00115	-0.00423***	-0.0173***	-0.0170***
	(0.00101)	(8.09e-04)	(0.00542)	(0.00144)	(8.36e-04)	(0.00112)	(0.00106)	(2.90e-04)
Average temp	0.0146***	0.0561***	0.0108***	-0.00168***	0.0705***	0.0294***	0.0834***	0.0485***
	(0.000924)	(0.00105)	(0.00175)	(0.000440)	(0.00107)	(0.00179)	(0.00249)	(0.000734)
Bill days	0.0279***	0.0262***	0.0341***	0.0343***	0.0199***	0.0288***	0.0345***	0.0272***
	(0.000672)	(0.000885)	(0.00172)	(0.000443)	(0.00103)	(0.00156)	(0.00182)	(0.000474)
Drought year	-0.00748**	-0.0539***	0.00587	0.00279	0.265***	0.205***	0.125***	0.108***
	(0.00366)	(0.00436)	(0.00786)	(0.00188)	(0.00642)	(0.0100)	(0.00847)	(0.00215)
Month dummy1	-0.0274***	-0.354***	0.0324***	-0.00530**	-0.299***	-0.115***	-0.0560***	-0.00183
	(0.00736)	(0.0117)	(0.00822)	(0.00208)	(0.0106)	(0.0155)	(0.00914)	(0.00232)
Month dummy2	0.0107	-0.247***	0.0169	-0.00427*	-0.0951***	-0.0380***	-0.174***	-0.0911***
	(0.0113)	(0.0172)	(0.0107)	(0.00255)	(0.00799)	(0.0110)	(0.00932)	(0.00243)
Constant	-0.0632***	0.244***	-0.00293	-0.00565***	0.0816***	-0.00753	0.0130*	0.0268***
	(0.00632)	(0.0105)	(0.00682)	(0.00175)	(0.00593)	(0.00890)	(0.00682)	(0.00170)
Observations	120,526	120,526	99,290	99,290	122,916	122,916	138,297	138,297

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.4. Class Membership Probabilities (Multinomial Logit)

VARIABLES	Fall	Winter	Spring	Summer
House size (sf)	-0.000969***	1.31e-05	0.000999***	-0.000672***
	(3.13e-05)	(2.93e-05)	(6.33e-05)	(3.83e-05)
# persons/house	0.149***	-0.147***	0.178**	-0.0906**
	(0.0415)	(0.0429)	(0.0781)	(0.0401)
New home	-0.0223	-0.459***	0.113	-0.693***
	(0.0594)	(0.0572)	(0.107)	(0.0643)
Grass area (acres)	-73.66***	-1.213	219.5***	9.922***
	(2.791)	(2.085)	(8.193)	(1.754)
Income	-0.0130***	-0.00769***	0.00463***	-0.0104***
	(0.000849)	(0.000868)	(0.00155)	(0.000855)
Constant	2.618***	-0.181*	-3.873***	0.789***
	(0.108)	(0.102)	(0.242)	(0.101)
Observations	120,526	99,290	122,916	138,297

Class 2 is the reference class
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Grass area increases the probability of being in the responsive class in spring, summer, and fall, but is insignificant in determining class probability in the winter season. This result is consistent with our belief that households with outdoor water use are more responsive than those households and seasons where water consumption is entirely comprised of indoor use.

Increasing the number of people per household decreases the likelihood that a household will be in the responsive class for summer and fall. Newer homes decrease the probability that you will be in the more responsive class in the summer and winter season and are insignificant in spring and fall. Both of these results are consistent with expectations. Newer houses with more efficient fixtures do not have the excess "slack" that can be tightened in response to prices or weather. For example, decreasing the instances of toilet flushing per day, will have a much smaller total impact on homes with low flow toilets. It is equally true that having more people in a house will likely prevent increased conservation, either because water use as a function of people per house is generally logarithmic in shape (DeOreo et al. 2016), or because coordinating conservations strategies with children and others can be difficult.

The size of the house increases the probability that a household will be in the responsive class in every season except summer, where it significantly decreases that chance. The specific mechanism or behavior that results in larger responses requires further investigation.

Higher incomes increase the probability that households are responsive in the fall, but decreases the probability that they are responsive in the winter and summer. We posit that wealthy customers may not respond in the summer because the value of a green lawn or children playing in a sprinkler is greater than the additional cost of water. Customers with more limited incomes may choose to cut back on water use in order to substitute into other goods. In winter months however, the same wealthy customers who were more responsive in the summer are likely to be less in the less responsive class during winter months where this inelastic indoor demand may result from the presence of high efficiency appliances. For example, a person who responds to a high cost of last month's bill may decide to take a shorter shower or run the washing machine less. Even with the same behavioral response, customers with inefficient appliances or shower heads are likely to appear much more responsive.

Forecasting Use under Weather and Price Changes

Using the above information, we predict annual consumption for each Block Group and various income levels in the utility's service area. The results of these predictions are reported in Figure 2, where it can be seen that changes in precipitation will have relatively little effect on consumption decisions, while shifts in price and temperature change consumption by as much as 6%. Note that due to the heterogeneity of customers in each Block Group, there are notable spatial differences in response to each scenario which may allow for more efficient city planning.

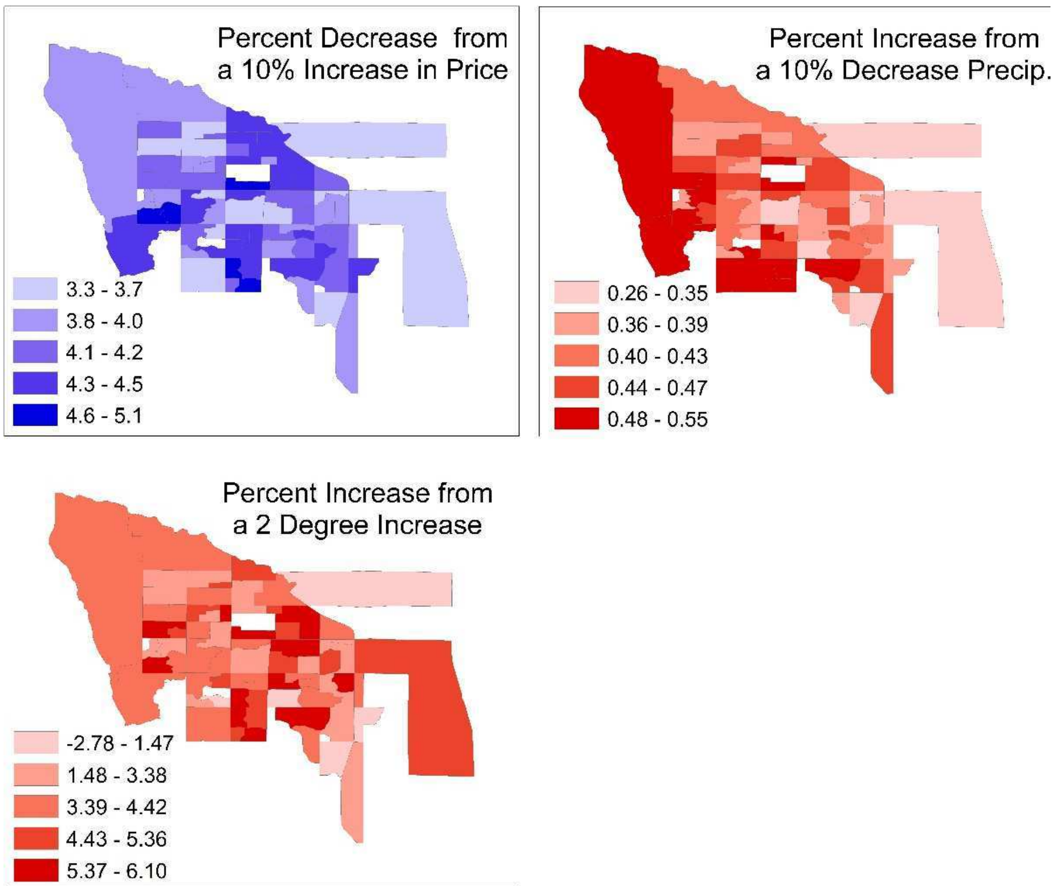


Figure 3.2. Spatial Distribution of Consumption under Price and Weather Scenarios

