DISSERTATION

THREE ESSAYS EXPLORING HETEROGENITY IN WATER POLICY PREFERENCES AND RESPONSIVENESS

Submitted by

Janine Stone

Department of Agricultural and Resource Economics

In partial fulfillment of the requirements

For the Degree of Doctor of Philosophy

Colorado State University

Fort Collins, Colorado

Summer 2015

Doctoral Committee:

Advisor: Christopher Goemans

Marco Costanigro
Stephan Kroll
Reagan Waskom

ABSTRACT

THREE ESSAYS EXPLORING HETEROGENITY IN WATER POLICY PREFERENCES AND RESPONSES

Water utilities throughout the western United States face increasing populations and frequent drought events that necessitate development of new water supplies, as well as use of policies that can decrease water demands. In the state of Colorado, water demand is projected to increase by roughly 50% by the year 2050; however, little is known about the types of policies households prefer to be used to meet future demand. Additionally, the extent to which varying demographic groups are more responsive than others to existing policies has not been extensively addressed in the literature.

The first paper in this dissertation examines demand-side management policies, such as price increases and watering restrictions, and evaluates households' responses to those policies in the short and long runs. A latent-class model is used to identify households with varying behavioral responses to policies. In doing so, the model allows for an evaluation of the extent to which average responsiveness to policies like price increases is influenced by a small set of households who are more responsive to policies during the drought, and for whom responsiveness is changing over time. Accordingly, the model may be used by utilities to determine whether the welfare losses associated with decreasing water consumption are shared across households and whether households who decreased water usage in the past may be expected do so during future shortages.

The second paper shifts to an examination of household preferences for meeting future water needs. Data from two surveys--one related to water policies, and one to water policy

impacts—is used in a latent-class model that explores heterogeneity in households' preferences for policies that could be used to meet future water demand in Colorado. Policies under consideration include use of supply projects, non-price conservation, price increases, and purchases of agricultural water rights. Impacts relate to changes in the marginal price of water, increases in base charges on households' water bills, changes in landscaping, and fallowing of agricultural land. Demographic groups that support policies are compared to the groups that support associated impacts to evaluate whether the decision-making process for individuals is impacted by the type of survey used, and overall support for alternatives to agricultural water transfers are evaluated. It is found that household preferences are driven by factors such as whether one lives in a rural or urban area in the policies survey, whereas one's water usage determines support for impacts. These results suggest that the types of user groups (and potentially voting blocs) that support a policy when it is being discussed prior to implementation may differ from the groups that support policies once they see how they are actually affected.

Building, on this result, the third paper compares rankings for water policies to "inferred rankings," or rankings obtained by calculating households' willingness to pay for impacts associated with water policies. Preferences for policies themselves may be influenced an individual's level of information, perceptions, and biases, whereas preferences deduced from impacts represent the opinions of informed consumers. Overall, it is found that households' willingness to pay for impacts associated with decreasing the volume of agricultural water transfers is compatible with the costs of nearly all policies being considered by the state. However, the specific policy mix preferred differs across the policies and impact surveys, suggesting a polices-type survey may be preferable when examining households' overall policy goals, whereas an impacts-type survey may be used to determine how those goals should be accomplished

TABLE OF CONTENTS

CHAPTER 1: HETEROGENEITY IN RESPONSE TO WATER POLICIES DURING AND AFTER DROUGHT: A FIXED-EFFECTS, LATENT-CLASS APPROACH

1.1 Synopsis

Water and electric utilities frequently use demand-side management policies (DSM) to decrease residential water and energy usage in both the short-run (during scarcity) and as part of an overall water supply plan. The impact of DSM on water usage has been well-researched; however, previous research has largely been limited to evaluating the impact of DSM on the "representative consumer," overlooking the fact that the underlying decision making process surrounding water and electric use may vary across households due to factors unobservable to the researcher. For example, differences in understanding of utilities' complex rate structures will affect households' responsiveness to price increases. Additionally, consumers' short-term responsees to DSM may impact long-term responsiveness via "demand hardening," meaning households become less responsive to policies over time if they exhaust all means of reducing water usage (Howe and Goemans, 2007). This research evaluates heterogeneity in both short and long-term DSM responsiveness using ten years of household-level monthly water consumption data in a fixed-effects, finite-mixture (latent-class) model (Deb and Trivedi, 2013). The model allows for testing the hypothesis that there are varying classes of households—i.e., individuals with similar behavioral responses to utility policies and for whom water demand may be more price-elastic than estimated in traditional models. We also test whether household decision making changes over time by comparing class membership during and after a major drought event in Colorado. To date, this is one of the first applications of a fixed-effects, latent-class model to empirical data and first study we are aware of to explore how drought-induced changes in demand impact post-drought responsiveness. Results show that a minority of consumers has an elasticity of water demand much higher than common estimates in the literature, especially during the drought. However, these consumers also appear to exhibit "demand hardening," wherein elasticity decreases over time. Thus, understanding heterogeneity in consumers' short-term responses to price increases tells utilities the extent to which consumers have shared the burden of decreasing consumption in the past and whether those same households can be expected to further reduce consumption.

1.2 Introduction:

Utilities frequently use demand-side management (DSM) policies to balance consumers' demand for water and energy with available supplies (Loughran and Kulick, 2004; Olmstead and Stavins, 2009). Such policies include price increases, use of block-rate pricing structures, information campaigns, and rebate programs for efficient appliances. Information on the effectiveness of DSM policies is vital for two reasons: first, utilities need to predict DSM's ability to decrease quantity demanded when policies are used during acute water or energy shortages. Second, long-term reductions in demand resulting from DSM are used in determining the need for costly investment in new infrastructure. Despite the common use of these policies, little work has evaluated their long-term impacts (Abrahamse, et al 2005). Furthermore, research has centered on responses for the average consumer, largely ignoring heterogeneity and welfare potential implications associated with subsets of households decreasing water consumption more than others.

Differences in short-term responses result from factors unobservable to the researcher, such as awareness (and understanding) of water bills and the decision-making processes used in response to water bill information (Liebman, 2004). Additionally, unobserved differences in water-use behaviors and habits or use of automated technologies may also impact responsiveness; for instance, a homeowner with a small, manual irrigation system will likely respond to price increases very differently from one with a large lot on automatic sprinklers.

Short-run responses, in turn, may impact consumers' long-run policy responsiveness, depending upon whether changes in water use result either of conscious behavioral modifications, or installation and use of more water-efficient appliances and landscaping. If an individual decreases usage by, for instance, temporarily changing how frequently he waters his lawn (and then reverts to his original habits after the shortage is over), this individual can be expected to be similarly responsive in future droughts. Alternatively, watering behavior that becomes a permanent habit, or installation of a low-water use irrigation system, may decrease the consumer's ability to reduce usage further in the event of future shortages (Kenney, 2015). This "demand hardening" (Howe and Goemans, 2007) diminishes the utility's ability to decrease average usage in the service area when necessary.

In order to predict how consumers may respond to future policies during acute shortages and to plan for future water supply needs, utilities need to understand the full distribution of household policy responses. Heterogeneity in responsiveness might, as an example, relate to a subset of households with higher price elasticities. Though it may not be a problem in the short run if average price elasticity is heavily influenced by a more-responsive sub-group, changes in responsiveness over time for this group would mean the utility needs to target other households in order to achieve future reductions in demand. Additionally, from a welfare perspective, it is important to understand whether short-term decreases in demand come from a majority of households, who share the losses in welfare associated with decreased water usage (Renwick and Archibald, 1998), or if a subset of households has borne the brunt of water-use reductions.

This research uses a fixed-effects, latent-class approach to explore responsiveness to utility policies adopted by a large Colorado water provider during and after a severe drought. We hypothesize that households make decisions in fundamentally different ways, and each household can be assigned to a different "class" of decision-making behavior endogenously identified in the model. We also propose that class membership, and the characteristics of the classes, may change over time. To test these hypotheses, separate latent class models are estimated for both a drought and post-drought period, with class membership parameterized as a function of pre-drought water usage in each model. As such, we are able to observe households that have similar demands and price elasticities, even if researchers would not think of those households as being of a similar "type" of consumer. A finding of differing price elasticities across the classes is also consistent with the idea that differences in awareness and understanding of price information on the water bill may impact price elasticities (Gaudin, 2006).

Results for the classes of behavioral responses seen in both periods are then compared, and evolution of the classes is evaluated by, for example, determining how high pre-drought water users responded to policies in both the drought and post-drought periods. Lastly, the latent-class approach is compared to traditional water demand models for the average consumer. To our knowledge, this is the first application of the fixed-effects, latent-class model to water demand data and, subsequently, the first attempt to characterize varying classes of behavior responses to water policies and how those responses change over time.

The remainder of the paper is organized as follows: Section 1.2 discusses relevant literature on water demand and latent-class modeling. Section 1.3 discusses the methodology used to estimate the latent-class models in the drought and post-drought periods and to compare these results with traditional water demand models. Section 1.4 presents results for the traditional and latent-class approaches; characterizes class membership; and evaluates changes in class-membership across periods. Section 1.5 concludes.

1.3 Previous Literature

The reality that two households that appear similar based on observed characteristics may make water use decisions in fundamentally different ways represents a significant challenge—one that has not been dealt with in previous water demand studies. The following presents an overview of the literature regarding sources of heterogeneity in policy responsiveness, followed by a discussion of challenges associated with specifying water demand models. We then describe basic water demand models based on a representative consumer, followed by previous efforts to control for unobserved heterogeneity using fixed-effects and sample-segmenting techniques. For comparison purposes coefficient estimates corresponding to the traditional average-demand estimation approach is also included in the results section.

1.3.1 Price Elasticities and Water Demand

Despite numerous potential sources of variation in policy responsiveness, a significant portion of the early literature focused on estimating water demand for a "representative consumer," meaning a single model is estimated wherein coefficients represent the average impact of included variables on household water demand (Hanemann, 1997). This occurs for three major reasons, the first of which is data limitations, as household-level data is not always available to the researcher. Other reasons for modeling the "representative consumer" result from two complications related to demand estimation in these settings. First, econometric issues related to block rate pricing structures create a variety of methodological challenges (e.g., Nordin, 1976; Jones and Morris, 1984; and Hewitt and Hanemann, 1995). Second, there is a great deal of uncertainty regarding how households understand and interpret price information when facing complex utility pricing structures, especially when block-rate pricing schemes are used (Gaudin, 2006; Nieswiadomy and Molina, 1991). For example, in a survey conducted in the service area of interest for this work, over 40% of households incorrectly identified the rate structure used by the utility, despite the fact that an increasing-block rate structure had been in place for eight years at the time of the survey.

Given that there is likely heterogeneity in how individuals interpret price information, it is not surprising that there are numerous studies supporting use of various price specifications, including average price, marginal price (Nieswiadomy, 1992) or the discrete continuous choice specification proposed by Hewitt and Hanemann (1995). Recent research suggests average price is the most appropriate specification (Ito, 2014; Taylor, McKean and Young, 2004), as many consumers' awareness of water bills amounts to (roughly) knowing what they paid for water the previous month. Nevertheless, even if households generally respond to the average price from their most recent bill, the level of understanding (or lack thereof) of the rate structure may cause consumers to have varying responses to this information. For instance, there may be some consumers who cut back usage dramatically in response to their first high water bill of the summer, whereas others consumers pay little attention. This type of heterogeneity in policy responsiveness is not captured by *any* price specification in the above-mentioned literature, as all assume the marginal effect of a change in price is the same for all users. Similarly, consumers may vary in how their policy responses change over time, and consumers in areas with a history of water scarcity are known to be less responsive to policies used to cut water usage during shortages (Larson et al., 2013). If heterogeneity exists, and if short-term responsiveness impacts consumers' ability to respond to future policies, then failing to account for these differences results in misleading estimates of future DSM effectiveness.

1.3.2 Previous Approaches to Specifying Water Demand Models

In general, the focus of the literature has been to correctly specify models of water demand to account for numerous econometric challenges presented by water demand data, including unobserved household characteristics and behaviors. In the context of these potentially unobserved determinants of household water usage, the density of water demand for household *i* at time *t* may be specified as follows:

$$f(y_{it} \mid \mathbf{x}_t, \mathbf{z}_{it}) = \mu\left(\mathbf{x}_t, \mathbf{z}_{it}; \boldsymbol{\beta}, \boldsymbol{\theta}\right) + \varepsilon_{it} \tag{1}$$

where $\mathbf{x}_t$ are observed policy-related variables and control variables for weather; $\mathbf{z}_{it}$ are (potentially unobservable) non-policy control variables related to characteristics of the household; and ε_{it} are disturbances that are not necessarily iid. Using this approach to demand estimation, one set of coefficients is estimated for policy/weather (β) and household-characteristic (θ) related variables, assuming that the impact of β and θ is the same for all households. Commonly included policy variables include prices, watering restrictions, and non-price conservation programs, whereas household-level variables include demographic characteristics (e.g., household size income, water technologies and lot size) (Arbués, Villanúa, and Barberán , 2010; Grafton et al, 2011). Model flexibility may be expanded by interacting policy-related variables with demographic information.

In many cases, both household demographics and behaviors that influence water consumption are unobservable to the researcher, making it impossible to control for all determinants of household water usage and, therefore, causing bias in the estimation of $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$. This problem is often solved by estimating fixed-effect models (usually by means of least squares techniques) of the form $f(y_{it} \mid \mathbf{x}_t, \mathbf{z}_{it})$ where the household-specific unobserved fixed effects z_i are conditioned out through a "within" transformation applied to the data as follows:

$$y_{it} - \bar{y}_i = (x_t - \bar{x}_t)'\beta + (z_{it} - \bar{z}_i)'\theta + (\varepsilon_{it} - \bar{\varepsilon}_i) \qquad (2)$$

yielding the equation

$$\tilde{y}_{it} = \tilde{x}_t{}'\beta + \tilde{z}_{it}{}'\theta + v_{it} \qquad (3)$$

where v_{it} is uncorrelated with the mean-centered regressors and time-invariant variables in $\mathbf{z}_{it}$ drop out of the model so that the associated coefficients cannot be estimated.

Regardless of whether determinants of water usage are observable, the researcher may believe that the impact of both policy and non-policy-related variables differs across distinct user groups or time periods—for example, summer versus winter outdoor usage. To this end, the researcher may estimate separate models for households assumed to have varying distributions of water demand. The resulting model, for the case of observable household characteristics, takes the form

$$f(y_{it} \mid \mathbf{x}_t, \mathbf{z}_{it}) = \sum_{j=1}^{m} d_{ijt}\left(w_{it}\right)\mu_j\left(\mathbf{x}_t, \mathbf{z}_{it}; \boldsymbol{\beta}_j, \boldsymbol{\theta}_j\right) + \varepsilon_{it} \qquad (4)$$

where $d_{itj} = 1$ if observation *it* belongs to class j, and *m* class-specific vectors of parameters are estimated for each of the researcher-defined classes, split based on thresholds or qualitative outcomes of observable variables w_{it} identified by the researcher.

For the case of unobservable household characteristics, the split-sample approach can also be implemented in conjunction with fixed effects,

$$f(y_{it} \mid \mathbf{x}_i, \mathbf{z}_{it}) = \sum_{j=1}^{m} d_{itj}\mu_j(\tilde{\mathbf{y}}_{it}, \tilde{\mathbf{x}}_t; \boldsymbol{\beta}_\mathbf{j}, \boldsymbol{\theta}_\mathbf{j}) + v_{it} \qquad (5)$$

and, where $\tilde{y}_{it}, \tilde{x}_t$ are the demeaned data for individual *i* after household-level fixed effects are conditioned out of the model, and d_{itj} is again a dummy variable equal to 1 if the researcher assigns an observation for individual *i* at time *t* is assigned to class *j*. An example of the fixed-effects, split-sample approach is provided by Kenney, et al. (2008) who use fixed effects after first dividing their data into high and low relative water users. In Kenney et al.'s case, the belief is that households with only indoor demands, for example, respond differently to policies such as outdoor restrictions than those who also have significant demands associated with outdoor water use. Thus, households are categorized under the assumption that, all else equal, households with high (low) total water use have high (low) outdoor demand for water.

1.3.3 Finite Mixture/Latent-Class Models

While the data partitioning approach is appealing for its simplicity, several shortcomings are apparent. Most notably, the approach requires *a priori* knowledge of which factors influence the class-membership process and pre-define the number of classes, so establishment of clear-cut thresholds used to specify $d(w_{itj})$ will, in most cases, involve some level of arbitrariness. An alternative approach, finite mixture (latent-class) modeling (Aitkin and Rubin 1985) takes a probabilistic approach to modeling heterogeneity and class membership, positing that the observed data are generated by the *m* mixing distributions. When used in conjunction with fixed-effects as proposed by Deb and Trivedi (2013), this yields

$$\sum_{j=1}^{m} \pi_j f_j(y_{it} \mid \tilde{\mathbf{x}}_t, \tilde{\mathbf{z}}_{it}, \boldsymbol{\beta}_j, \boldsymbol{\theta}_j); \tag{6}$$

where π_j are class shares (probabilities) to be endogenously estimated, and $\sum_{j=1}^{m} \pi_j = 1$.

Thus, the latent class-approach endogenously identifies heterogeneity in response to water policies by identifying classes of consumers with similar water demands. Optionally, if the researcher has information on what likely affects the probability of class membership, the process governing class membership can be further parameterized as a function of observables, typically via a logistic function $\pi_j(w_{itj}, \gamma_j)$ where γ_j are parameters used to predict class membership. In doing so, it is assumed that households sharing the characteristics (variables) included in the parameterization have fundamental differences in how the variables included in $f_j(y_{it} \mid \tilde{\mathbf{x}}_t, \tilde{\mathbf{z}}_{it}, \boldsymbol{\beta}_j, \boldsymbol{\theta}_j)$ affect their water demand but, unlike split-sample approach (Equation 5), the relationship is probabilistic rather than deterministic. After estimation of the latent class-model, posterior probabilities of class membership can then be calculated to assign each observation to a class according to:

$$\text{Prob}\left(y_{it} \in \text{class}\, j\right) = \frac{\pi_j f_j(y_{it} \mid \tilde{\mathbf{x}}_t, \tilde{\mathbf{z}}_{it}, \boldsymbol{\beta}_j, \boldsymbol{\theta}_j)}{\sum_{j=1}^{m} \pi_j f_j(y_{it} \mid \tilde{\mathbf{x}}_t, \tilde{\mathbf{z}}_{it}, \boldsymbol{\beta}_j, \boldsymbol{\theta}_j)} \tag{7}$$

Though the latent-class approach requires no assumptions about the nature of heterogeneity prior to estimation, it does require the researcher to define the data generating process for the mixing distributions and determine the optimal number of latent classes. The latter is a somewhat subjective process based on use of Akaike and Bayesian information criteria and whether addition of a class yields results for consumer "type" that is qualitatively distinguishable from existing classes (Deb and Trivedi, 2002). Unlike the previously described approaches, the maximization of the likelihood function for latent-class models must be solved via iterative methods (most commonly, the EM algorithm; see Wedel et al. 1993), and the researcher must specify both the number of latent classes and the form of the distributions for each class.

1.3.4 Previous Applications of Latent- Class Models

Latent-class models have frequently been used with cross-sectional data. Applications include use in the health care demand literature to identify classes of users of health care services (Bago d'Uva, 2005; Deb and Trivedi, 2002), modeling of heterogeneity in recreation demand (Scarpa, Thiene, and Tempesta, 2007); heterogeneous timing of energy usage (Singh, Pal, Jabr, 2010), and use in the marketing and choice-experiment literatures (Boxall and Adamowicz, 2002). However, use of latent-class modeling with water and energy data is limited, likely as a result of a lack of established methodologies for including fixed effects in latent-class models. To date, we are aware of only one article using latent classes to model water demand. Uridales et al. (2014) combine two years of billing data from Granada, Spain with demographic information to identify latent classes of households, where the impact of household characteristics on water demand varies across consumer types. In contrast, use of fixed effects in conjunction with the latent class model here means this research identifies behavior types, holding household-level characteristics constant.

1.4 Data and Methods

In the following section, the timeline of policies used by the utility is first described, as a structural break in policies used by the utility motivates the estimation procedure. Methods for estimating and comparing the latent classes for the drought and post-drought periods are then discussed, followed by details of the specification of the water demand model.

1.4.1 Policy Background

We analyze how policies adopted by a large municipal water provider affected household water demand in Colorado. As in many other areas of the western United States facing drought, the utility adopted numerous DSM policies during a widespread drought from 2001-2005. Figure

1 shows a timeline of utility policies and the average-price consumers paid for water over bill periods spanning 1998-2010. Price increases, the block-rate pricing structure, and watering restrictions (varying in the number of days of allowed watering at different points in the drought) were implemented simultaneously in response to the drought in June of 2002. Watering restrictions were later lifted in October of 2005, signaling the end of the drought; however, in order to meet the long-term water demands of a growing service area, the utility made block rates permanent in June of 2006, and annual price increases occurred from 2006 to 2010. The 2006 price increases were actually larger in magnitude than those that occurred during the drought. Based on this timeline, the utility's policies can be divided into three distinct phases: the pre-drought (1998-2000), drought (2001-2005), and post-drought (2006-2010) periods. The year 2006 signals a shift from seasonal policies aimed at decreasing demand in the short-term during acute water scarcity events, to policies focused more on revenue generation to cover the costs of future infrastructure.

1.4.2 Estimation Procedure

The approach used here overcomes two econometric challenges: first, it allows for unbiased estimates of variables within each of the latent classes, which may not be possible unless all individual-level variables are controlled included. Second, use of fixed effects means that latent classes relate to behavioral types, as opposed to being characterized by demographic characteristics included in the model. Each identified class represents a type of behavioral response an individual may exhibit during any bill period in the panel. The latent-class approach is compared to the single distribution (Equation 3) model, which estimates the demand function for the average consumer. The following section details how models are estimated for both the drought and post-drought periods, and changes in responsiveness over time are quantified.

1.4.3 Latent-Class Model

The latent-class model is estimated using the two-stage fixed-effects approach as outlined by Deb and Trivedi (2013). In the case of a mixture of normal distributions, Deb and Trividi (2013) show that a two-stage approach wherein the latent-class model is estimated after implementation of fixed-effects produces results identical to single-stage EM algorithm maximization of a likelihood function specified for finite mixtures of panel data. Thus, household-level fixed effects are implemented as a first step in the analysis, and then the data are treated as a cross section in which class shares and coefficients are estimated via maximum likelihood and standard errors are clustered by individual.

The probability of class membership, $\pi_j\left(\mathbf{z}_{ijt}\right)$ is parameterized as follows:

$$\pi_j(z_{itj}) = \theta_0 + \theta_1 LowOutdoor_{it} + \theta_2 MediumOutdoor_{it} + \theta_3 HighOutdoor_{it} + \theta_4 BpTrend_t \quad (8)$$

Using the pre-drought data (1998-2000), households are defined as *low, medium, and high outdoor* users (Table 1), similar to approach used by Kenney et al. (2008).[1] This parameterization does not affect estimated coefficient for the latent classes, but means that higher users of irrigation water may be expected to belong to different classes of behavior types with fundamentally different responses to included variables $\mathbf{z}_{it}$ (e.g., price and percent of bill period under watering restrictions). Also included in the class membership parameterization is a bill period trend variable, which captures changes in the probability of class membership with each subsequent monthly bill received by the consumer. After the latent-class model is estimated, the posterior probability of class membership (Equation 7) is calculated and used to assign each bill

[1] The start of the drought occurred in late summer/fall of 2001, though most utilities did not feel its affects until the following spring of 2002. Here, we include summer of 2001 in the drought period so that the effect of watering restrictions, first implemented in summer of 2002 and in place through 2005, may be estimated.

period to a latent class. Households are then identified as high and low price-elasticity responders, based on the number of times a household had bill periods with larger relative price elasticities of water demand.

Next, the latent classes and determinants of class membership models are re-estimated for the drought period. We then compare latent classes (types of behavioral policy responses); class membership (which households belong to observed classes); and households' frequency of membership to each class to evaluate changes in policy responsiveness over time.

Lastly, to examine the welfare implications of heterogeneity in household responsiveness to utility policies, the water savings from billing periods in identified latent classes are calculated. To do so, a linear regression for water demand is estimated for the pre-drought period. The resulting coefficient estimates are used to predict the amount of water that would have been used in each billing period in the drought and post-drought periods, assuming the average price paid by households had remained at pre-drought levels (prior to price increases and implementation of the block-rate pricing structure). For both periods, results from the latent-class model are compared to estimated results for the fixed-effects, full data model (Equation 3). For all models, water demand is specified using a log-log specification (e.g., Renwick and Greene, 2000; Nieswiadomy, 1992) on the demeaned data, where ~ denotes the transformed data (equation 3) for individual *i.*

$$\begin{aligned} ln\tilde{y}_{it} &= b_1 lnavgprice_{it} + \beta_2 rpe\tilde{r}bpdays_{it} + \beta_3 wate\tilde{r}3days_{it} + \\ &\beta_4 tot\tilde{p}recip_{it} + \beta_5 ma\tilde{x}temp_{it} + \beta_6 b\tilde{p}days_{it} + \tilde{v}_{it} \end{aligned} \tag{10}$$

Variable definitions appear in Table 1.

Average price is used in all specifications. Average price is also lagged, given that households' consumption choices in a period *t* are based on the bill received for water use in period *t-1.* As has become standard in the literature using average price, endogeneity between price and water demand is addressed by using a two-stage instrumental variables approach ((Nieswiadomy, 1992). In the first stage, average price is regressed on parameters of the utility's block rate structure (price of water within each consumption block), and predicted average price from this regression is used as price variable within second-stage model estimated as in equation 10.

1.4.4 *Data*

Monthly billing records for all customers over the period 1998-2000 were provided by the utility. The original dataset included nearly 12 million (monthly) bill period observations for more than 85,000 customers. The dataset was restricted to focus exclusively on summer water use (June, July and August) for residential customers who had continuous billing data from 2000-2010. The data set was restricted in this manner for a number of reasons. First, the estimation approach (the latent-class model together with fixed effects and instrumental variables) adopted herein is computationally intensive and necessitated a reduction in the number of observations. Analysis focuses on summer months when policies can be expected to have the largest impact on behavior. Additionally, households that participated in utility-sponsored rebate programs were excluded from the analysis to avoid potential endogeneity caused by self-selection into such programs. The restricted dataset included summer water demand and policy variables for approximately 28,000 households for demand and policy variables. Additional weather-related data was provided by the Colorado Climate Center.

1.5 Results

Results for the single distribution (Equation 3) and latent class approaches (Equation 6) are presented and compared for the drought (Table 2) and post-drought (Table 3) periods. Results for latent class membership (Table 4), which identify the types of users most likely to have bill periods in a given class, are discussed, followed by changes in class membership across the drought and post-drought periods (Table 5).

1.5.1 Estimates across the 3 approaches for the drought period

Table 2 presents estimates for the full sample and the latent-class approaches. As expected, average price, the percent of the bill period under watering restrictions, and total precipitation decrease water usage in all three models, whereas increases in allowed watering, the number of bill period days, and temperature increase water demand.

In the latent-class model, two classes[2] of behavior types are identified. Classes can be compared in terms of policy and non-policy variables. Latent Class 1 (86.5% class share) has a price elasticity of -0.26, over 30% lower than the price elasticity in the full distribution model. Latent Class 2 (13.5% class share), however, has a price elasticity of -1.15. Class 2 is also more responsive to watering restrictions (coefficient of -0.241 for *rperbpdays* in the latent-class model compared to -0.167 in the full sample), but then increases water use more than does Class 1 when watering restrictions are relaxed to allow three days of watering (0.137 Class 2 versus 0.067 full sample). Lastly, while Class 2 is more responsive to policy-related variables, Class 1 is more responsive to precipitation, with a coefficient for *totprecip* of -0.01 compared to 0.008 for Class 2. As such, the latent-class model finds two key behavior types—individuals who respond to utility policies, and individuals for whom summer water use is related to changes in weather. Overall, the latent-class model provides two key insights: first, that some households have the potential (at least in the short run) be much more responsive to demand-management policies such as prices increases and restrictions than utilities might expect if only looking at the full distribution estimates, which are the weighted average of the latent-class results. Second, this

[2] The decision on optimal number of classes was based on the number that yielded classes with statistically significant (determined through a Wald test) coefficients for policy-related variables.

higher responsiveness comprises only a small share of total bill periods, meaning the bulk of short-term reductions may come from a small set of households. Though we are unable to determine what causes such high-elasticity responses at some times, one conjecture is that these responses occur when a consumer first receives (or looks at) a high summer water bill. Furthermore, the large difference between high and low-elasticity bill periods may also explain why, while elasticties average around -0.4 in the literature, some studies using average price have found price elasticities to be much larger, in the range of -0.6 to -0.75 (Arbués, Fernando, Garcıa-Valiñas, and Martınez-Espiñeira, 2003). Thus, it may be that some researchers' data comes from time periods where large proportions of consumers have strong behavioral responses, increasing the average elasticity found with the traditional models for those samples.

1.5.2 Estimates across the 3 Approaches for the Post- drought Period

Table 3 presents results for the full-distribution and latent-class models in the post-drought period. Key differences from the drought period emerge with respect to the policy variables. During this time watering restrictions are no longer in place, and the coefficient for average price in the full distribution is approximately -0.3, decreased roughly 25% from its drought level. This is surprising given the magnitude of price increases that occurred during this period and the fact that watering restrictions, which may constrain users' responses to price increases (Goemans, Costanigro and Stone, 2012) were not used from 2006-2010.

Using the latent-class approach on post-drought data, two classes of behavioral responses are again identified. Latent Class 1 (90% class share) has a price elasticity of -0.26 (versus -0.29 during drought); bill periods in Latent Class 2 (10% class share) again have a higher price elasticity at -0.47, but this price elasticity is greatly decreased relative to the drought period (1.15). Furthermore, the share of bill periods with the Class-2 (higher elasticity) behavior responses decreases by approximately 5%. Thus, both the frequency and magnitude of strong behavioral responses decrease in the post-drought period. This occurs despite the larger relative price increases that occurred from 2006-2010 and may be evidence of demand hardening.

1.5.3 Characterizing Class Membership in the Drought and Post-drought Periods

Table 4 gives results for the probability of class membership (equation 7). Again, parameterizing class membership allows us to determine if households with varying levels of summer water usage are likely to belong to the different classes, meaning they have fundamentally different responses to policies such as price increases. The negative coefficients for low (-0.59) and high (-0.31) outdoor water users mean these groups are less likely than medium users (omitted for identification purposes) to have bill periods in Latent Class 1. —i.e., they are more likely to have Class-2 (high elasticity) bill periods. This is surprising, given that previous literature has generally found lower water users to have less elastic demands. However, low-outdoor water users as defined here are individuals who use up to twice as much water in winter as summer. As such, they still have significant irrigation needs and may have been more conscious of their water use in the context of the newly-implemented block rate pricing structure than were the medium-outdoor users. Conversely, high outdoor users may have more elastic demand because they are more affected by the price increases. Lastly, the bill-period trend variable is also positive and significant, meaning individuals of all types are more likely to have Class-1 (low elasticity) responses with each subsequent bill period. This decreased price responsiveness over time is evidence of demand hardening, inability of consumers to make further reductions in demand after they make permanent changes in behaviors/infrastructure to decrease usage.