Specifically, it is clear that the north central and southwest regions of the city respond considerably more to price. The northern area is the oldest part of the city, while the southwest is relatively new buildings. A key similarity in these regions is their relatively high median income.

Figure 1 also visually describes not only the different magnitude of effects for temperature and precipitation, but also the seemingly inverse responsiveness in response to them. The demand response to precipitation is extremely small compared to that of temperature. Moreover, block groups that response more to precipitation seem to respond less to temperature, and vice versa. The catalyst for this result is unclear and will be investigated in future work. Given the author's familiarity with the region, one anecdotal explanation is the presence of gardens versus lawns. Many of the homes on the west side of town have large gardens. Although we cannot test this hypothesis, it may be that homes with gardens respond more to precipitation while homes with turf, respond to temperature.

Income and Distributional Effects

This methodology also allows us to identify which households are cutting back. To gain insight into the distributional effects of changes to price and weather, we predict how the 5 year period of the analysis would have looked with a 10% increase in price, a 2 degree rise in temperature, or a decrease in precipitation. Table 5 displays the corresponding mean changes in summer water consumption by income level.

Table 3.5. Consumption Changes under 3 Scenarios

	Change in Summer Monthly Use		
	10% Price Increase	2°C Increase	10% decrease in precipitation
Low income (<$30k)	-643.89	1449.06	78.95
	(423.19)	(952.07)	(53.97)
Middle income ($30-$60k)	-708.56	1592.33	88.14
	(418.19)	(939.70)	(54.22)
High income (>$60k)	-830.75	1862.38	103.84
	(424.10)	(950.83)	(54.21)

standard errors in parentheses

Consistent with our previous results and expectations, high income households are the most responsive in absolute terms to all three shocks. These households have more slack in their water consumption choices, or said another way, more and larger margins on which to adjust. At a city-wide level a 10% increase in price results in a 5.2% decrease in summer use, but the conservation is not spread evenly across income groups. Low income users make up just 0.3% of the reduction in summer use; while middle income and high income users make up 2.3% and 2.7% respectively. Our results also suggest that the percent change in the total variable cost faced by customers is fairly consistent across income types at just over 3%. In absolute terms, higher income households will face slightly higher total variable costs, because this portion of their bill is larger to begin with. These results are reported in Table 6.

Table 3.6. Consumption Changes by Income under a 10% Increase in Price

	Summer Monthly Use				
	% of City Decrease	Avg. Variable Bill (before)	Avg. Variable Bill (after)	Avg. % Change	Consumer Surplus Change
Low income (<$30k)	4.94	$26.59 (20.16)	$27.42 (20.30)	3.13	-2.71 (1.82)
Middle income ($30-$60k)	43.97	$30.87 (20.88)	$31.89 (21.04)	3.32	-3.19 (1.92)
High income (>$60k)	52.09	$39.50 (22.87)	$40.95 (23.11)	3.66	-4.16 (2.13)

standard errors in parentheses

Discussion

Our research suggests that the effect of different pricing strategies and potential changes in weather will depend largely on the households to which they are introduced. This work suggests that average price elasticity estimates across geographic regions may help with large scale planning, but does not allow for targeted conservation efforts. Moreover, city planning around household type and demographic characteristics may lead to more water efficient growth, or at least planning for growth. Separating heterogeneous households allows us to identify the effectiveness and distributional effects of a given policy at various spatial scales—a tool that will be crucial as the low hanging conservation fruit begins to run out.

Our work also quantifies the effects of potential changes in precipitation and temperature on heterogeneous households. It should be obvious that households with large turf areas will respond differently to rain than those individuals with no lawns. This analysis discriminates between households' responses to weather such that more accurate estimates of demand are possible with reduced concerns over endogeneity in model estimation.

This analysis has numerous implications for future land use and conservation strategies. With concern over water scarcity at a fever pitch, it becomes necessary not only to focus on conservation efforts within the municipalities we have, but also focus on future municipalities we will have. If lawns create higher demand for water and that areas of high population density generally have lower household demands, it is clear that the development strategies of cities will affect future water needs. As populations increase, cities have the choice of growing "up" (high-rise buildings) or "out" (suburban sprawl). However, there is an implicit tradeoff with these development types. While households in high density areas may use less water overall, they also are less responsive to policies meant to encourage conservations. Accordingly, cities with these types of unresponsive homes may not have the "slack" necessary to conserve in times of extreme drought.

While economists generally agree that higher municipal water prices will reduce demand and thus conserve water, such a mechanism has significant implications for equity and human rights (Berk et al. 1980; Gleick 1998). We see that in relative terms, price increases affect different income levels about equally. In absolute terms, higher income homes are paying considerably more each bill.

Future work will take the methodology described in this paper and apply it on the national scale. Recent work has suggested that the effect of explanatory variables on consumption may be less sensitive to spatial scale (Ouyang et al. 2014), such that census tract information may be enough to accurately identify household demand factors. Our next step is to more thoroughly validate our results to out of sample cities and use nationally available datasets to predict water demand responses at both the household and block group level for each ecoregion across the country the United States.

REFERENCES

Arbués, Fernando, Marıa Ángeles Garcıa-Valiñas, and Roberto Martınez-Espiñeira. 2003. "Estimation of Residential Water Demand: A State-of-the-Art Review." *The Journal of Socio-Economics* 32 (1). Elsevier: 81–102.

Baerenklau, Kenneth A, Kurt A Schwabe, and Ariel Dinar. 2014. "The Residential Water Demand Effect of Increasing Block Rate Water Budgets." *Land Economics* 90 (4). University of Wisconsin Press: 683–99.

Barberán, Ramón, and Fernando Arbués. 2009. "Equity in Domestic Water Rates Design." *Water Resources Management* 23 (10). Springer: 2101–18.

Berk, Richard A, Thomas F Cooley, C J LaCivita, Stanley Parker, Kathy Sredl, and Marilynn Brewer. 1980. "Reducing Consumption in Periods of Acute Scarcity: The Case of Water." *Social Science Research* 9 (2). Elsevier: 99–120.

Bluemel, Erik B. 2004. "The Implications of Formulating a Human Right to Water." *Ecology Law Quarterly* 31: 957.