In the post-drought period, both low and high-outdoor water users are again less likely to have Class-1 responses. However, the probability of a high-elasticity response is increased for high outdoor users and decreased for low outdoor users, relative values found for the drought period. Additionally, the magnitude of the trend variable is increased relative to the drought period, implying that the ability of all households—and especially low outdoor water users—to cut further reduce demand in response to price increases is decreased in the post-drought period.

1.5.4 Changes in Class Membership Across the Drought and Post-Drought Periods

Results presented above show that the frequency of high-elasticity bill periods, and the magnitude of those responses, changes across the drought and post-drought periods. In the following section, the distribution of Class-1 and -2 bill periods will be discussed; that is, we can test whether the number of *households* exhibiting high-elasticity bill periods changes across the drought and post-drought periods. This shows the overall percentage of households that may at times be highly responsive to DSM policies and reveals whether the burden of decreasing demand during acute shortages is shared. Additionally, it allows us to determine if the number of households exhibiting high policy responsiveness declines across the drought and post-drought periods. If so, then utilities' ability to depend upon Class-2 households for short-term demand reductions (for example, during drought) may be diminishing as a result of demand hardening. Lastly, we show and discuss the welfare implications of results for average water savings from Class-1 and Class-2 bill periods.

The percent of households who had 1 or more Class-2 (high-elasticity) bill periods in the drought and post-drought periods can be seen in Figure 2. As seen, the proportion of households with one or more high- elasticity bill periods decreases from roughly 40% in the drought to 32% in the post-drought period. Conversely, the share of households with zero Class-2 responses increases. These results show, first, that in both periods less than half of households have a Class-2 response in any bill period. Second, the proportion of households with such high-elasticity responses declines after the drought—combined with the decreased price elasticity estimated for Latent Class 2, this is further evidence of demand hardening.

Table 5 further details movement between the classes in the drought and post-drought periods. Specifically, the tables show the percent of households who do (or do not) remain high responders in the post-drought period after they were high responders during the drought. As seen in row 1, 68.7% of individuals with 0 high-elasticity bill periods post-drought were also non-responders during the drought, whereas 31.3% of households had previously been class-2 households in at least one bill period. With regards to households with at least one class-2 response post-drought, 43.7 % had no previous class-2 responses, whereas 56.3% were also responsive in the drought period. Combined with previous result, key insights from evaluating households' class membership are as follows: first, nearly 70% of households never exhibit a Class-2 bill period, and only just over half of those with at least one high-elasticity bill period during the drought are high responders again post-drought. Second, the price elasticity for post-drought Class-2 responses is decreased relative to the drought period (Tables 3 and 4), so even households with Class-2 responses in both periods show a diminished ability to respond to price increases. Lastly, we do see 43.7% of post-drought, Class-2 households had not been high responders previously, so there is movement into this class of households who exhibit higher price elasticities in some bill periods. Yet, it was seen that the overall share of Class-2 responses fell by 5% post drought, so the overall trend of movement in the classes reflects a pattern of demand hardening, or a decreased tendency to have a high response to increases in price.

The above-mentioned results show water demand was more elastic than average estimates in a subset of billing periods. Table 6 shows the actual water savings associated with those high-elasticity bill periods; specifically, the average percent reduction in water from Class-1 and Class- 2 bill periods relative to predicted consumption, had prices remained at pre-drought levels. In the drought period, water use in Class-2 bill periods was reduced -36.5% relative to predicted levels, but only -20.9% in Class 1-bill periods. In the drought period, total reductions relative to pre-drought levels are -44.9% and -27.9% from Class-2 and Class-1 bill periods, respectively. Thus we see, first, water reductions in Class-2 bill periods were, on average, at least 15% higher than reductions for Class-1 bill periods. Second, much of initial demand reductions occurred during the drought, with Class-2 and Class-1 users only further reducing demand by roughly 8% in the post-drought period, relative to predicted water use at pre-drought prices. This decline in responsiveness, despite steep price increases seen from 2006 to 2010, again shows that households may have made permanent changes in behaviors or technologies make them less responsive to utility policies.

1.6 Conclusions

This paper uses a fixed-effects, latent-class model to explore heterogeneity in behavioral responses to policies used by a large Colorado water provider during and after drought. Results for the latent-class approach are compared to a traditional single distribution models of water demand. In comparison the traditional model estimating demand for the average consumer, the latent-class approach finds significant behavioral heterogeneity in responsiveness to utility policies, even when individual-level (time invariant) sources of heterogeneity are eliminated from the model through fixed effects. Households were approximately three times more responsive to prices, respectively, in high-elasticity, Class-2 bill periods than they were in the rest of the panel during the drought and roughly twice as responsive post-drought. Additionally, both high and low outdoor water users were more likely to have high elasticity responses than medium users, households with presumed to have some (but not extensive) landscaping. It may be that low outdoor water users are more attentive to their water bills (which comprise a larger share of income) than are medium users, and high outdoor users are most-affected by large price increases.

The latent class results presented here provide important insights for policy makers. First, use of traditional models would lead utilities to believe that the average household was more responsive to price increases that was truly the case throughout both periods. In fact, the latent class model finds that, in a majority of drought bill periods, water demand was over 30% less elastic than estimated with a traditional model that cannot capture heterogeneity. The estimate for the average consumer is increased due to the minority (15%) of bill periods where households have high-elasticity responses. This finding of a class of consumers highly-responsive to policies is positive in the sense that it shows the potential for price-induced demand reductions far exceeding those commonly seen in the literature. However, the share of these households drops by 8% in the post-drought period, and the price elasticity for households belonging to this class during the panel also decreases. This may be evidence that the low and high-outdoor users belonging to this behavior may have made permanent changes in water use behavior and infrastructure, decreasing the potential for large responses to further price increases.

The fact that this average is heavily influenced by a minority of consumers--whose responsiveness is decreasing over time--may lead utilities to overestimate future policy effectiveness if the full distribution of responses if not considered. Furthermore, from a welfare perspective it may be concerning to utilities that a subset of households decreased water by at least 20% more than other users in high-response bill periods, given that many policies, including use of block rates, are designed with the intent of ensuring households share the burden of conservation. Successful use of DSM to decrease water demand will depend upon the ability of utilities to target previously unresponsive households (here, the medium outdoor water users) and to determine the factors (awareness of water bills, water-bill information, large changes in weather) that may have driven the strong behavioral responses to utility policies seen here in a subset of bill periods.

Table 1.1: Variables and Definitions

Variables Parameterizing Water Demand	
Lnw	Natural log of water (cubic feet) consumed per billing period
lnavgprice	Natural log of average price in bill period *t-1* per billing period
rperbpdays	Percent of days in billing period in which watering restrictions were in place
water3days	Dummy variable equal to 1 for bill periods where the number of weekly allowed watering days was increased from 2 to 3
totprecip	Average daily precipitation during the billing period
maxtemp	Average maximum temperature during the billing period
bpdays	Number of days included in the consumer's bill
Variables Parameterizing Class Membership	
low outdoor	Household uses up to twice as much water in winter (Nov.-Jan.) vs. summer (June-Aug.)
medium outdoor	Household uses up to 2-3 times as much water in winter vs. summer
high outdoor	Household uses more than three times as much water in winter vs. summer
bptrend	Trend variable for each consecutive bill period for a household

Table 1.2: Parameter estimates for each approach in the drought period

Dependent Variable: LNW	All Observations	Class 1	Class 2
LagAvp	-0.381***	-0.268***	-1.150***
	(0.011)	(0.010)	(0.000)
Rperbpdays	-0.179***	-0.167***	-0.241***
	(0.002)	(0.002)	(0.000)
Water3days	0.075***	0.067***	0.137***
	(0.002)	(0.000)	(0.000)
Totprecip	-0.013***	-0.016***	0.008***
	(0.000)	(0.000)	(0.003)
Maxtemp	0.031***	0.030***	0.032***
	(0.000)	(0.000)	(0.000)
Bpdays	0.046***	0.044***	0.041***
	(0.000)	(0.000)	(0.000)
n (billing periods)	427,674	369,730	57,944
Class Share		86.5%	13.5%
R^2/Log-pseudolikelihood	0.261	-124,241.2	-127,608.7
*α=.10, **α=.05, ***α=.01			

Table 1.3: Parameter estimates for each estimation approach in the post-drought period

Dependent Variable: LNW	All Observations	Class 1	Class 2
LagAvp	-0.276*** (0.007)	-0.257*** (0.000)	-0.470*** (0.000)
Totprecip	-0.030*** (0.000)	-0.034*** (0.000)	0.001 (0.7591)
Maxtemp	0.029*** (0.000)	0.027*** (0.000)	0.045*** (0.000)
Bpdays	0.079*** (0.000)	0.078*** (0.000)	0.085*** (0.000)
N (billing periods)	363,240	323,318	39,922
Class Share		90%	10%
R^2	0.176		
*α=.10, **α=.05, ***α=.01			

Table 1.4: Results for parameterization of class membership (multinomial logit for probability a bill period belongs to latent class 1)

	Drought Coefficient	Marginal Effects	Post-Drought Coefficient	Marginal Effects
High outdoor	-0.3116*** (0.000)	-0.0003	-0.426*** (0.000)	-0.0005
Low outdoor	-0.594*** (0.000)	-0.0006	-0.238*** (0.000)	-0.0003
BPtrend	0.012*** (0.000)	0.0001	0.045*** (0.000)	0.0007
Constant	2.104*** (0.000)		2.026*** (0.000)	
*α=.10, **α=.05, ***α=.01				

Table 1.5: High responders in drought and post-drought periods

Percent of households with 0 post-drought, class-2 bill periods who had	0 drought class-2 bill periods	68.7%
	1 or more class-2 bill periods	31.3%
Percent of households with at least 1 post-drought, class-2 bill period who had	0 drought class-2 bill periods	43.7%
	1 or more class-2 bill periods	56.3%

Table 1.6: Decrease in water consumption, relative to predicted consumption at pre-drought prices

	Class-1 Bill Periods	Class-2 Bill Periods
Drought	-36.5%	-20.9%
Post-drought	-44.9%	-27.9%

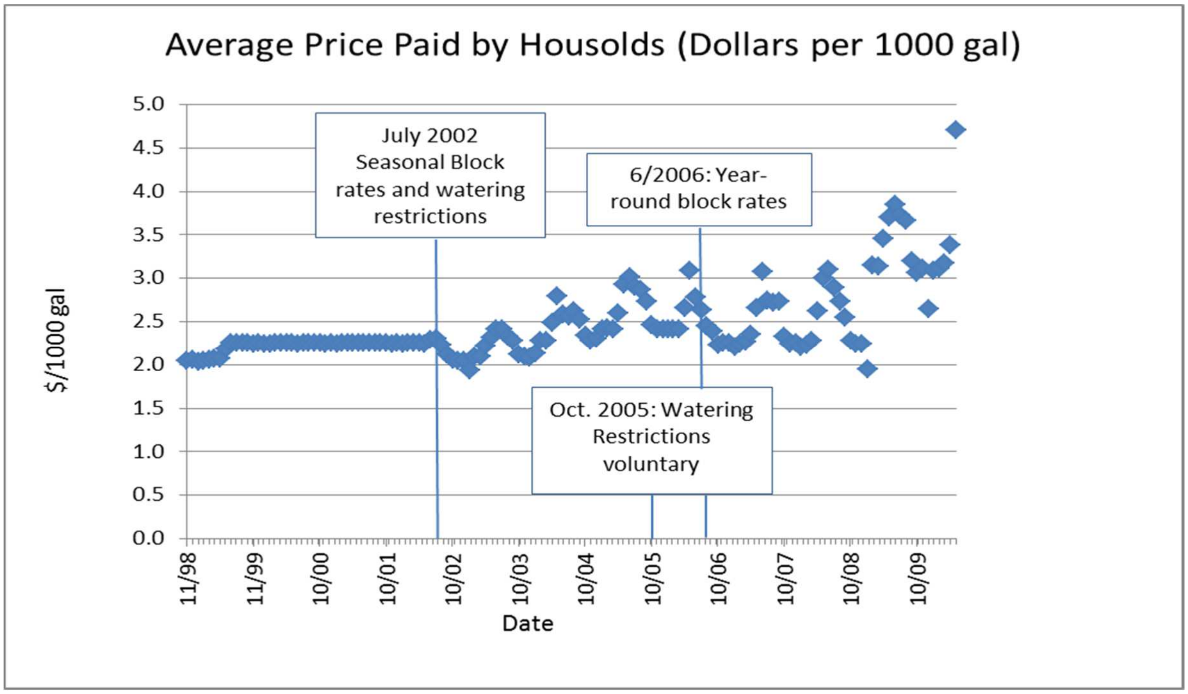

Figure 1.1: Timeline of Policies and Average Prices

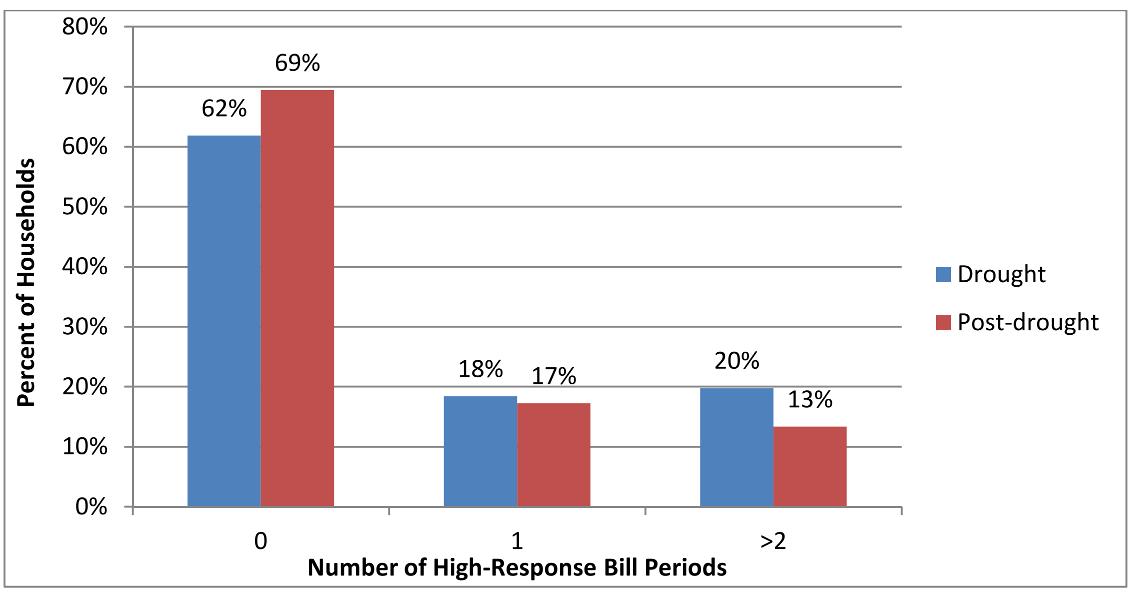

Figure 1.2: Percent of Households with "high response" (Latent Class 2) bill periods in the drought and post-drought periods

REFERENCES

Abrahamse, Wokje, Linda Steg, Charles Vlek, and Talib Rothengatter. "A review of intervention studies aimed at household energy conservation." *Journal of Environmental Psychology* 25, no. 3 (2005): 273-291.

Arbués, Fernando, Inmaculada Villanúa, and Ramón Barberán. "Household size and residential water demand: an empirical approach*." *Australian Journal of Agricultural and Resource Economics* 54, no. 1 (2010): 61-80.

Arbués, Fernando, Marıa Ángeles Garcıa-Valiñas, and Roberto Martınez-Espiñeira. "Estimation of residential water demand: a state-of-the-art review." *The Journal of Socio-Economics* 32, no. 1 (2003): 81-102.

Bago d'Uva, Teresa. "Latent class models for use of primary care: evidence from a British panel." *Health Economics* 14, no. 9 (2005): 873-892.

Davis, Lucas W. "Durable Goods and Residential Demand for Energy and Water: Evidence from a Field Trial." *The RAND Journal of Economics* (2008): 530-546.

Deb, Partha. "FMM: Stata module to estimate finite mixture models." *Statistical Software Components* (2012).

Deb, Partha, and Pravin K. Trivedi. "Finite mixture for panels with fixed effects." *Journal of Econometric Methods* 2, no. 1 (2013): 35-51.

Deb, Partha, and Pravin K. Trivedi. "The structure of demand for health care: latent class versus two-part models." *Journal of Health Economics* 21, no. 4 (2002): 601-625.

Gaudin, Sylvestre. "Effect of price information on residential water demand." *Applied Economics* 38, no. 4 (2006): 383-393.

Goemans, Christopher, Marco Costanigro, and Janine Stone. "The Interaction of Water Restriction and Pricing Policies: Econometric, Managerial and Distributional Implications." *Journal of Natural Resources Policy Research* 4, no. 1 (2012): 61-77.

Grafton, R. Quentin, Michael B. Ward, Hang To, and Tom Kompas. "Determinants of residential water consumption: Evidence and analysis from a 10-country household survey." *Water Resources Research* 47, no. 8 (2011).

Hanemann, W. Michael, "Determinants of Urban Water Use," in Chapter 2 in *Urban Water Demand Management and Planning* by Baumann, D.D., Boland, J.J., and M.W. Hanemann, (New York, McGraw-Hill, 1997).

Hewitt, Julie A., and W. Michael Hanemann. "A discrete/continuous choice approach to residential water demand under block rate pricing." *Land Economics* (1995): 173-192.

Howe, Charles W. Chuck, and Christopher Goemans. "Manager to Manager--The Simple Analytics of Demand Hardening." *Journal-American Water Works* Association 99, no. 10 (2007): 24-25.

Ito, Koichiro. "Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing." *The American Economic Review* 104*,* no. 2 (2014): 537-563.

Jones, C. Vaughan, and John R. Morris. "Instrumental price estimates and residential water demand." *Water Resources Research* 20, no. 2 (1984): 197-202.

Kenney, Douglas S. "Understanding utility disincentives to water conservation as a means of adapting to climate change pressures." *Journal of American Water Works Association* 106, no. 1 (2014): 36-46.

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

Larson, Kelli L., Colin Polsky, Patricia Gober, Heejun Chang, and Vivek Shandas. "Vulnerability of water systems to the effects of climate change and urbanization: A comparison of Phoenix, Arizona and Portland, Oregon (USA)."*Environmental management* 52, no. 1 (2013): 179-195.

Liebman, Jeffrey B and Richard J. Zeckhauser. “Schmeduling.” Working paper, Harvard University and NBER, 2004.

Loughran, David S., and Jonathan Kulick. "Demand-side management and energy efficiency in the United States." *The Energy Journal* (2004): 19-43.

Mansur, Erin T., and Sheila M. Olmstead. "The value of scarce water: Measuring the inefficiency of municipal regulations." *Journal of Urban Economics* 71, no. 3 (2012): 332-346.

Nieswiadomy, Michael L. "Estimating urban residential water demand: Effects of price structure, conservation, and education." *Water Resources Research* 28, no. 3 (1992): 609-615.

Nieswiadomy, Michael L., and David J. Molina. "A note on price perception in water demand models." *Land economics* (1991): 352-359.

Nordin, John A. "A proposed modification of Taylor's demand analysis: Comment." *The Bell Journal of Economics* (1976): 719-721.

Olmstead, Sheila M., and Robert N. Stavins. "Comparing price and non-price approaches to urban water conservation." *Water Resources Research* 45, no. 4 (2009).

Olmstead, Sheila M., W. Michael Hanemann, and Robert N. Stavins. "Water demand under alternative price structures." *Journal of Environmental Economics and Management* 54, no. 2 (2007): 181-198.

Pielke Sr, Roger A., Nolan Doesken, Odilia Bliss, Tara Green, Clara Chaffin, Jose D. Salas, Connie A. Woodhouse, Jeffrey J. Lukas, and Klaus Wolter. "Drought 2002 in Colorado: an unprecedented drought or a routine drought?" *Pure and Applied Geophysics* 162, no. 8-9 (2005): 1455-1479.

Renwick, Mary E., and Richard D. Green. "Do residential water demand-side management policies measure up? An analysis of eight California water agencies." *Journal of Environmental Economics and Management* 40, no. 1 (2000): 37-55.

Renwick, Mary E., and Sandra O. Archibald. "Demand side management policies for residential water use: who bears the conservation burden?" *Land Economics* (1998): 343-359.

Scarpa, Riccardo, Mara Thiene, and Tiziano Tempesta. "Latent class count models of total visitation demand: days out hiking in the eastern Alps." *Environmental and Resource Economics* 38, no. 4 (2007): 447-460.

Singh, Ravindra, Bikash C. Pal, and Rabih A. Jabr. "Statistical representation of distribution system loads using Gaussian mixture model." *IEEE Transactions on Power Systems* 25, no. 1 (2010): 29-37.

Strbac, Goran. "Demand side management: Benefits and challenges." *Energy policy* 36, no. 12 (2008): 4419-4426.

Taylor, R.G., John R. McKean and Robert A. Young Alternate Price Specifications for Estimating Residential Water Demand with Fixed Fees, *Land Economics*, Vol. 80, No. 3 (Aug., 2004), pp. 463-475

Pérez-Urdiales, María, María A. García-Valiñas, and Roberto Martínez-Espiñeira. "Responses to Changes in Domestic Water Tariff Structures: A Latent Class Analysis on Household-Level Data from Granada, Spain." *Environmental and Resource Economics* (2014): 1-25.

CHAPTER 2: HETEROGENEITY IN PREFERENCES FOR WATER POLICIES AND ASSOCIATED IMPACTS: A LATENT-CLASS APPROACH

2.1 Synopsis:

By 2050, Colorado's population is expected to double relative to 2010 levels, creating a projected gap between current water supplies and forecasted demands of 500,000 to 1,000,000 acre-feet of water per year[3]. Numerous policies exist for "closing the gap," via either demand management (price increases or non-price conservation) or new supply development (reservoirs). Each of these policies will impact consumers both by increasing water costs and changing the "greenness" of the urban landscape. Absent the use of these policies, meeting 2050 water needs may require up to 25% of Colorado agricultural lands be "dried up" via sales of agricultural water rights to municipalities. Fearing the impacts such transfers may have on rural communities, the state of Colorado has funded numerous grant projects that would mitigate the volume of agricultural water transfers. However, it is unknown to extent which consumers support these policies, and how support varies across different consumer demographics. Furthermore, support for agricultural transfer policies wane as policies are implemented. Prior to adoption of the policy, consumers may support/oppose policies based on ideology and preconceived understanding of policies, as they may not have detailed knowledge of how policies may impact them individually (Jeffrey and Seaton, 2004). However, water managers need to adopt policies that are supported by consumers both "on paper" and after adoption, when consumers realize their effects. This research uses two separate best-worst scaling surveys—one eliciting preferences over policy alternatives to agricultural water transfers, and one where

[3] Colorado Water Conservation Board, "The Municipal and Industrial Water Supply and Demand Gap," Available < http://cwcb.state.co.us/water-management/water-supply-planning/Pages/TheWaterSupplyGap.aspx>.

consumers are asked about policy-related impacts—to evaluate potential support for policies both prior to and after implementation. Heterogeneity in support for policies/impacts is evaluated using a latent-class model with demographic variables as predictors of class membership, allowing us to identify the types of voting blocs that might support/oppose water transfers at various stages of the policy-making process. In both surveys, we find support for policies (and associated impacts) used to avoid agricultural water transfers; however, we also identify a distinct latent class of consumers that does not support such policies. Furthermore, preferences vary across the two surveys, meaning various stakeholders may change their support for policies after policy effects materialize.

2.2 Introduction:

Throughout the United States, utilities must develop long-term water supply plans in order to meet the water needs of increasing populations, often while simultaneously coping with frequent drought. In the state of Colorado, population growth is forecasted to increase water demands roughly 50% by the year 2050, potentially increasing the state's water needs by 710,000 acre feet of water per year.[4] This is true despite predictions for adoption of water-efficient appliances and landscaping in both existing and new developments. Providing this water is complicated by the fact that, as in many western states, areas of population growth are located far from adequate natural water supplies; in Colorado, over 75% of forecasted population growth will occur in the "Front Range," or eastern slope of the Rocky Mountains, whereas much of the state's precipitation falls on the western slope.

Water policies can be categorized as aiming to either augment current supplies, or decrease household water demands. Demand-side management approaches include pricing

[4] Colorado Water Conservation Board, "The Municipal and Industrial Water Supply and Demand Gap," Available < http://cwcb.state.co.us/water-management/water-supply-planning/Pages/TheWaterSupplyGap.aspx>.

policies (price increases, use of block-rate pricing structures) and non-price conservation (watering restrictions, utility incentive programs and messaging). Alternatively, water supplies may be increased either through new development (i.e. new reservoirs) and/or purchases of water rights from agricultural users. The latter is common in westerns states, where municipalities frequently purchase agricultural water rights, and water is transferred out of its basin of origin. Table 1 depicts policies and related impacts.

Agricultural water right transfers are often the policy of choice for urban water providers in that they provide a permanent (low risk) supply of water. Other benefits of water transfers include the fact that the cost of these transactions is largely borne by developers (and passed onto residents) of new housing. As such, transfers provide water for new residents of a utility's service area without the need to increase water prices or change water-use behavior of current residents. From the agricultural producer's perspective, municipalities are often willing to pay water right prices that exceed water's production value (Ward and Michelson, 2002). As a result of these large potential gains for both utilities and agricultural producers, water rights sales are a common way of securing additional water supplies, and the state of Colorado predicts that up to 25% of agricultural water will be sold to meet water demands by 2050, absent use of other policies.[5]

Despite the potential welfare gains from water transfers, the state of Colorado has created grant programs to induce utilities to pursue alternative options to permanent agricultural water transfers. [6] This occurs in part because agricultural water transfers, while beneficial for buyers and sellers of water rights, may have negative effects on rural economies (Howe and Goemans,

[5] Colorado Water Conservation Board, "The Municipal and Industrial Water Supply and Demand Gap," Available < http://cwcb.state.co.us/water-management/water-supply-planning/Pages/TheWaterSupplyGap.aspx>.
[6] Colorado Water Conservation Board Alternative Agricultural Water Transfer Methods Grants Program, available < http://cwcb.state.co.us/loansgrants/alternative-agricultural-water-transfer-methods-grants/Pages/main.aspx>.

2003; Howe, Lazo and Weber, 1990). Both rural and urban communities' perception of water transfers may also be negative (Keenan, Krannich and Walker, 1999) because consumers value the idea of preserving agricultural land for reasons beyond production value, such as food security (Rosegrant and Ringler, 2000) and landscape amenities (Sayadi, González-Roa, and Calatrava-Requena 2009; Bergstrom and Ready, 2009; Johnston and Duke, 2007). This view of agricultural water transfers may also be interpreted as a "rural versus urban" conflict, where households have an aversion to changes from an irrigated to natural landscape, as occurred in the aftermath of the Owens Valley water transfers in California (Libecap, 2005). This type of ideological opposition to water transfers may cause them to be underutilized and/or ruled out prior to adoption (Tisdell and Ward, 2003). However, while some work has been done to quantify preferences for transfers and for other water provision alternatives (Thorvaldson, Prichett and Goemans, 2010; Hensher, Shore and Train, 2006; Haider, 2002; Blamey, Gordon and Chapman, 1999), less is known about if and how support changes after policies are implemented, and consumers realize the impacts on their water bills and in their communities.

Differences in policy support (i.e., which policies "sound good" on paper) and households' reactions to policies once they are implemented may occur for a number of reasons. Lusk [7] proposes the "consumer versus citizen" and "information" hypotheses as reasons households behaviors may not match intentions—or, in this framework, policy and impact support do not coincide. In an example of the former, households say they support a policy because it sounds like the right thing to do, but, in reality, impacts prove too costly to sustain support for associated policies. In the case of the latter, households may support (or reject) policies only because they do not know how policies will affect them, especially in areas such as

[7] Lusk, Jayson. "Why Don't People Vote Like They Shop." 13 March 2015. Available http://jaysonlusk.com/blog/2015/3/12/food-demand-survey-foods-march-2015.

water policy where households often have little prior knowledge (Thorvaldson, Pritchett and Goemans, 2010).

Depending upon consumers' understanding of agricultural water transfers and their impacts, policymakers face two possible scenarios: in one case, agricultural water transfers may be opposed, but that opposition may decrease over time as consumers better understand transfers' impacts (or realize that they are largely unaffected by the policy). Conversely, those who support using transfers as an alternative to increased conservation, price increases, etc. could change their opinions after seeing the impacts to landscapes and rural communities associated with agricultural dry-up. In either case, policy-makers wishing to develop policies that minimize the costs and political exposure associated with a heated public debate need to understand how water policies will be supported/ opposed both before and after policy adoption.

To examine preferences for water policies and for associated impacts, we adopt a between subject experimental design and conduct two best-worst scaling surveys: one where we ask consumers about policies, and a second where we elicit preferences regarding the household-level impacts of such policies. Using a latent-class model, we analyze the nature and extent of heterogeneity in support for policies and related impacts, and then identify the determinants of such differences. Cross-survey differences in the level of support and in heterogeneity driving support for polices/impacts is evidence that different demographic groups may be expected to support (oppose) agricultural water transfers and alternatives at varying stages of the policy-adoption process.[8]

Results show significant support for policies mitigating agricultural water transfers, though this support is slightly decreased when consumers choose between impacts rather than

[8] Here we examine if there is heterogeneity in the two types of surveys; in a separate paper, we evaluate the potential welfare costs associated with that heterogeneity.

policies. We also find significant differences in the nature of heterogeneity in opinions: in the policies survey, differences in demographics (region, age, income) correlate with membership to the latent classes, and this allows us to identify groups of consumer preferring agricultural water transfers to alternative policies. Conversely, in the impacts survey heterogeneity in preferences correlates with factors related to how much water a household uses. In sum, the "rural versus urban" conflict is visible when consumers make choice across policies, but diminishes when the impact of such policies is made to be the matter of contention. This implies that different types of demographic groups may express varying concerns about utility policies at different stages of the policy-making process.

The following sections describe the relevant literature regarding the best-worst scaling techniques and latent-class analysis used for both the "Policies" and "Impacts" surveys. The survey design is then discussed, followed by results and conclusions.

2.3 Methods: Best-Worst Scaling and Econometric Models

Best-worst (B-W) scaling, a variant of discrete choice experiments, requires respondents to pick their most-and least-preferred options in a choice set, which can contain either individual attributes or attribute bundles. The former may be used to evaluate the relative importance of attributes (Louviere, 1992), whereas attribute bundles may be used to determine their ranking and/or the marginal utility of an individual attribute (Marley and Philens, 2012).