Charney, Alberta H, and Gary C Woodard. 1984. "A Test of Consumer Demand Response to Water Prices: Comment." *Land Economics* 60 (4). JSTOR: 414–16.

Deb, Partha, and Pravin K Trivedi. 2013. "Finite Mixture for Panels with Fixed Effects." *Journal of Econometric Methods* 2 (1): 35–51.

DeOreo, William, Peter Mayer, Benedykt Dziegielewski, and Jack Kiefer. 2016. *Residential End Uses of Water*.

Espey, Molly, James Espey, and W Douglass Shaw. 1997. “Price Elasticity of Residential Demand for Water: A Meta-Analysis.” *Water Resources Research* 33 (6). AGU AMERICAN GEOPHYSICAL UNION: 1369–74.

Gleick, Peter H. 1998. “The Human Right to Water.” *Water Policy* 1 (5). Elsevier: 487–503.

Hagenaars, Jacques A, and Allan L McCutcheon. 2002. *Applied Latent Class Analysis*. Cambridge University Press.

Hardberger, Amy. 2005. “Life, Liberty, and the Pursuit of Water: Evaluating Water as a Human Right and the Duties and Obligations It Creates.” *Northwestern University Journal of International Human Rights* 4 (2): 331–62.

Hewitt, Julie A, and W Michael Hanemann. 1995. “A Discrete/continuous Choice Approach to Residential Water Demand under Block Rate Pricing.” *Land Economics*. JSTOR, 173–92.

Ito, Koichiro. 2012. *Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing*. National Bureau of Economic Research.

Jedidi, Kamel, Harsharanjeet Jagpal, and Wayne DeSarbo. 1997. “Finite-Mixture Structural Equation Models for Response-Based Segmentation and Unobserved Heterogeneity.” *Marketing Science* 16 (1). INFORMS: 39–59. doi:10.1287/mksc.16.1.39.

Kamakura, Wagner A, Byung-Do Kim, and Jonathan Lee. 1996. “Modeling Preference and Structural Heterogeneity in Consumer Choice.” *Marketing Science* 15 (2). INFORMS: 152–72. http://www.jstor.org/stable/184191.

Kamakura, Wagner A, and Michel Wedel. 2004. “An Empirical Bayes Procedure for Improving Individual-Level Estimates and Predictions from Finite Mixtures of Multinomial Logit

Models." *Journal of Business & Economic Statistics* 22 (1). Taylor & Francis: 121–25.

Kenney, Douglas S, Christopher Goemans, Roberta Klein, Jessica Lowrey, and Kevin Reidy. 2008. "Residential Water Demand Management: Lessons from Aurora, Colorado1." *JAWRA Journal of the American Water Resources Association* 44 (1). Wiley Online Library: 192–207.

Klaiber, H Allen, V Kerry Smith, Michael Kaminsky, and Aaron Strong. 2014. "Measuring Price Elasticities for Residential Water Demand with Limited Information." *Land Economics* 90 (1). University of Wisconsin Press: 100–113.

Moore, William L. 1980. "Levels of Aggregation in Conjoint Analysis: An Empirical Comparison." *Journal of Marketing Research* 17 (4). American Marketing Association: 516–23. doi:10.2307/3150504.

Nieswiadomy, Michael L. 1992. "Estimating Urban Residential Water Demand: Effects of Price Structure, Conservation, and Education." *Water Resources Research* 28 (3). Wiley Online Library: 609–15.

Olmstead, Sheila M, and Robert N Stavins. 2009. "Comparing Price and Nonprice Approaches to Urban Water Conservation." *Water Resources Research* 45 (4). Wiley Online Library.

Opaluch, James J. 1984. "A Test of Consumer Demand Response to Water Prices: Reply." *Land Economics* 60 (4). JSTOR: 417–21.

Ouyang, Yun, Elizabeth A Wentz, Benjamin L Ruddell, and Sharon L Harlan. 2014. "A Multi-Scale Analysis of Single-Family Residential Water Use in the Phoenix Metropolitan Area." *JAWRA Journal of the American Water Resources Association* 50 (2). Wiley Online

Library: 448–67.

Renwick, Mary E, and Sandra O Archibald. 1998. “Demand Side Management Policies for Residential Water Use: Who Bears the Conservation Burden?” *Land Economics*. JSTOR, 343–59.

Rogers, Peter, Radhika De Silva, and Ramesh Bhatia. 2002. “Water Is an Economic Good: How to Use Prices to Promote Equity, Efficiency, and Sustainability.” *Water Policy* 4 (1). Elsevier: 1–17.

Scheierling, Susanne M, John B Loomis, and Robert A Young. 2006. “Irrigation Water Demand: A Meta-analysis of Price Elasticities.” *Water Resources Research* 42 (1). Wiley Online Library.

Wichman, Casey J. 2014. “Perceived Price in Residential Water Demand: Evidence from a Natural Experiment.” *Journal of Economic Behavior & Organization* 107. Elsevier: 308–23.

Willis, Rachelle M, Rodney A Stewart, Damien P Giurco, Mohammad Reza Talebpour, and Alireza Mousavinejad. 2013. “End Use Water Consumption in Households: Impact of Socio-Demographic Factors and Efficient Devices.” *Journal of Cleaner Production* 60. Elsevier: 107–15.

Willis, Rachelle M, Rodney A Stewart, Kriengsak Panuwatwanich, Philip R Williams, and Anna L Hollingsworth. 2011. “Quantifying the Influence of Environmental and Water Conservation Attitudes on Household End Use Water Consumption.” *Journal of Environmental Management* 92 (8). Elsevier: 1996–2009.

Worthington, Andrew C, and Mark Hoffman. 2008. "An Empirical Survey of Residential Water Demand Modelling." *Journal of Economic Surveys* 22 (5). Wiley Online Library: 842–71.

APPENDIX. CHAPTER 1

A.1 *Example of the Effect of Uncertainty on Consumption*

There exists a number of cases where increasing or decreasing $\beta - \alpha$ may cause a change in discrete choice, γ, that may increase or decrease total consumption. In the simplest case, imagine D_j is sufficiently large such that all individuals stay in the safe zone ($\gamma_1 = 1$). For this to be true, $b_j'\left(\bar{r}_{j,k=1}; R_{-j}\right) < \frac{D_j}{\beta-\alpha}\ \forall\, j$. Increasing $\beta - \alpha$ in this case will initially decrease requests because $\bar{r}_{j,k=1} = \alpha - R_{-j}$. Thus, a mean preserving increase in $\beta - \alpha$, leads to a decrease in $\alpha - R_{-j}$. However, as $\beta - \alpha$ increases, $\frac{D_j}{\beta-\alpha}$ decreases. When $\beta - \alpha$ becomes sufficiently large, $b_j'\left(\bar{r}_{j,k=1}; R_{-j}\right) > \frac{D_j}{\beta-\alpha}$, and individuals will switch from $\gamma_1 = 1$ to $\gamma_2 = 1$ which corresponds to an increase in consumption. This phenomenon exists for both the individual and the social planner. Thus, without further parameterization, the effect of uncertainty on consumption is ambiguous.