The assumptions underlying B-W scaling models are based on Random Utility Theory (RUT), which assumes that overall utility U_{ij} an individual *i* receives from good *j* can be broken down into a sum of deterministic and random components. In each choice set, utility is often assumed to be a linear function of the attributes ($\mathbf{x}_{ij}$) of good *j*, a conforming vector of preference parameters $\boldsymbol{\beta}$, and a random error term (ε_{ij}), yielding $U_{ij} = \mathbf{x}_{ij}'\boldsymbol{\beta} + \varepsilon_{ij}$. An individual chooses a good *j* as preferred over another good in the choice set, *k,* if the utility from good *j* is larger than the utility from *k*, i.e.,

$$x_{ij}'\beta + \varepsilon_{ij} > x_{ik}'\beta + \varepsilon_{ik}$$

With best-worst (also called maximum difference) scaling, the choice of an attribute/attribute bundle *j* as most preferred and *k* as least preferred means the difference in latent utility provided by this attribute/bundle is larger than it would be for any other attribute pair (Lee, Soutar and Louviere, 2007)

Preferences can be recovered from data either at the aggregate or individual levels (Flynn, Louviere, Peters and Coast 2008). At the aggregate level, use of a balanced experimental design allows the choice data to be summarized by giving each attribute (or attribute bundle) a "score" calculated based on the number of times the attribute is ranked as most preferred minus the number of times it is ranked as least-preferred. This method has been shown to give results identical to those found in maximum-likelihood estimation for an aggregate-level data "max-diff" multinomial model (Finn and Louviere, 1992). Furthermore, the attribute level scores can be standardized (relative to a chosen attribute and level) and interpreted directly in terms of their relative importance.

At the individual subject level, analysis of the best-worst scaling task data can be accomplished by using an "exploded model," wherein a respondent's best and worst choices become individual observations to be analyzed and conditioned (generally on $\mathbf{x}_{ij}$) via logit or multinomial models. Here, we use a sequential best-worst multinomial logit model (Lanscar and Louviere, 2008) which, similar to a rank ordered logit (Chapman and Staelin, 1982), allows for a complete ranking of all available alternatives. When more than three options are available the procedure is iterative: participants are asked to choose their most and least preferred alternative from a choice set (which are eliminated) and then the task is repeated until all alternatives are ranked. Under the assumption that errors are Gumbel distributed, a given respondent's best-worst choices are expressed as a series of multinomial probabilities, where the probability an option is *j* is chosen as most/least preferred by individual *i* on choice occasion *t* is $P_{ijt} = \frac{\exp(\gamma x_{ijt}'\beta)}{\sum_{J=1}^{J} \exp(\gamma x_{ijt}'\beta)}$.

The scale factor γ is positive for "best" choices and negative for "worst" choices, within P_{ijt}, the probability alternative *j* is chosen most (or least) preferred by individual *i* on choice occasion *t* (Lanscar and Louviere, 2008; Collins and Rose, 2013). In the case of best-worst choices over attribute bundles, estimated coefficients can be used to calculate the marginal utility of each attribute within a bundle. When rankings occur over individual attributes, estimated coefficients will represent the relative ranking of each attribute.

2.3.1 Latent-Class Model

The pervasive phenomenon of preference heterogeneity has received increasing attention in the applied economics literature (Heckman 2001). Simple models capturing the average behavior of a representative agent run the risk of omitting important, economically relevant sources of variation—*and* may produce misleading econometric estimates if important decision factors are not included in the model. Conceptually, heterogeneous preferences can be modeled by specifying articulated, well specified conditional mean models, perhaps by introducing interactions and/or socio-demographics covariates. Even assuming researchers can appropriately model heterogeneity, interpretation of results and hypothesis testing may be hindered by an overly complex specification.

Latent-class models (Ben-Akiva, et al, 1997; Swait, 1994) have the advantage of allowing the estimation of preference parameters specific to different types of consumers (i.e.

consumer classes), while modeling the socio-demographic determinants of heterogeneity in a separate, *ad hoc* process. The approach is fully parametric, requiring a detailed specification of the data generating process, and estimation is generally implemented via maximum likelihood. Here, we use an estimation routine developed by Pacifico (2012) and based on Greene and Hensher's (2003) likelihood function for latent-class discrete choice models. The likelihood function is represented as follows:

$$\ln(L) = \sum_{i=1}^{N} \ln\left[\sum_{q=1}^{Q} \pi_{iq} \left(\sum_{t=1}^{T} \sum_{j=1}^{J} \left(\frac{\exp(\gamma x_{ijt}{}'\beta)}{\sum_{J=1}^{J} \exp(\gamma x_{ijt}{}'\beta)} \right)^{d_{ijt}} \right)\right] \tag{1}$$

where Q is the total number of consumer classes, N is the total sample size, T is the total number of choices, J is vector of choice set attributes, and d_{ijt} is a dummy variable for the alternative chosen as most (or least) preferred by individual *i* at time *t*. An EM algorithm is used to iteratively estimate class share parameters π_{iq} and attribute coefficients β_q for each class. In our application, $\frac{\exp(\gamma x_{ijt}{}'\beta)}{\sum_{J=1}^{J} \exp(\gamma x_{ijt}{}'\beta)}$ is again the multinomial probability for the sequential best-worst model, where γ is positive/negative for best/worst choices. π_{iq},the probability that individual *i* belongs to class *q,* is the process that determines heterogeneity, and is typically parameterized as a logit function of exogenous variables *z* and class membership parameters θ according to

$$\pi_{iq} = \frac{\exp(z_i{}'\theta_q)}{\sum_{q=1}^{Q} \exp(x_i{}'\theta_q)} \tag{2}$$

For a detailed explanation of the derivation of the log-likelihood function and maximization routine see Pacifico (2012) and Train (2008).

2.4 Experimental Design and Model Parameterization:

Creating a preference-revealing choice experiment requires the adoption of an experimental design ensuring parameter identification, but also an artful calibration in the choice of attributes and levels, so that the tradeoffs in each choice set are realistic and intelligible. As such, it is important to include all relevant policy options/impacts but, at the same time, not to overwhelm respondents with too much information (Flynn, Louviere, Peters and Coast, 2007). To limit the cognitive burden, we adopted a between subject design where participants answered only one of the two surveys. Both the policies and impacts surveys were constructed using a main-effects, fractional factorial sequential design (see Scarpa and Rose, 2008). We refer to Street, Burgess and Louviere (2005) for more information on optimal designs. The chosen design maximizes the variation in attributes in each choice set while ensuring that no options are strictly dominated.

Attributes and attribute levels for both of the surveys—policies and impacts—were chosen based on the strategies currently under consideration for meeting the water supply gap in Colorado, and selected levels were validated using the Colorado Water Conservation Board's (CWCB) "Water Supply Future Portfolio and Trade-off Tool[9]. The portfolio tool allows the user to create policy scenarios for meeting the state's future municipal and industrial water needs by modulating agricultural water transfers, household conservation and supply developments within ranges considered feasible by the CWCB. Attributes and levels for both surveys are presented in Table 2. In the policies survey, respondents were presented with a portfolio of policies that could

[9] "Colorado's Water Supply Future Portfolio and Trade-Off Tool." *Colorado Water Conservation Board*, http://cwcb.state.co.us/technical-resources/portfolio-tool/Pages/main.aspx

be used to meet the water supply gap. Policies included supply projects, non-price conservation, and price increases, each with two levels (0% or 30%) specifying how much of the water gap was being met by a specific policy. Residual demand, the percentage of the water gap not fulfilled by the three policy options, identified the level of agricultural water transfers, so that each policy scenario would sum to 100%. The survey was composed of eight choice sets, each containing three alternative policy portfolios. Figure 1 shows a sample policy choice set. Both surveys included a "cheap talk" script (Carlsson, Frykblom, Lagerkvist, 2005) to remind participants that choices, though hypothetical, may impact them in the future through the water management policy choices which the study was designed to inform (Carson and Groves 2007).

In the impact survey attributes included changes in private landscaping (15% or 30% decreases), changes in public landscaping (30% or 70% decreases), increases in base charges on the water bill ($15 or $30), increases in per-unit water prices (25% or 50%), and decreases in irrigated farmland (15% or 30% decreases). Levels for changes in base charges and in prices were calculated using CWCB's estimates of the average cost ($/acre foot of water) of conservation programs and supply development.[10] Potential changes in landscaping were based on planning documents from the state's largest water utility, Denver Water, which identify viable landscaping options for low and high-conservation scenarios. It should be noted that there are potentially other impacts—such as changes in environmental and recreational uses of water—that might result from the policies we considered. However, because these impacts have not yet

[10] The tool allows the user to identify potential water savings (in acre feet/year) from conservation, supply projects, and agricultural water transfers. State estimates of the average cost/acre foot for each of these categories of water savings were multiplied by estimated savings to obtain a range of potential total costs of each option. These costs were divided by estimates of Colorado's 2050 population to obtain household-level costs of each policy. For supply projects, it was then assumed that new residents of the state would pay 40% of the costs of new supply (per conversations with the CWCB and local water utilities) with additional costs passed on to new residents. Potential price increases were determined by assuming that water savings from price increases would be similar to those from conservation and by assuming an elasticity of demand of -0.6.

been quantified by the state, they were not included in the choice sets. While the potential environmental impacts of water policies could not be quantified, we collected information about environmental preferences and motivations by asking participants to rank which types of water uses, including environmental and recreational use, should receive priority for water rights during scarcity (Table 5). This information was included the parameterization of class membership to determine how environmental concerns affect preferences for policies and impacts in both surveys.

The impact survey consisted of eight choice sets, each containing five alternative impacts, which participants ranked on a scale from “most concerning” to “least concerning.” Full ranking of the five impacts was obtained by iterating two best-worst selections for each choice set. In the first round, participants picked the most and least concerning out of five impacts, and then the remaining three options were ranked in the second round. A sample choice set appears in Figure 2. It should also be noted that each choice sets in this survey presents impacts associated with some feasible water policy combination, but no single choice set directly corresponds with the impacts of a specific policy.

2.5 Data, Sample Characteristics, and Empirical Model Specification:

2.5.1 Data and Sample Characteristics

Each survey was administered to 1,000 Colorado residents using the internet-based survey company Qualtrics and with funding provided by the Colorado Water Conservation Board. Participation was limited to those at least 21 years and older, as younger individuals are less likely to pay their own water bills. To ensure that our results would be representative of the preferences of all Coloradoans, each sample was stratified to match the income and geographic distributions of Colorado’s population. The sample demographics presented in Table 3 show minimal, statistically insignificant differences between the two samples and a reasonable matching with the state's demographics.

In addition to demographic information, data regarding individuals' water consumption habits were also collected (Table 4). Respondents were asked to report the cost of their average winter and summer water bills, which are indicative of water used for basic household activities (winter use) versus outdoor irrigation and landscaping (summer). Participants were also asked whether they paid per-unit (marginal) prices versus flat monthly rates for water and how much water they use in summer months relative to winter months.

Table 6 defines the variables entering the latent-class models as predictors of class membership. Preliminary models and correlation analysis revealed high collinearity between water-use variables, resulting in inflated variance of the model coefficients. To address the multicollinearity problem, water use variables (*marginal, summeruse, winterbill*) were aggregated using principal-component analysis. PCA allows the dimensionality of the data to be reduced into orthogonal "components" that fully capture the variance-covariance matrix of the data, thus fixing the problem of multicollinearity. We chose to follow Ashok, Dillon, and Juan (2002) and include only a subset of the water-use variables in the PCA so that we could estimate marginal effects of individual variables whenever possible.[11] Results for the PCA are presented in Table 7. The first component presents a contrast between *summeruse* (0.48) and *winterbill* (-0.58), plus a positive coefficient (0.65) for *marginal*. This component explains a large portion of variation (67%) in the data, and captures the correlation structure for households who irrigate in the summer, pay marginal prices and therefore have significant difference between winter and

[11] Principal components were derived from a polychoric correlation matrix (Olsson, 1999), which accounts for the presence of dichotomous and ordinal variables. Principal components are essentially identical for the policy and impact surveys, providing further evidence of the equivalence of the two stratified random samples. For brevity, we focus the interpretation on the policy sample.

summer bills. We label this component "*irrigateduse.*" The second component loads on both *summeruse* (0.82) and *winterbill* (0.55), capturing the patterns of the households with higher year-round consumption, perhaps indicative of larger size families. We label this component "*hightotaluse.*"

2.5.2 Empirical Model Specification

As detailed earlier, the RUM states that the utility an individual *i* receives from each option on a given choice occasion *t* is a linear function of the choice's *j* attributes (at their respective levels), and an additive error term, $U_{ijt} = \mathbf{x}_{ijt}{}'\boldsymbol{\beta} + \varepsilon_{it}$. In our model specification, utility is made to be a function either of the policy levels, or their impacts (see Table 2), depending on the survey. Given that the choice set is constant for individual *i* on choice occasion *t*, the deterministic component of utility may be expressed as a function of attributes only. For the policies and impacts surveys, respectively, this yields

$$\mathbf{x}_j{}'\boldsymbol{\beta} = \beta_1 Supply_j + \beta_2 Conserve_j + \beta_3 Price_j\,; \tag{3}$$

and

$$\begin{aligned}\mathbf{x}_j{}'\boldsymbol{\beta} = \beta_1 AgTransfer_j + \beta_2 Price_j + \beta_3 BaseCharge_j + \\ \beta_4 PrivateLandscape_j + \beta_5 PublicLandscape_j\end{aligned}. \tag{4}$$

With regards to parametrizing class membership (equation 2), π_{iq}, the probability an individual *i* belongs to class *q* is parametrized as a function of the demographic and water use variables $\mathbf{z_i}$, as detailed in equation 5.

$$\begin{aligned}\mathbf{z}_i{}'\boldsymbol{\theta}_q = \theta_0 + \theta_1 Irrigateduse_i + \theta_2 Hightotaluse_i + \theta_3 Age_i + \\ \theta_4 Income_i + \theta_5 Env.Pref_i + \theta_6 Urban_i\end{aligned} \tag{5}$$

2.6 Results:

2.6.1 Aggregate Results: Preferences for Policies vs Impacts

Table 8 shows standardized scores for the policy portfolios, or each portfolio's score ranking as a percentage of the score for the highest-ranked alternative. The most-preferred portfolio meets 30% of future demands via supply projects and 30% through non-price conservation, meaning 40% of demand would be met by agricultural water transfers. The second-best portfolio, 57% as preferable as the highest-ranked portfolio, further decreases agricultural water transfers through use of price increases. The least-preferred portfolio would meet 30% of demand via price increases and 70% with water transfers. Overall, we find that Coloradoans generally support the use of supply and conservation-based portfolios, with a preference for supply projects. It can also be noted that consumers tend to prefer an "all of the above" type of approach, where portfolios include a balanced mix of policies.

Table 9 shows the ordering (from most to least concerning) of the five impacts at their low and high levels, as well as standardized scores relative to high levels of retirement of land from irrigated agriculture. Reduction in irrigated land is the most concerning impact, with respondents scoring low the level of ag dry-up 76% as concerning as the high level, which would fallow 30% of agricultural land. High level price increases (50%) and base charges ($30) are then 58% and 53% as concerning as high levels of dry-up. Changes in private and public landscape are the least-concerning impacts, as both high and low levels for these attributes are less than 20% as concerning to residents as is high-level dry up of agricultural land.

Aggregate portfolio results show preferences for policies as a whole, but yield no information regarding why an individual may perceive a policy as preferable. The impact survey fills this void by showing individuals' level of concern for policy-related impacts; results for policies and associated impacts rankings may then be compared to yield an additional set of results. Here, we see that households are most-concerned with agricultural dry-up in the impacts survey, consistent with ranking of (nearly) all policy portfolios as preferable to the 100% ag transfer portfolio. Preferences diverge, however, in examining preferences for policies/impacts associated with decreasing the volume of agricultural dry-up. In the policies survey, households strongly support policy portfolios using supply projects as opposed to price increases. However, in the impacts survey, respondents concern over high-level price increases than high-level base charge (which are used to fund supply projects) are nearly equal—a results suggesting households do not understand that non-price water policies may also lead to large changes in water bills.

2.6.2 Latent-Class Results: Policies and Impacts

Estimation results for the latent-class models in the policy and impacts surveys are presented side by side in Table 10. For each survey, we first describe the preference estimates within each latent class (equations 3 and 4) as well as the coefficient estimates for variables parameterizing the class-membership process (equation 5). The intention is to provide a nuanced description of citizens' preferences, identify any notable difference across groups, and determine whether a set of group-defining characteristics exists. Then, we proceed to compare and contrast the results from the two surveys, highlighting if and how people's decision-making processes change when the question of how to address the water scarcity problem is framed as a choice between policies, or as a choice between their consequences and tradeoffs.

In both surveys, we identified three distinct classes of consumer preferences. [12] Within each class, a positive/negative coefficient means that including the policy in a portfolio increased/decreased its probability of being selected as most/least preferred. With regards to class membership, parameters of the membership process can only be identified in contrast with an omitted class (here, Class 3), and should be interpreted accordingly. As an example, positive coefficients for age in Class 1 means that increasing age makes an individual more likely to have Class 1, as opposed to Class 3, preferences. As seen in Table 10, coefficients for all preference parameters options are statistically significant at a one percent level of confidence, though this is not true for all variables included as predictors of class membership. [13]

In the policies survey, Class 1 preferences ("save agriculture strong," 43.7% of observations) represent respondents for whom supply projects, non-price conservation, and price increases are all preferable to (the omitted variable) agricultural transfers. As such, Class 1 can be said to strongly support all policies that would be used to avoid agricultural water transfers, especially supply projects. Coefficients for class-membership variables *hightotaluse, age, income* and *envpref* are positive, and the coefficient for *urban* is negative. This means that people with very strong aversion to agricultural water transfers tend to be higher income, older individuals living in rural communities who tend to have greater total water consumption than Class-3 types.

For Class 2 ("save agriculture moderate," 29.5% of observations), coefficients are positive for supply projects and non-price conservation but negative for price. Therefore, this group still supports adopting policies to avoid agricultural water transfers, but not if this entails price increase policies. The only (marginally) significant estimate in the class-membership

[12] Bayesian criteria favored models with more than 3 classes, yet the estimated coefficients of many classes were quite similar, providing little additional economic insight. We therefore favored a more parsimonious three class specification (see also Pacifico 2012).
[13] Standard errors were clustered at the respondent level.

process is the negative coefficient for the variable "*urban,*" implying that Class-2 members, just as Class-1 types, tend to be more "rural" than Class-3 participants, but are otherwise undistinguishable from the reference class. Finally, Class-3 individuals ("transfer water from agriculture", 23.2% of participants) would clearly prefer using agricultural water transfers to meet demand, as evidenced by negative coefficient for all policies. With regards to class membership, parameters have been normalized to zero for identification purposes, but it can be said that, compared with Classes 1 and 2, Class-3 members tend to be lower income, live in urban areas, and use less total water.

Results for the impact survey latent-class model are presented in the right half of Table 10. Within each class, the coefficient associated with each potential impact is interpreted relative to the low level of agricultural land fallowing, the impact omitted for identification purposes. Therefore, a positive coefficient means that an attribute is ranked more concerning than low-level dry-up, while a negative coefficient means it is less concerning. In the table, estimated coefficients are sorted in decreasing order, thereby providing a ranking of impacts from most to least concerning. Interestingly, we were able to match each class in the policy survey to a corresponding class in the impact survey based on a qualitative assessment of the type of preferences displayed.

Class 1 respondents ("save agriculture strong," 38.7% of the observations) see high level of agricultural land dry-up as the most concerning potential result of water policies, followed by the low level of dry-up and increases in base charges and marginal prices. For this group of individuals, the least concerning outcomes are reductions in the "greenness" of private and public landscaping. Class-membership coefficients are positive for *age* and negative for *urban, hightotaluse, and irrigateduse.* Thus, in the impact survey people who are extremely concerned about losing agricultural land tend to be older individuals from rural communities with *lower* water consumption than Class-3 members. This stands in contrast to the policies survey results, where rural individuals with both high irrigated and total water saw water transfers as least-preferred policy option.

Class 2 (“save agriculture moderate,” 33.8% of observations) also considers losing 30% or 15% of agricultural land to water transfers as the most concerning impact, though the magnitude of the coefficients is smaller relative to Class 1. The most visible difference between Class 1 and Class 2 is the relative concern for the greenness of the living environment. For this class, a 70% reduction in the water used in public landscaping is the second most concerning outcome, and 30% reductions in public and private landscaping use of water are considered more concerning than a $15 increase in base charges or a 25% increase in marginal prices. Class-membership coefficients for *age, income*, and *envpref* are positive and significant, whereas coefficients for *irrigateduse* and *hightotaluse* are again negative. Thus, similarly to Class-1 members, Class-2 types tend to be older individuals with higher income but lower water consumption than Class-3 individuals. Unlike Class-3 types, members of Class 2 display stronger environmental preferences than Class-1 individuals, which seems to correlate with a greater concern over landscaping changes dictated by water policies.

Last, Class 3 (“transfer water from agriculture,” 27.5% of observations) ranks both increases in prices and base charges as more concerning than changes in irrigated land. Again, the characterization of the determinant of class membership is simply the converse of what was established for Classes 1 and 2. Accordingly, individuals with higher irrigated and total water consumption were more likely to believe water supply needs should be met through agricultural water transfers.

The comparison of the policy vs. impact surveys results provides some additional insight. In both surveys, we identified three classes of consumers with varying levels of support for preserving agricultural land from being dried up and retired from production. Class 1 portrays the strongest willingness to protect agricultural land, endorsing the use of all available alternative policies, or stating that dry-up of agricultural land is by far the most concerning possible impact resulting from policies used to meet the increasing water needs of Colorado. At the other extreme, Class-3 types prefer having most of the water gap met via agricultural dry-up, and are mostly unwilling to face negative impacts in order to prevent losses of irrigated land. However, some migration away from this stance is observed when participants considered policy impacts, rather than directly choosing policies. Class 1 membership decreases from 43.7% in the policies survey to 38.7% in the impacts survey. Conversely, Class 3 increases from 23.2% to 27.5% across the two surveys. Thus, households appear to be more willing to use agricultural water transfers to meet future water demands when faced with the costs—in terms of increases in base charges, marginal prices, and landscaping changes—of meeting demand though alternatives.

In addition to a cross-survey shift in the support for agricultural transfers, we also find that the determinants of class membership vary across the two surveys. When asked to make choices among policies, older, rural-dwelling individuals—including those with high irrigated/total water use who face large increase in their water bills if dry-up is avoided--are more likely to support preserving agricultural land. Conversely, younger individuals who use less water and live in urban areas were more likely to support agricultural water transfers, a less costly option. However, when asked to make choices between policy impacts rather than the policies themselves, people with high irrigated and total water use were more likely to support agricultural water transfers. That is, older, rural individuals may only prefer water transfer alternatives so long as their water bills are not greatly affected by increases in marginal prices and base charges. This finding signals a shift in the types of individuals that might be expected to support agricultural water transfers before and after they are adopted by water managers.

2.7 Discussion and Conclusions:

To our knowledge, this is the first study to examine preferences for both policies and policy-related impacts in the same context. The policy survey reveals respondents' support for policies as a whole, while the impact survey yields additional insights into why households may favor certain policies. Both the policies and impact surveys were administered to representative samples of Coloradoans and based upon realistic scenarios being considered for meeting the state's future water supply needs. To the extent possible, the impact levels were based upon calculations of actual costs associated with meeting future water demands via supply projects, non-price conservation, and agricultural water transfers.

Results from both the policies and impacts surveys show that a majority of Coloradoans support meeting the state's future water demands with policies other than agricultural water transfers. Support is especially strong for supply projects and non-price conservation programs, which do not affect the marginal price of water. However, while overall support for ag transfer alternatives is surprisingly strong in both the policies and impact surveys, significant heterogeneity is seen in preferences, with a large share of respondents (over 20% in both surveys) believing ag transfers should be the primary policy used to meet future water demands. Heterogeneity results also suggest that the decision-making process for individuals may be affected by whether a survey presents policies or impacts. Whereas demographic variables (age, urbanicity) primarily drive support in the policies survey, water-use levels determine support for impacts, with the highest water users believing demands should be met via ag transfers.

Accordingly, there may be shifts in the types of demographic and voting groups that support the idea of preserving agricultural land after the effects of doing so are realized. Though potentially opposed by older, rural-dwelling individuals prior to implementation, water transfers, at least in the long run, may face less opposition than would be expected because they do not marginal prices or base charges on utility bills. This may be especially true in service areas where residents have little knowledge of where there water comes from (i.e., via agricultural transfers, conservation savings, reservoir storage), but may strongly react to changes increases in their water bills.

While every effort was made to design surveys such that all the impact survey included all outcomes that may be associated with implementing water policies, there are limitations to the scope of the surveys used here. Specifically, we are unable to quantify the potential indirect impacts of considered policies. Such impacts include changes in "greenness" of the community (which we included as an impact but could not directly quantify in relation to policies); changes in instream flows; and social consequences of dry-up on rural communities. As such, the consistencies in preferences for policies used to mitigate agricultural water transfers could be affected if the above-mentioned indirect impacts were included in the impact survey. Furthermore, as in any survey, the preferences described here are still hypothetical in nature, so preferences in both surveys may be influenced by individuals' desire to choose options that would lead them to be viewed positively (Andreoni, 1990), leading to dominance of ag transfer/dry-up as the worst policy/impact in the two surveys. If this is the case, then the share of households who viewed price increases and base charges as the most-concerning impacts can be expected to increase. Lastly, the comparisons made between the policies and impact surveys were largely qualitative in nature; in a separate work, we directly further compare choices for policies to inferred policy preferences. Differences in policy rankings versus “inferred” policy rankings implied by impact results represent the value of informing consumers so that they know potential impacts of all policies under consideration. This would allow for policies to be chosen that are supported at all stages of policy implementation.

Table 2.1: Policies and Associated Impacts

	Supply Projects	Non-price Conservation Programs	Price Increases	Agricultural Transfer
Price Increases	Yes	No	Yes	No
Base Charge Increases	Yes	Yes	No	No
Decreases in Private Landscaping	No	Likely (depending on conservation program participation)	Likely (depends upon responsiveness to price)	No
Decreases in Public Landscaping	No	Likely (depending on conservation program participation)	Likely (depends upon responsiveness to price)	No

Table 2.2: Experimental design: attributes and levels

Polices Survey	**Level 0**	**Level 1**
Supply Projects	0%	30%
Non-Price Conservation	0%	30%
Price Increases	0%	30%
Agricultural Transfers	Complement to 100% (10%, 40%, 70%, 100%)	
Impacts Survey	**Level 0**	**Level 1**
Agricultural land dry up	15%	30%
Price Increase	25%	50%
Base Charge Increase	$15	$30
Reduction in Public Landscaping	30%	70%
Reduction in Private Landscaping	15%	30%

Table 2.3: Demographic characteristics

Characteristic	Range	% Colorado (2012*)	% Policies Survey	% Outcomes Survey
Income	<$25,000	20.7	12.91	12.56
	$25,001-$50,000	23.4	22.07	21.07
	$50,001-$75,000	18.6	22.86	21.66
	$75,001-$100,000	13.1	22.46	22.55
	$100,001-$200,000	19.3	15.86	17.41
	>$200,000	5.0	3.84	4.75
Gender	Male	51.1	49.66	50.74
	Female	49.9	50.34	49.26
Region	Front Range	82	75.07	72.3
	West Slope and Mountains	13.1	10.74	10.68
	Eastern Plains	3	14.19	17.01
Age	21-30	14.4	9.06	10.48
	31-40	14.1	13.3	12.76
	41-50	14.3	13.99	14.84
	51-60	11.9	26.6	27.5
	61-70	9.1	29.26	25.32
	>71	7.4	7.78	9.1
Education	High School	22.4	7.49	6.33
	Some College	22.8	33.69	36.2
	Bachelor's	23.4	22.96	21.56
	Graduate or Professional Degree	13.2	32.02	31.85
	Vocational or Technical Degree	8.1	3.84	4.06
Type of home	Single Family Home	74.2	75.85	75.87
	Multiple Family Home	25.8	1.08	1.68
	Condominium or Townhouse	N/A	12.61	13.25
	Apartment	N/A	9.46	9.2
Owner or Renter	Own	65.9%	79.01	79.72
	Rent	34.1%	20.99	20.28

*2012 American Community Survey 5-year estimates

Table 2.4: Water use characteristics

Characteristic	Range	Policy Survey %	Impact Survey %
Summer Water Use	Primarily use water indoors; summer use (May to August) does not differ greatly from water use in average winter month (November to February)	38.82	35.11
	Summer water use up to 2 x winter water use	46.21	48.07
	Summer use more than 3 x winter use	14.98	16.82
Water Billing	Pay a monthly or bi-monthly water bill based on amount used	73.4	76.36
	Pay a fixed charge (monthly or bi-monthly) regardless of use	2.66	2.77
	Water included in HOA payment	16.35	14.84
	Do not pay for water	7.59	6.03
Average water bill in winter (Nov. to Feb.)	$0-$24.99	22.56	22.75
	$25-$49.99	35.47	34.82
	$50-$74.99	15.86	16.42
	$75-$99.99	4.73	6.53
	$100 or more	1.38	1.98
	Do not pay for water	20	17.51
Average water bill in summer (May-Aug.)	$0-$24.99	7.98	7.72
	$25-$49.99	20.1	18
	$50-$74.99	19.31	21.56
	$75-$99.99	15.57	15.43
	$100 or more	17.04	19.78
	Do not pay for water	20	17.51

Table 2.5: "Which uses of water should receive priority during scarcity?"