A.2 *Graphical Representation of Treatments*

The cases of interest and their NE solutions are presented graphically in Figure A3 for each of the treatments (discretized payoffs are represented with continuous marginal benefit functions to facilitate interpretation). In each case an individual maximizes a net payoff conditional on what others do. In the certainty case (Figure A3a), the *partially defect* NE occurs where the marginal benefit curve intersects the known threshold (NE^1). Beyond the threshold, the damage incurred exceeds the increase in value for both high- and low-productivity users. In the case where individuals believe the group will exceed the threshold, the best response is to set the marginal benefit of extracting to zero, resulting in the *fully defect* NE (NE^2).

Figure A2. Uncertainty Treatments

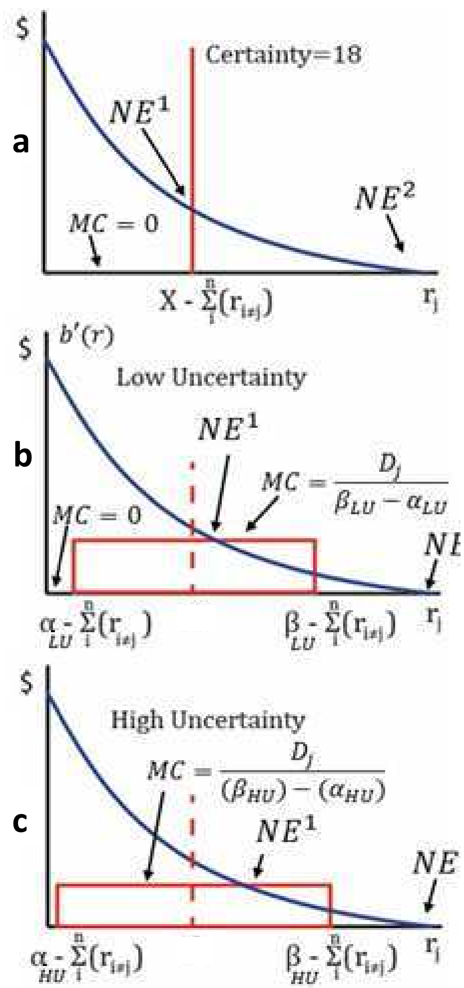


Figure 1 graphically illustrates the uncertainty cases used in our experiment. The possible NE are denoted by superscript 1 (partially defect) and 2 (fully defect).

LU = (Low Uncertainty)

HU = (High Uncertainty)

In the low-uncertainty case (Figure A3b), it is optimal for the user to enter the uncertain range and equate the marginal benefit of extraction to the expected marginal cost of increasing r_j (NE^1). Note that a second NE (NE^2) exists where the user exceeds the threshold with a probability of 1 and sets the marginal benefit of extraction to zero.

Finally, the third Figure (A3c) shows the high-uncertainty case. Comparing this to the low-uncertainty case, it becomes clear that the *partially defect* NE is higher when uncertainty increases, but the *fully defect* NE remains the same in all three cases.

The model was parameterized such that both the *partially* and *fully defect* NE exist in both uncertainty treatments. The individual *partially defect* NE is in the uncertainty zone under both low and high uncertainty, and the payout from that equilibrium is always higher than that of the *fully defect* NE.

A.3 *Effect of Risk Preferences*

If we assume individuals have a constant relative risk aversion in token payouts, we can model their utility at the *partially defect* NE with the following function:

$$U\left(\bar{r}^*_{j,k=2}\right) = \frac{p\left(b\left(r_{j,\pi=2}\right)^{1-\gamma}\right)}{1-\gamma} + \frac{(1-p)\left(\left(b\left(r_{j,\pi=2}\right) - D_j\right)^{1-\gamma}\right)}{1-\gamma}$$

where:
p is the probability that the resource survives at the partially defect NE
γ is a factor of risk preference

By comparison, there is no uncertainty at the *fully defect* NE such that an individual's utility is simply:

$$U\left(\bar{r}^*_{j,k=3}\right) = \frac{\left(b\left(r_{j,\pi=3}\right) - D_j\right)^{1-\gamma}}{1-\gamma}$$

Under the parameterizations used in this experiment, it is possible to solve for the risk preference factor that results in an individual's indifference between the higher expected payoff of *partially defecting* and the certainty payoff of *fully defecting*. These values are presented in table A1.

Table A3. Gamma Values at which $U\left(\bar{r}^*_{j,k=2}\right) = U\left(\bar{r}^*_{j,k=3}\right)$

	Low Productivity	High Productivity
Low Uncertainty	.075	.016
High Uncertainty	.068	.019

A.4 *Experiment Instructions*

You are about to participate in an experiment on decision-making that is being funded by the Colorado State University Department of Agricultural and Resource Economics. This experiment should last about an hour. You have the opportunity to earn cash, which will be paid to you at the end of the session. Your payout depends on your decisions, the decisions of your group and chance. Please read the following instructions carefully.

Throughout the experiment your earnings will be reported in lab dollars. At the conclusion of the experiment your lab dollars will be converted to U.S. dollars as follows:

16 Lab dollars = 1 US Dollar

During the entire experiment communication of any kind and the use of cell phones are strictly prohibited. Communication between participants will lead to your exclusion from the experiment and the forfeit of all earnings. Please raise your hand if you have any questions and a member of the research team will come to you and answer your questions privately. Also, please turn off your cell phones to minimize disruption during the experiment.

Note you must complete the entire experiment to be eligible to be paid.

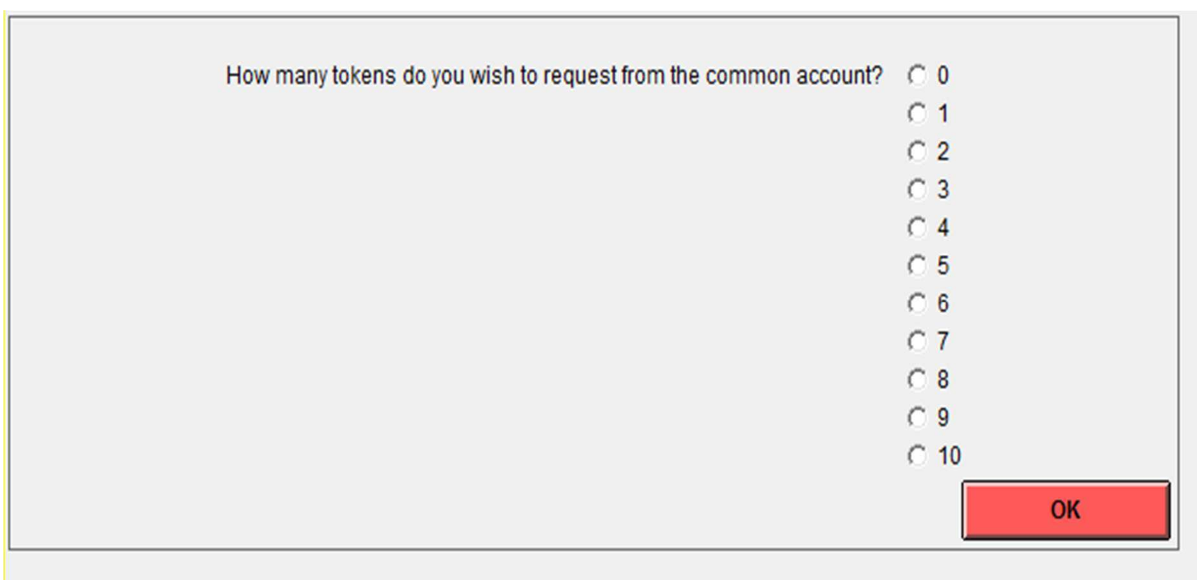
1. **Experiment Overview and Timeline**

Your basic task in this experiment will be to request tokens from a group account. The experiment is made up of 12 independent rounds, each of which contains 8 periods. Each period you will be randomly placed into a group with 3 other players and given the opportunity to request tokens from your group's account. You will be placed in a different group each period, but each group will always have 4 total players.