Water Use	Percent of Respondents ranking use as first priority (average for policies and impact surveys)
Household Use	59%
Irrigated Farmland	18%
For the Natural Environment	14%
For Natural Resource management	6%
Industrial Use	0.50%
For Private Landscaping	0.40%
Recreation	0.30%
Municipal Landscaping	0.20%

Table 2.6: Variables included as predictors of class membership

Initial Variables	
Variable	**Description**
Marginal	=1 if individual pays a per-unit price for water
Summeruse	=1 if summer water use at least double winter water use
Winterbill (represents indoor usage)	=1 if \$0-\$24.99 =2 if \$25-\$49.99 =3 if \$50-\$74.99 =4 if \$75-\$99.99 =5 if \$100 or more
Not Included in PCA	
Income	=1 if <\$25,000 =2 if \$25,001-\$50,000 =3 if \$50,001-\$75,000 =4 if \$75,001-\$100,000 =5 if \$100,001-\$200,000 =6 if >\$200,000
Envpref	=1 for those who indicated environmental/natural resource-based uses of water should be prioritized
Age	Ordinal variable based on six age categories
Urban	=1 if zipcode is in a census-defined urbanized area*

Table 2.7: PCA for water use variables

Policies					
	Components	Eigenvalue	Difference	Proportion	Cumulative
	Component 1	2.026	1.285	0.675	0.675
	Component 2	0.741	0.509	0.247	0.922
	PCA Loadings	Variable	Component 1	Component 2	
		summeruse	0.484	0.826	
		marginal	0.651	-0.119	
		winterbill	-0.585	0.551	
Impacts					
	Components	Eigenvalue	Difference	Proportion	Cumulative
	Component 1	2.006	1.242	0.669	0.669
	Component 2	0.764	0.533	0.255	0.923
	PCA Loadings	Variable	Component 1	Component 2	
		summeruse	0.484	0.815	
		marginal	0.656	-0.096	
		winterbill	-0.579	0.572	

Table 2.8: Best-worst ranking of policies aggregate results

Policy Portfolio				**# Times Most-Preferred**	**# Times Least-Preferred**	**M-L**	**Standardized**
Supply	**Conservation**	**Price**	**Ag Transfer**				
30%	30%	0%	40%	517	65	452	100.00
30%	30%	30%	10%	464	176	288	57.57
30%	0%	30%	40%	253	172	81	43.00
30%	0%	0%	70%	206	169	37	39.15
0%	30%	30%	40%	186	185	1	35.55
0%	30%	0%	70%	178	427	-249	22.89
0%	0%	0%	100%	153	479	-326	20.04
0%	0%	30%	70%	60	524	-464	12.00

Table 2.9: Best-worst ranking of impacts, aggregate results

Attributes and Levels	Most Concerning	Least Concerning	M-L	Standardized
Ag Land Dry-Up, High (30%)	2391	228	2163	100
Ag Land Dry-Up, Low (15%)	1965	320	1645	76.54
Price Increase, High (50%)	1294	362	932	58.33
Base Charge Increase, High ($30)	752	247	505	53.70
Price Increase, Low (25%)	631	497	134	34.88
Base Charge Increase, Low ($15)	331	668	-337	21.60
Reduction in Public Landscaping, High (70%)	315	1091	-776	16.67
Reduction in Public Landscaping, Low (30%)	153	1192	-1039	11.11
Reduction in Private Landscaping, High (30%)	151	1637	-1486	9.23
Reduction in Private Landscaping, Low (15%)	104	1846	-1742	7.41

Table 2.10: Estimation results of latent-class models for policies and impacts surveys

	Policies Survey			Impacts Survey		
Classes	**Regressor**	**Coef.**	**Std. Err.**	**Regressor**	**Coef.**	**Std. Err.**
Class 1: Save Agriculture Strong				Ag Transfer (30%)	0.818***	0.089
				Price (50%)	-0.939***	0.084
				Base Charge ($30)	-1.483***	0.080
	Supply	3.224***	0.085	Price (25%)	-1.938***	0.085
	Conserve	2.980***	0.073	Base Charge ($15)	-2.501***	0.083
	Price	1.952***	0.067	Public Landscape (70%)	-3.792***	0.105
				Public Landscape (30%)	-4.129***	0.095
				Private Landscape (30%)	-4.168***	0.095
				Private Landscape (15%)	-4.339***	0.094
Class 1 Membership	*Irrigateduse*	0.033	0.088	*Irrigateduse*	-0.220***	0.088
	Hightotaluse	0.264**	0.119	*Hightotaluse*	-0.230**	0.110
	Age	0.349***	0.064	*Age*	0.198***	0.059
	Income	0.211***	0.066	*Income*	-0.016	0.062
	Envpref	0.216*	0.125	*Envpref*	0.154	0.128
	Urban	-0.331*	0.181	*Urban*	-0.285*	0.171
	Constant	-1.928***	0.445	*Constant*	0.395	0.413
Class 2: Save Agriculture Moderate				Ag Transfer (30%)	0.694***	0.069
				Public Landscape (70%)	-0.729***	0.062
				Base Charge ($30)	-1.115***	0.063
	Supply	0.588***	0.044	Price (50%)	-1.226***	0.064
	Conserve	0.467***	0.042	Public Landscape (30%)	-1.257***	0.067
	Price	-0.413***	0.050	Private Landscape (30%)	-1.627***	0.074
				Base Charge ($15)	-1.789***	0.067
				Price (25%)	-1.811***	0.066
				Private Landscape(15%)	-1.916***	0.073
Class2 Membership	*Irrigateduse*	0.105	0.098	*Irrigateduse*	-0.322***	0.089
	Hightotaluse	0.168	0.131	*Hightotal use*	-0.262**	0.114
	Age	0.074	0.069	*Age*	0.271***	0.061
	Income	0.040	0.073	*Income*	0.118*	0.063
	Env. Pref	0.180	0.138	*Env. Pref*	0.427***	0.127
	Urban	-0.343*	0.202	*Urban*	0.132	0.177
	Cons.	-0.454	0.471	*Cons.*	-0.754	0.436

Table 2.10 Continued	Policies Survey			Impacts Survey		
Classes	**Regressor**	**Coef.**	**Std. Err.**	**Regressor**	**Coef.**	**Std. Err.**
Class 3: Transfer Water from Agriculture				Price (50%)	2.541***	0.097
				Base Charge ($30)	1.556***	0.079
	Supply	-0.659***	0.062	Price (25%)	1.399***	0.074
	Conserve	-0.730***	0.093	Base Charge ($15)	0.537***	0.070
	Price	-2.641***	0.113	Ag Transfer (30%)	0.309***	0.066
				Private Landscape (30%)	-0.708***	0.069
				Public Landscape (70%)	-0.720***	0.069
				Private Landscape (15%)	-0.899***	0.068
				Public Landscape (30%)	-1.024***	0.070

*=.10, **=.05, ***=.01 level of significance

Choose your most and least-preferred policy portfolios.

	Portfolio 1	Portfolio 2	Portfolio 3
	Supply Projects: 0%	**Supply Projects:** 30%	**Supply Projects:** 0%
	Non-Price Conservation: 30%	**Non-Price Conservation:** 30%	**Non-price Conservation:** 0%
	Pricing Policies: 30%	**Pricing Policies:** 30%	**Pricing Policies:** 0%
	Results in:	**Results in:**	**Results in:**
	Percent of gap met with ag transfer: 40%	**Percent of gap met with ag transfer:** 10%	**Percent of gap met with ag transfer:** 100%
Most preferred	○	○	○
Least preferred	○	○	○

Figure 2.1: Sample choice set for policies survey

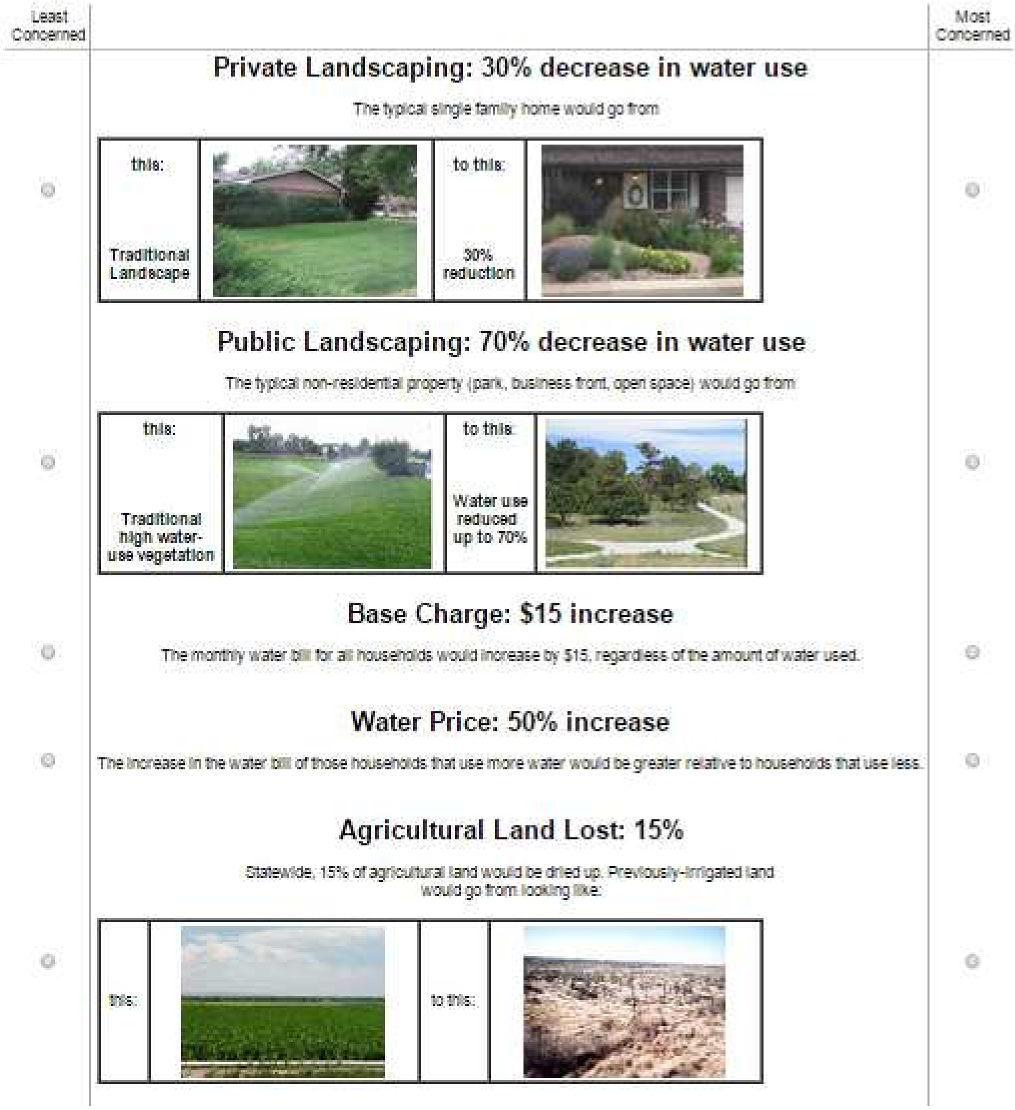

Figure 2.2: Sample choice set for impact survey

REFERENCES

Andreoni, James. "Impure altruism and donations to public goods: a theory of warm-glow giving." *The Economic Journal* (1990): 464-477.

Ashok, Kalidas, William R. Dillon, and Sophie Yuan. "Extending discrete choice models to incorporate attitudinal and other latent variables." *Journal of Marketing Research* (2002): 31-46.

Ben-Akiva, Moshe, Daniel McFadden, Makoto Abe, Ulf Böckenholt, Denis Bolduc, Dinesh Gopinath, Takayuki Morikawa et al. "Modeling methods for discrete choice analysis." *Marketing Letters* 8, no. 3 (1997): 273-286.

Bergstrom, John C., and Richard C. Ready. "What have we learned from over 20 years of farmland amenity valuation research in North America?" *Applied Economic Perspectives and Policy 31*, no. 1 (2009): 21-49.

Blamey, Russell, Jenny Gordon, and Ross Chapman. "Choice modelling: assessing the environmental values of water supply options." *Australian Journal of Agricultural and Resource Economics* 43, no. 3 (1999): 337-357.

Carlsson, Fredrik, Peter Frykblom, and Carl Johan Lagerkvist. "Using cheap talk as a test of validity in choice experiments." *Economics Letters* 89, no. 2 (2005): 147-152.

Carson, Richard T., and Theodore Groves. "Incentive and informational properties of preference questions." *Environmental and Resource Economics* 37, no. 1 (2007): 181-210.

Chapman, Randall G., and Richard Staelin. "Exploiting rank ordered choice set data within the stochastic utility model." *Journal of Marketing Research* (1982): 288-301.

Collins, Andrew T. and John M. Rose. "Estimation of Stochastic Scale with Best-Worst Data" (working paper, Institute of Transport and Logistic Studies, University of Sydney, 2013).

Finn, Adam, and Jordan J. Louviere. "Determining the appropriate response to evidence of public concern: the case of food safety." *Journal of Public Policy & Marketing* (1992): 12-25.

Flynn, Terry N., Jordan J. Louviere, Tim J. Peters, and Joanna Coast. "Best–worst scaling: what it can do for health care research and how to do it." *Journal of Health Economics* 26, no. 1 (2007): 171-189.

Greene, William H., and David A. Hensher. "A latent class model for discrete choice analysis: contrasts with mixed logit." *Transportation Research Part B: Methodological* 37, no. 8 (2003): 681-698.

Haider, Wolfgang, and Harun Rasid. "Eliciting public preferences for municipal water supply options."*Environmental Impact Assessment Review* 22, no. 4 (2002): 337-360.

Heckman, James J. 2001. “Micro Data, Heterogeneity, and the Evaluation of Public Policy: Nobel Lecture.” *The Journal of Political Economy* 109 (4): 673–748.

Hensher, David, Nina Shore, and Kenneth Train. "Water Supply Security and Willingness to Pay to Avoid Drought Restrictions." *Economic Record* 82, no. 256 (2006): 56-66.

Howe, Charles W., and Christopher Goemans. "Water transfers and their impacts: Lessons from three Colorado water markets." *Journal of the American Water Resources Association* 39, no. 5 (2003): 1055-1065.

Howe, Charles W., Jeffrey K. Lazo, and Kenneth R. Weber. "The economic impacts of agriculture-to-urban water transfers on the area of origin: a case study of the Arkansas River Valley in Colorado." *American Journal of Agricultural Economics* 72, no. 5 (1990): 1200-1204.

Johnston, Robert J., and Joshua M. Duke. "Informing preservation of multifunctional agriculture when primary research is unavailable: an application of meta-analysis." *American Journal of Agricultural Economics* 91, no. 5 (2009): 1353-1359.

Keenan, Sean P., Richard S. Krannich, and Michael S. Walker. "Public perceptions of water transfers and markets: Describing differences in water use communities." *Society & Natural Resources* 12, no. 4 (1999): 279-292.

Lancsar, Emily and Jordan J. Louviere. "Estimating individual level discrete choice models and welfare measures using best-worst choice experiments and sequential best-worst MNL." University of Technology, Centre for the Study of Choice (Censoc) (2008): 08-004.

Lee, Julie Anne, Geoffrey N. Soutar, and Jordan Louviere. "Measuring values using best-worst scaling: The LOV example." *Psychology & Marketing* 24, no. 12 (2007): 1043-1058.

Libecap, Gary D. "The Myth of Owens Valley" *Regulation* 28 (2005): 10-17.

Louviere, Jordan J. "Experimental choice analysis: Introduction and overview." *Journal of Business Research* 24, no. 2 (1992): 89-95.

Marley, A. A. J., and David Pihlens. "Models of best–worst choice and ranking among multiattribute options (profiles)." *Journal of Mathematical Psychology* 56, no. 1 (2012): 24-34.

Olsson, Ulf. "Maximum likelihood estimation of the polychoric correlation coefficient." *Psychometrika* 44, no. 4 (1979): 443-460.

Pacifico, Daniele. "lclogit: A Stata command for fitting latent-class conditional logit models via the expectation-maximization algorithm." *Stata Journal* 13, no. 3 (2013): 625-639.

Rosegrant, Mark W., and Claudia Ringler. "Impact on food security and rural development of transferring water out of agriculture." *Water Policy* 1, no. 6 (2000): 567-586.

Sayadi, Samir, M. Carmen González-Roa, and Javier Calatrava-Requena. "Public preferences for landscape features: the case of agricultural landscape in mountainous Mediterranean areas." *Land Use Policy* 26, no. 2 (2009): 334-344.

Scarpa, Riccardo, and John M. Rose. "Design efficiency for non-market valuation with choice modelling: how to measure it, what to report and why." *Australian Journal of Agricultural and Resource Economics* 52, no. 3 (2008): 253-282.

Street, Deborah J., Leonie Burgess, and Jordan J. Louviere. "Quick and easy choice sets: constructing optimal and nearly optimal stated choice experiments." *International Journal of Research in Marketing* 22, no. 4 (2005): 459-470.