In every period each group member, including yourself, will be asked how many tokens you want to withdraw from your group's account. You may request from 0 to 10 tokens. Each group member will receive exactly the amount of tokens he or she requested. However, if the sum of tokens requested by your group is greater than a certain threshold level (described below), then each member of the group will also incur a loss of a specified number of lab dollars. Note: when making the request you will not know how many tokens each of the other members of your group is requesting.

Figure 1 shows a portion of the screen on which you will request tokens.

Figure 1



2. **How tokens are converted to lab dollars**

At the end of each period your tokens will be converted into lab dollars. At the beginning of the experiment, and at other times during the experiment, you will be provided with a payoff table that will tell you exactly how many lab dollars you will earn for each token requested. The rate at which your tokens are converted into lab dollars will remain constant throughout the session, but may differ from other individuals in your group. As illustration, a sample payoff table is presented below in Table 1 (note that this sample payoff table will differ from the payoff table in the actual experiment).

Table 1: Example Payoff Table

Lab Dollars For Tokens Received											
# of Tokens	0	1	2	3	4	5	6	7	8	9	10
Lab Dollars Per Token	0.00	12.00	7.00	5.40	4.25	3.30	2.50	1.75	1.10	0.50	0.00
Total Lab Dollars	0.00	12.00	19.00	24.40	28.65	31.95	34.45	36.20	37.30	37.80	37.80

Example: What if I requested 4 tokens?

> You would receive 12 lab dollars for the first token, 7 for the second token, 5.40 for the third token, and 4.25 for the fourth token, for a total of 28.65 lab dollars. Had you requested 5 tokens instead of 4, you would have received 3.30 lab dollars more; had you requested only 3 tokens instead of 4, you would have received 4.25 lab dollars less.
>
> *Note your total payoff will not only depend on your token choice but also on whether or not the sum of your group's request exceeded the threshold and on other factors described below.

Your actual payout table will be displayed when the experiment starts and may be different for each player. For example, one player may receive 14 lab dollars for his first token while another player may only receive 11. In addition to the payoff difference, players may also suffer a different loss if the total group requests exceed the threshold.

3. The Group Threshold and the Threshold Loss

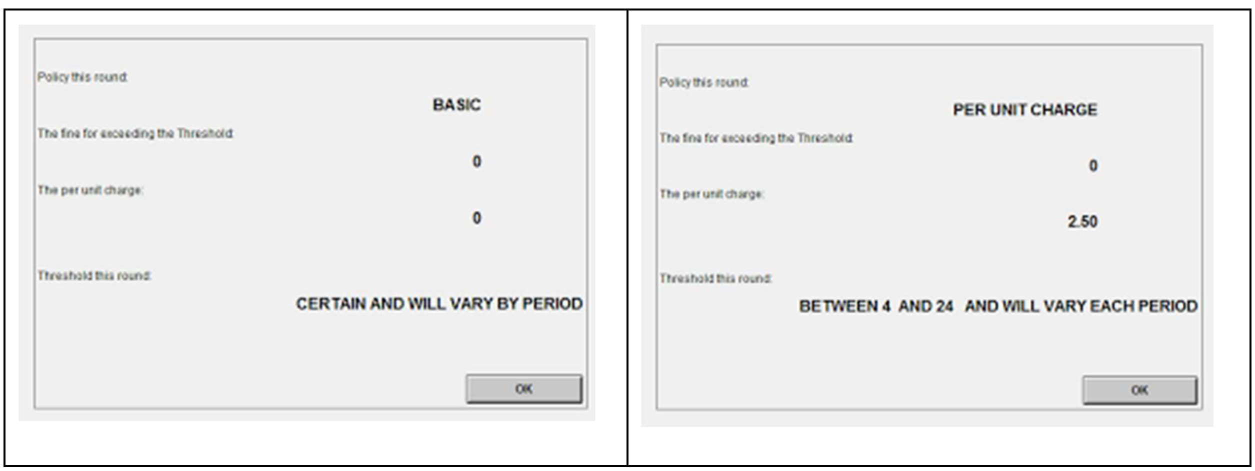
In each period your group will randomly be assigned a token threshold. If the total number of tokens requested by the group in that period exceeds the threshold number of tokens, each member of the group will incur a loss of a specified amount of lab dollars. You will be told the amount of the loss in lab dollars at the beginning of the experiment and it will remain constant throughout today's session. Losses may vary across players--those players with higher payoffs per token requested will also face larger losses if the threshold is exceeded.

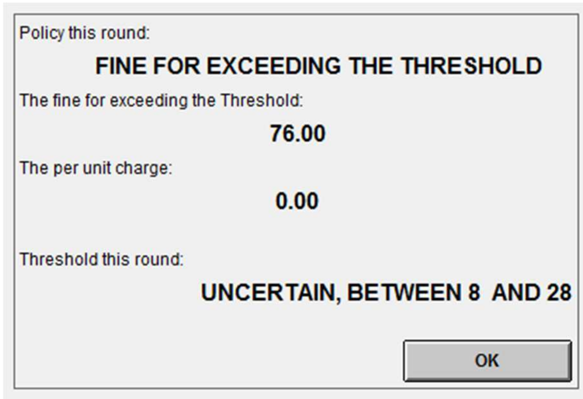
In some rounds the true value of the threshold in each period will be known and in others it will not. Prior to each round you will be told whether or not the threshold will be revealed to you in the upcoming periods for that round. In rounds where you are told the value of the threshold prior to beginning each period it will be displayed at the top of the screen. In rounds where the exact threshold is unknown, you will only know that the true threshold was chosen at random between an upper and lower bound. The true threshold will have an equal probability of being any number in that range. Each round may have different lower and upper bounds within which the true threshold will be randomly selected.

4. Policies Across Trials

In each round, you will be presented with one of three policy types: 1) Basic, 2) Per-Unit Charge, 3) Fine for Exceeding the Threshold. Prior to each round you will be told which policy will be in place. A particular policy will be in place for every period during that round. Figure 2 provides examples of what you will see prior to each round. Note that at this time you will also be provided information regarding the nature of the threshold.

Figure 2





A description of each policy follows:

Basic

The basic setting will work just like it is explained above. For example, using the payoff schedule in Table 1 above, and assuming your group's total request did not exceed the threshold, if you requested 3 tokens your total payout for the period would be $24.40. However, if your group's total request exceeded the threshold, the threshold loss would be deducted from the $24.40.

Per-Unit Charge

The per-unit charge will add a cost for each token you request, whether or not your group's request exceeds the threshold. For example, if the per unit charge is $2, and you request 3 tokens, the total charge to you would be $6. Using the payoff table in Table 1, and assuming that your group's total request did not exceed the threshold, your total payout for the period would be $24.40 - $6 = $18.40. If your group's total request exceeded the threshold, the threshold loss would be deducted from $18.40.

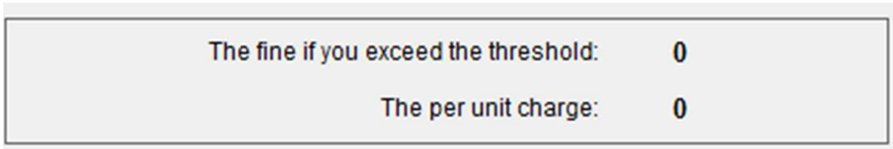
Each period, the charge per token will be displayed at the top of the screen (Figure 3), and may or may not change depending on the round you are in.

Fine for Exceeding the Threshold

Under this policy you will incur a fine if your group's total request exceeds the threshold. For example, assume the fine is $30 dollars and you request 3 tokens. Using the payoff table in Table 1, and assuming that your group's total request did not exceed the threshold, your total payout for the period would be $24.40. However, if the threshold was exceeded, you would receive $24.40 minus both the fine of $30 **and** the threshold loss. If, for example, the threshold loss was 20, you would earn negative $25.60 in that period.

Each period, the amount of the fine will be displayed at the top of the screen (Figure 3).

Figure 3



Note: The size of the per unit charge and fine will change across rounds

Table 2 Summarizes these Policies

Table 2: Summary of Policies and Costs

	Which Rounds	**What you Pay**	**When you Pay it**
Threshold Loss	All Rounds	Lump sum loss of lab dollars	Only if the group requests exceed the threshold
Fine	Only if policy is: *Fine for exceeding the Threshold*	Lump sum loss of lab dollars	Only if the group requests exceed the threshold
Per Unit Charge	Only if policy is: *Per-Unit Charge*	Cost per token requested	Whenever you request a token regardless of the threshold

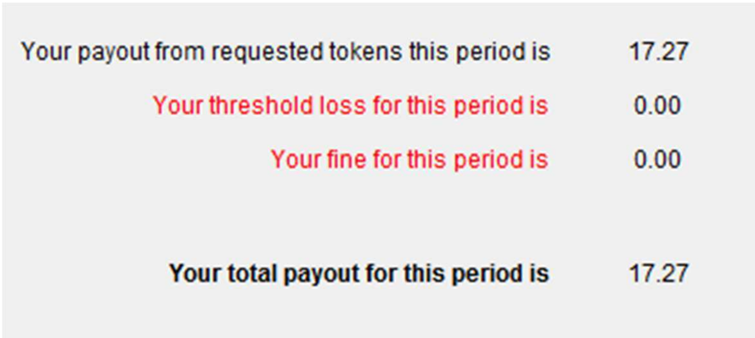
5. Calculating your Total Payoff

In all 12 rounds, regardless of policy type, you will be asked how many tokens you wish to request from the group account. The request screen will look like it does in Figure 1.

At the end of each period, a screen will be displayed that shows how many tokens you requested, if your group went over the threshold that period, and your payoff information for the period (Figure 4).

Figure 4

Example 1: Basic You requested **6** tokens YOUR GROUP STAYED UNDER THE THRESHOLD Your payout from requested tokens this period is 17.27 Your threshold loss for this period is 0.00 **Your total payout for this period is** 17.27	This example is a basic policy setting so the only possible cost is the threshold loss. Since the group stayed under the threshold, the loss is 0.
Example 2: Per Unit Policy You requested **10** tokens YOUR GROUP WENT OVER THE THRESHOLD Your payout from requested tokens this period is 11.26 Your threshold loss for this period is 16.00 Your total charge this period is 40.00 **Your total payout for this period is** -44.74	In this example, the group requested too many tokens, and the threshold was exceeded In this example the per token charge was $4, so by requesting 10 tokens, the total charge is 4 * 10 = $40
Example 3: Fine for Exceeding the Threshold Policy You requested **6** tokens YOUR GROUP STAYED UNDER THE THRESHOLD	In this example the threshold was not exceeded so neither the fine for the threshold loss occurred.

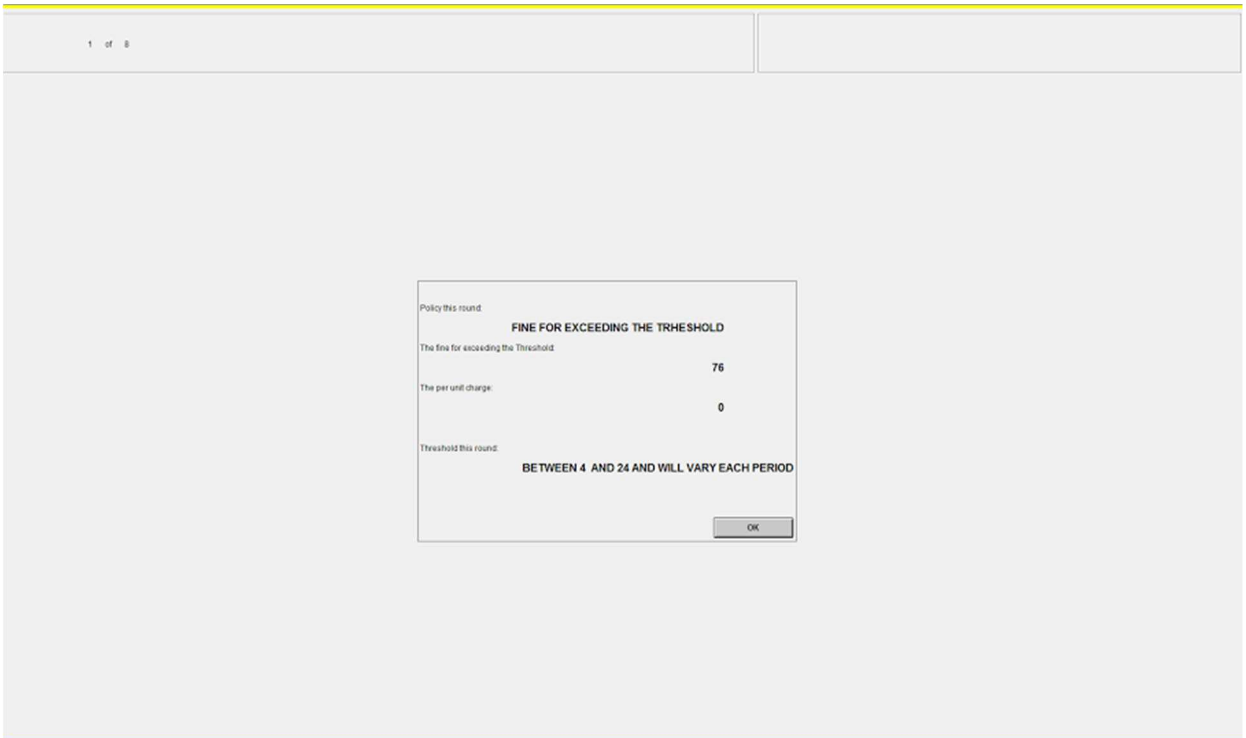


Your take-home payout in US$ will depend on how you performed in the experiment. Every player starts with 100 lab dollars and can increase their lab dollars through requesting tokens. One period will be randomly selected and you will be paid in lab dollars the sum of whatever you made in that period across all 12 rounds. Note that it is possible to receive negative lab dollars in any given round. If the sum of your payouts across all 12 rounds is negative, then this sum will be subtracted from the 100 lab dollars with which you started. The conversion of Lab dollars to US dollars is displayed at the beginning of these instructions. Note: Payouts will be rounded to the nearest quarter.

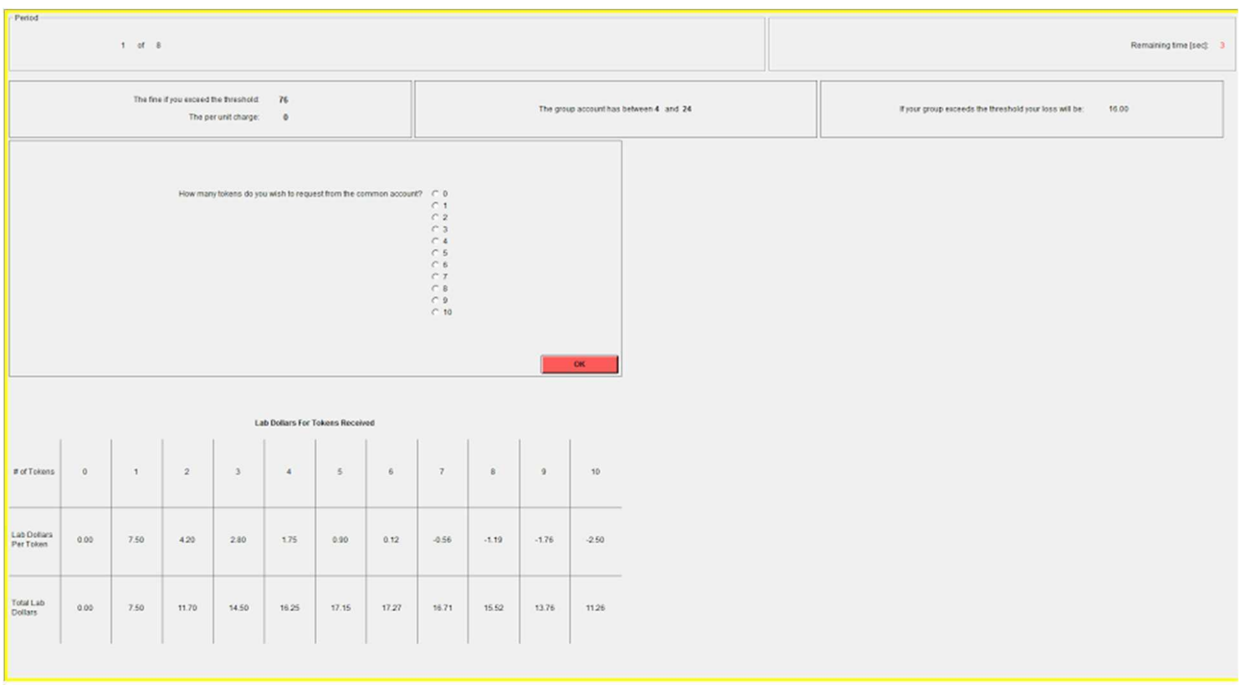
Below are some sample screenshots from the experiment.

Sample Screenshots

Screen 1 (scene at the beginning of each round)

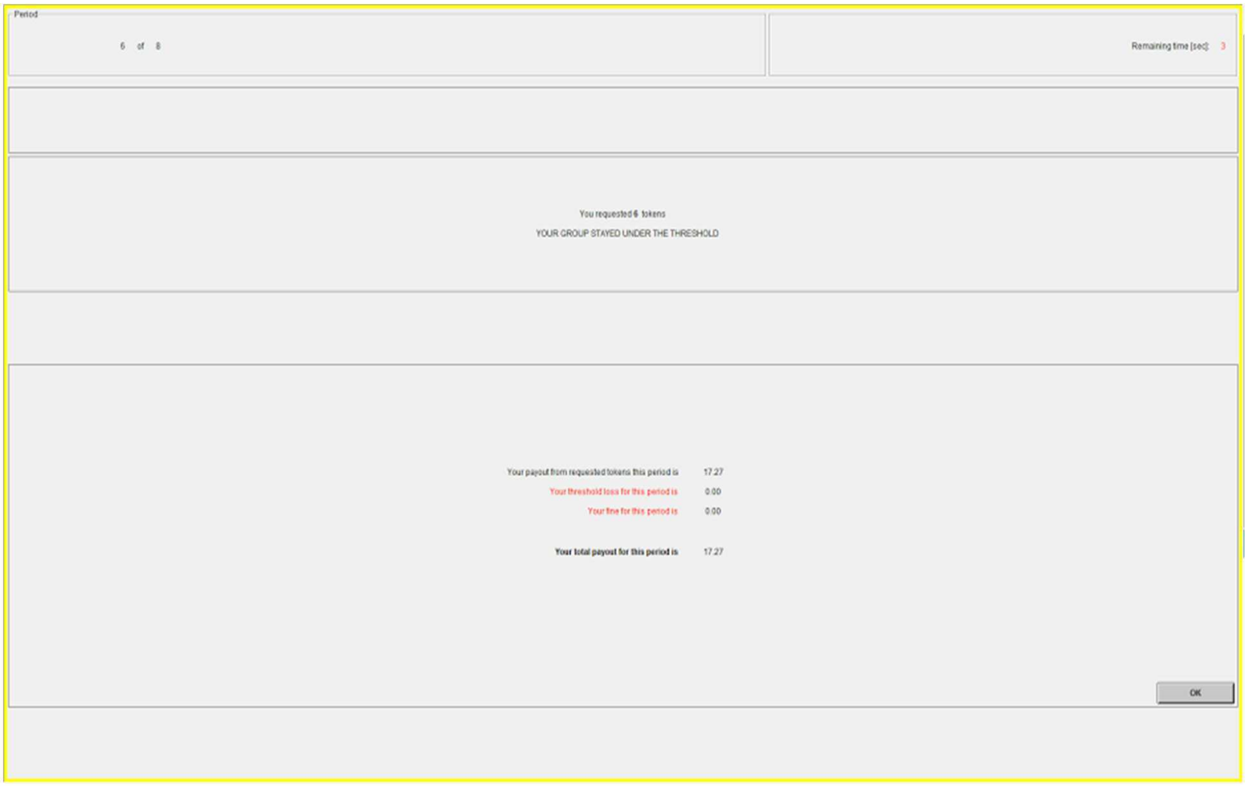


Screen 2 (scene at the beginning of each period)



# of Tokens	0	1	2	3	4	5	6	7	8	9	10
Lab Dollars Per Token	0.00	7.50	4.20	2.80	1.75	0.90	0.12	-0.56	-1.19	-1.76	-2.50
Total Lab Dollars	0.00	7.50	11.70	14.50	16.25	17.15	17.27	16.71	15.52	13.76	11.26

Screen 3 (scene at the end of each period)



Practice Questions (Please use Table 1 to answer the following practice questions)

For questions 1-3 assume you are in the Basic policy setting and that the threshold loss is $30.

1. If the threshold is 12 and everyone in your group (including yourself) requests 3 tokens, what is your lab dollar payout for the period?

   ____

2. If the threshold is 12 and everyone in your group requests 3 tokens but you request 10, what is your lab dollar payout for the period?

   ____

3. If the threshold is 14 and everyone in your group requests 10 tokens but you request 3, what is your lab dollar payout for the period?

   ____

For questions 4-6 assume you are in the Per Unit Charge policy setting, the threshold loss is $30 and that the per unit charge is $2.00.

4. If the threshold is 12 and everyone in your group (including yourself) requests 3 tokens, what is your lab dollar payout for the period?

   ____

5. If the threshold is 20 and everyone in your group requests 3 tokens but you request 10, what is your lab dollar payout for the period?

   ____

6. If the threshold is 14 and everyone in your group requests 10 tokens but you request 3, what is your lab dollar payout for the period?

   ____

For questions 7-9 assume you are in the Fine for Exceeding the Threshold policy setting, the threshold loss is $30, and the fine for exceeding the threshold is $60.

7. If the threshold is 14 and everyone in your group requests 3 tokens, what is your lab dollar payout for the period?

   ____

8. If the threshold is 14 and everyone in your group requests 3 tokens but you request 10, what is your lab dollar payout for the period?

   ____

9. If the threshold is 12 and everyone in your group requests 10 tokens but you request 3, what is your lab dollar payout for the period? ______________

APPENDIX. CHAPTER 2

A1. *Variables Used in the Analysis*

Table A1 describes the specific variables used in the regression analysis.

Table A1. Description of Variables

Consumption (gal)	Number of gallons used in billing period
Price	Average Variable Price of last month's bill
Bill days	Number of days for which consumer was billed
Precipitation	cumulative precipitation of billing period (mm)
Temperature	Daily average temperature of billing period, calculated as: $\frac{\sum_{1}^{bill\ days}\left[\frac{daily\ high + daily\ low}{2}\right]}{bill\ days}$
Summer dummy	A dummy variables that takes a value of 1 for June, July and August, and 0 otherwise.
Middle income	A dummy variable that takes the value of 1 if survey respondents claimed an income between \$35,000 and \$74,999 and 0 otherwise
High income	A dummy variable that takes the value of 1 if survey respondents claimed an income above \$74,999 and 0 otherwise
Single family home	A dummy variable that takes the value of 1 if survey respondents lives in a single family home and 0 otherwise
# of persons	Number of persons in the household as recorded by the survey
E&S (dummy)	A dummy variable that takes the value of 1 if survey respondents answers were such that Q2+Q3 > Q4+Q5 and 0 otherwise
Grass area	Acres of turf, estimated by 2012 LiDar
House size (sf)	Square footage of home, defined by the Larimer Assessor's office
conservationist	A dummy variable that takes the value of 1 if survey respondents answers were such that Q1 > 5 and 0 otherwise

A2. ***Data Cleaning***

Given the necessity to merge datasets from various sources, mistakes present in the billing data, and oddities that may not represent normal water use, the data used in our regression analyses has been cleaned according to a number of rules. Specifically, observations were dropped if:

- Consumption > 60,000 gallons per month
- Consumption < 300 per month
- Bill ($) < 0
- Surveys were not complete
- | [Parcel area (LiDar) – Parcel Area (Assessor)] | >200sqft
- Bill days < 26 or Bill days > 36
- Customer account number existed for > 2 properties
- Observation could not be merged across all datasets
- Average Variable Price < 0
- Customer code changes for a given tap (suggests a change in occupancy)

A3. ***Additional Analysis and Grouping Criteria***

While the motivation to group socially and environmentally motivated individuals was a function of the altruistic nature of both motivations—as opposed to cost or convenience motivations, it is worth noting that the correlation between these two responses is extremely high (0.72). By comparison, being concerned with convenience is negatively correlated with both social and environmental concerns.

Table A3-1.

Correlation Matrix of Survey Responses (n=119)

	conserve	enviro	social	cost	convenience
conserve	1.000				
enviro	0.398	1.000			
social	0.300	0.720	1.000		
cost	0.220	0.184	0.223	1.000	
convenience	0.118	-0.108	-0.48	0.041	1.000

To test for robustness in our results, a number of additional model specifications are included in Table A3. When survey questions are included in the OLS model as continuous variables, the results are qualitatively similar to those reported in the body of the paper. Note that increases in the scores of environmental motivation are associated with the largest decrease in water use, which is consistent with our finding that E&S consumers use less than C&C consumers. It is worth noting that increases in the scores of both the social and convenience motivations are associated with increased water use, suggesting that the motivation for lower water use seen in E&S consumers is largely environmental.

Table A4 presents the regression results of customer motivation types similar to that presented in the main paper, except groups were created only with the environmental and cost questions. Note that the same qualitative results persist, suggesting that environmentally motivated households consume less and that there is no significant difference in how each household type responds to changes in price and weather.

Table A3-2. Pooled OLS Regression with Continuous Survey Variables

VARIABLES	OLS Pooled
Ln(Price)	-0.407***
	(0.0503)
Bill days	0.0399***
	(0.00337)
Precipitation	-0.00150***
	(0.000250)
Temperature	0.0459***
	(0.00132)
Summer dummy	0.149***
	(0.0260)
New home	-0.389***
	(0.0314)
Middle income	0.0756***
	(0.0204)
High income	0.242***
	(0.0207)
Single Family home	0.920***
	(0.0404)
# of persons/household	0.120***
	(0.00510)
Grass Area	-0.875
	(1.213)
House size (sf)	0.000136***
	(1.62e-05)
Environmental (0-9)	-0.0381***
	(0.00397)
Social (0-9)	0.0263***
	(0.00356)
Cost (0-9)	-0.00495*
	(0.00287)
Convenience (0-9)	0.0215***
	(0.00446)
Constant	3.026***
	(0.316)
Observations	6,582
R-squared	0.495

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A3-3. Regression Output only Considering Environmental and Cost Motives

VARIABLES	(1) OLS Pooled with Dummy	(2) FE Interactions
Ln(Price)	-0.362***	-0.170***
	(0.0537)	(0.0519)
Bill days	0.0398***	0.0424***
	(0.00364)	(0.00353)
Precipitation	-0.00153***	-0.00151***
	(0.000273)	(0.000210)
Temperature	0.0450***	0.0444***
	(0.00143)	(0.00133)
Summer dummy	0.141***	0.123***
	(0.0282)	(0.0254)
New home	-0.289***	
	(0.0356)	
Middle income	-0.0113	
	(0.0224)	
High income	0.0933***	
	(0.0221)	
Single Family home	1.056***	
	(0.0411)	
# of persons/household	0.130***	
	(0.00545)	
Grass Area	3.123**	
	(1.290)	
House size (sf)	0.000152***	
	(1.81e-05)	
d_E (dummy)	-0.105***	
	(0.0157)	
Price*d_E		-0.108
		(0.0765)
Precipitation*d_E		-0.000581
		(0.000537)
Temperature*d_E		0.00169
		(0.00194)
Bill days*d_E		-0.00564
		(0.00542)
Summer dummy*d_E		0.0552
		(0.0443)
Constant	3.207***	5.687***
	(0.336)	(0.242)
Observations	5,687	5,687
R-squared	0.480	0.537
Number of households		102

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1