Swait, Joffre. "A structural equation model of latent segmentation and product choice for cross-sectional revealed preference choice data." *Journal of Retailing and Consumer Services* 1, no. 2 (1994): 77-89.

Thorvaldson, Jennifer, James Pritchett, and Christopher Goemans. "Western households' water knowledge, preferences, and willingness to pay." *Canadian Journal of Agricultural Economics* 58, no. 4 (2010): 497-514.

Tisdell, John Graeme, and John Robert Ward. "Attitudes toward water markets: an Australian case study." *Society &Natural Resources* 16, no. 1 (2003): 61-75.

Train, Kenneth E. "EM algorithms for nonparametric estimation of mixing distributions." *Journal of Choice Modelling* 1, no. 1 (2008): 40-69.

Ward, Frank A., and Ari Michelsen. "The economic value of water in agriculture: concepts and policy applications." *Water policy* 4, no. 5 (2002): 423-446.

CHAPTER 3: IS A POLICY THE SUM OF ITS EFFECTS?: COMPARING PREFERENCES FOR WATER POLICIES TO WILLINGNESS TO PAY FOR ASSOCIATED IMPACTS

3.1 Synopsis

Surveys used to evaluate households' preferences for natural resource policies typically elicit preferences either for policies themselves or for the impacts of policies, from which overall policy preferences may be inferred. While there is a great deal of literature evaluating differences resulting from use of various preference elicitation methods (e.g., contingent valuation versus choice experiments), scant literature exits regarding differences across policies versus inferred policy preferences. In the case of natural resource policies, where individuals are unable to actually consume the "good" (policy) they are choosing, variations in individuals' policy knowledge and "warm glow" effects (Andreoni, 1990) may cause differences when the survey is presented as a choice over policies versus impacts. This research uses two separate policy and impact-related surveys to solicit Colorado households' preferences for policies that could be used as alternatives to agricultural water transfers in meeting future water demands. Rankings for policies are compared to inferred rankings, found by calculating willingness to pay for each impact (relative to agricultural water transfers) associated with a specific policy. In both surveys individuals tend to support policies that would mitigate agricultural water transfers in the state, despite the magnitude of monetary impacts associated with doing so. Impact results show that households would be willing to pay up to $60 a month via either increased base charges or price increases in order to avoid agricultural water transfers. This value exceeds the cost of nearly all policy options presented; however, the actual policy mix that would be used to meet future water demands differs when policy rankings are compared to inferred policy preferences.

3.2 Introduction:

Survey methods such as contingent valuation, discrete choice experiments, and best-worst scaling are frequently used to evaluate preferences for natural resource policies. Within the water literature, examples include contingent valuation for improvements in water quality (Hanley, Bell, and Alvarez-Farizo 2003) and in ecosystem services along rivers (Loomis et al., 2000); revealed preference techniques have been used to value attributes of a water system such as frequency of shortage (Hensher, Shore and Train, 2005) and preferences for the source of a water supply (Haider and Rasid, 2002).With each method, households may be asked questions that elicit preferences for a policy, or they may be asked questions regarding a policy's potential impacts, from which overall policy preferences are inferred. When a survey elicits preferences for policies as a whole--often through contingent valuation or policy rating tasks--results may be similar to what one would expect from a vote, where households have varying levels of information regarding how policies will impact them individually. Choices over policies may also reflect utility received as a result of personal/political beliefs that may make a policy preferred (regardless of its impacts). Conversely, policy preferences inferred from choices over the impacts or characteristics of a policy represent the choices of informed consumers, where the only relevant information to the household is that included in the survey.

Whereas the seller of a good (be it a politician selling a policy, or a firm selling a product) may not care about information levels so long as his product is purchased, economists typically believe chosen policies should reflect informed preferences in order to maximize consumer welfare. However, in the case of water—and other "hotbed issues" debated in government but little understood by the public—it may not be the case that "popular" policies are the same policies preferred by informed consumers. If differences exist, then policy makers must ask whether they want to force individuals to evaluate tradeoffs implied by polices, or whether they want to know how consumers feel about policies within the everyday informational setting. Both methods are justifiable, as households are known to have strong preferences regardless of information levels, yet it has also been found that information can greatly affect preferences (Lusk et al., 2004).

In this work, two best-worst scaling surveys, one related to policies and one to policy impacts, are separately administered to representative samples of Colorado households. The context of the two surveys is evaluating consumers' preferences for policies that could be used as alternatives to agricultural water transfers in Colorado. Policy survey results reflect the preferences of households absent any additional information that may affect choices. Impact results reflect preferences of informed households, where information relates to the direct impacts policies will have on individuals. Preferences are estimated for both surveys using both an aggregate-level maximum difference scoring model (Flynn et al., 2007) and a random parameters logit (RPL) (Train, 1998). Policy rankings (policies survey) are then compared to "inferred policy rankings," rankings based on willingness to pay estimates for impacts that may be directly linked to policies. Additionally, the total value of policies, as implied by willingness to pay for associated impacts, is compared to actual policy costs; this allows us to determine if preferred policies are realistic (affordable) options for households. Differences in policy rankings reflect both the effects that non-quantifiable factors such as policy perceptions and individual experiences may have on households' overall policy preferences, as well as the value of informing households of policy impacts prior to policy adoption. To our knowledge, this is the first work to examine preferences for policies versus policy-related impacts using the same valuation method. Results show overall support for alternatives to water transfers is strong in both the policies and impact surveys, and the costs households would be willing to pay in the form of impacts such as increased base charges and marginal prices are compatible with most policy scenarios presented. As such, the difference between preferences elicited over policies versus impacts is much less than anticipated for the direct impacts considered.

3.3 Background and Previous Literature

Colorado's population is expected to double by the year 2050, creating a projected annual gap between current water supplies and municipal and industrial demands of between 500,000 and 1,000,000 acre feet of water.[14] The state is considering numerous options for "closing the gap," which may be broadly lumped into the categories of demand management and supply development. Demand management includes use pricing policies and other non-price conservation programs;[15] supply development includes building new reservoirs and agricultural water transfers, where municipalities purchase agricultural water rights.

Each individual policy will have a cost for Colorado's residents, and the magnitude of future water demands will likely require that a portfolio of multiple policy options be used to meet the water supply gap. In the case of supply projects and non-price conservation programs, base charges on household water bills will be increased. These increased fees, which are the same for all households regardless of the amount of water used, pay for new reservoir projects and fund conservation programming. In contrast, changes in prices increase the marginal cost of water, and the overall cost to a consumer will depend upon how much water is used. Water transfers are generally free for current residents of the state because water rights are purchased by home developers and costs passed on to new residents. Though "free" in literal terms, there is

---

[14] Colorado Water Conservation Board, "The Municipal and Industrial Water Supply and Demand Gap," Available < http://cwcb.state.co.us/water-management/water-supply-planning/Pages/TheWaterSupplyGap.aspx>.
[15] Non-price conservation programs include water audit programs, rebates and incentives for installation of water efficient appliances, and public information campaigns.

a large non-monetary cost to meeting demand entirely through agricultural water transfers, as doing so may require up to 30% of Colorado agricultural lands to be fallowed or "dried up."

Though water transfers are mutually beneficial transactions for involved water providers and farmers, water transfers are generally viewed negatively by rural communities (Keenan, Krannich and Walker,1999), where loss of water can lead to economic decline (Howe and Goemans, 2003). In some cases, the impression is often that cities are "stealing" rural water, and interested groups at both local and state levels may seek to decrease the volume of water transfers. In Colorado, the state's Colorado Water Conservation Board has directed over $3M in funds to projects that mitigate the volume of agricultural water transfers.[16] However, it is unknown the extent to which consumers support these policies and how that support is related to an understanding of policy impacts. Because policies are both experience and credence goods, not goods that can actually be consumed, individuals may not understand how resource policies impact them individually, either before or, at times, even after they are adopted. In fact, previous research has shown that households actually have very little knowledge regarding how much they pay for water, much less how changes in base charges and price increases are used to support new supply projects and/or decrease water demands (Thorvaldson, Pritchett and Goemans, 2010).

3.4 Previous Literature

3.4.1 Policies v. Impacts

Previous survey work has elicited preferences either for policies or policy-related impacts, but not both. Within the water literature, impact-related surveys are most common and usually take the form of discrete choice or best-worst scaling experiments that value the possible

---

[16] http://cwcb.state.co.us/about-us/about-the-ibcc-brts/Documents/RoundtableSummit2012/ATM%20Group%20-%20ATM%20Fact%20Sheet.pdf

environmental impacts of policies (Blamey, Gordon and Chapman, 1999). Similarly, contingent valuation may be used to estimate households' willingness to pay for policy-induced changes in a specific environmental attribute, such as presence of farmland near urban areas (Beasley, Workman, and Williams, 1986). Impact-related surveys may also be used to find what characteristics (e.g., water quality, taste, source, reliability) of a water supply are most important to households (Haiser and Rasid, 2002; Hensher, Shore and Train 2005). Policy preferences may then be deduced from impacts results if there is a direct relationship between impacts and policies.

With regards to policies, surveys may ask consumers to rate policies with (Fleishman, De Bruin, and Morgan, 2010) or without (Zarnikau, 2003) giving information on potential policies or potential outcomes. Though one might expect uninformed consumers to be ambivalent over polices, respondents often exhibit strong preferences. This is especially true for water and energy policies perceived as high risk, such as wastewater reuse. Additionally, preferences for policies are known to be influenced by "warm glow" effects, where individuals exaggerate their support for a policy because they gain utility from knowing they made the correct choices, as viewed by society (Andreoni, 1990). Despite these factors that may influence preferences, previous research has found mixed results regarding whether giving households information has an impact on supported policies (Gilens, 2001; Shwom, Dan, and Dietz, 2008).

Previous cross-survey analyses have compared valuation methods (e.g., contingent valuation versus discrete choice experiments) in terms of their willingness to pay estimates for environmental goods (Boxall et al., 1996). Others have addressed differences in preferences for environmental amenities when they are presented in a choice experiment setting, versus a contingent valuation survey that depicts the larger policy/environmental setting in which the marginal change in the attribute occurred (Hynes, 2007). In doing so, researchers caution that households may value a policy in its entirety differently than they value impacts removed from the larger policy context. Similarly, researchers have found differences in preferences when households are asked to rate policies before and after receiving information on impacts (de Best-Waldhober and Faaij, 2009). A problem with the above-mentioned studies is that giving policy-related information before a policy-rating task does not force households to make realistic tradeoffs across possible impacts of policy options but, rather, presents a policy and all available information as a "package" good. Similarly, comparing results from contingent valuation versus choice experiments tests whether the two methods yield different willingness to pay estimates, but does not evaluate the difference between soliciting preferences for policies versus associated impacts when using identical experimental methods.

Preferences for policies versus impacts may differ if the household either lacks information, or receives utility from policy-related impacts that are unknown to the researcher. Lusk[17] et al. (2014) demonstrate their "information hypothesis" in an experiment where households were asked whether they believe there should be a ban on small-cage eggs and then had their actual egg purchases monitored. The authors found that many ban-supporting households did not know what eggs they were actually purchasing. Alternatively, Lusk and his colleagues propose the "consumer versus citizen" hypothesis to explain scenarios where households support use of cage bans because it sounds like the right thing to do, but in practice cage-free eggs are too expensive. In a policy context, where goods cannot actually be purchased, households may support policies either because they sound good on paper, or due to the perceived impacts of policy options (Jeffrey and Seaton, 2004); this support may change when

[17] Lusk, Jayson. "Why Don't People Vote Like They Shop." 13 March 2015. Available http://jaysonlusk.com/blog/2015/3/12/food-demand-survey-foods-march-2015.

households' choices are based on realistic trade-offs made across policy-related impacts. Neither method can be said to produce "correct" policy rankings, as both perceptions and information will likely enter into the actual decision-making process faced outside an experimental setting. However, the policy-maker needs to know if policies chosen by households in a policies-type survey are associated with impact costs the households is willing to bear. To our knowledge, previous literature has not examined the different preferences that may result from choices over policies, as compared to choices over impacts, in any context. The area of water policy provides a unique opportunity for the comparison of policies versus impacts both because households often have strong preferences for certain policies (e.g., reservoir projects), but often lack and understanding of related impacts (Thorvaldson, Pritchett and Goemans, 2010). Additionally, many of the monetary impacts of these projects are quantifiable and, as such, can be used in the comparison of policy and impact-related preferences

3.4.2 Best-worst scaling and surveys for policies versus impacts in the random utility framework

Surveys typically ask respondents to make choices across policies, or across policy-related impacts (from which policy preferences may be inferred). In best-worst choice experiments, respondents are presented with choice sets from which they are asked to select their most- and least-preferred options, which may be either attributes (individual characteristics of a good), or attribute "bundles" (combinations or attributes). Attribute choices have been frequently used in the health care literature to determine the relative importance of policy characteristics (Flynn et al., 2007). If two attributes are selected as most- and least-preferred, then the difference in latent utility provided by the best and worst options is larger than would be the case for any other attribute combination (Lee, Soutar and Louviere, 2007). The choice over attribute bundles is a variant on traditional discrete choice experiments (Lanscar et al., 2013), and assumes the utility a consumer *i* receives from a good *j* on can be broken into deterministic function of the attributes (characteristics) of good *j* and an additive error term, ε_{ij}, yielding $U_{ij} = \mathbf{x}_{ij}'\boldsymbol{\beta} + \varepsilon_{ij}$. The respondent chooses a good as most-preferred if it provides the largest utility of all options presented. By requiring respondents to select both their most and least-preferred options, the researcher obtains more information (and additional observations) compared to a traditional discrete choice experiment where respondents select only their most-preferred attribute bundle.

Let case 1 represent a best-worst task where households make choices across policy bundles; i.e.,—in this context, the bundle (or portfolio) of policies that will be needed to meet future water demands. The utility an individual receives from a bundle *j* is a linear function of the *k* policies included policies in *j* and an additive error term,

$$U(\mathbf{x}_j) = U(\mathbf{x}_j'\boldsymbol{\beta} + \varepsilon_j) = U\left(\sum_k \beta_k x_k + \varepsilon_j\right) \tag{1}$$

The household chooses bundle *j* as most-preferred if the utility received from bundle *j* is larger than that for any other policy bundle. When choosing across policies in this way, the household is assumed to receive utility from policies themselves, but the researcher is unaware of the extent to which knowledge of policies, personal experience, etc. may impact these preferences. Consequently, estimated models may be influenced by consumers individualized knowledge (or lack thereof) of policies, as well as warm glow (Nunes, and Schokkaert, 2003) type effects.

Next, let case 2 instead assume the utility a household receives from a policy portfolio *j* is actually a function of impacts associated with policies included in *j*. Each individual policy x_k may be linearly related to a specific set of impacts, meaning $x_k = \psi(\mathbf{z}_k)$.

Utility for an individual policy x_k in the bundle is the sum of utility derived from *m* impacts in x_k --i.e,

$$U(x_k) = U(\mathbf{z}_k{}'\boldsymbol{\theta} + v_k) = U(\sum_m \theta_m z_m) + v_k). \quad (2)$$

Prior to policy adoption, these impacts may be unknown to the household. As an alternative to making choices over policies, respondents could be asked to complete a best-worst scaling task and select their most-and least-preferred impacts, and the respondent chooses an impact as most-preferred if the utility from impact *m* is larger than for any other impact in the choice set. Here, the researcher presents the information deemed relevant to policy adoption, and the choice task forces respondents to make trade-offs across policy-impacts.

If a price attribute is included in the experiment, willingness to pay for each impact may also be calculated using standard methods (Louviere and Islam, 2008), where willingness to pay is equal to the marginal utility received from an impact divided by the marginal utility of money. Given that policies can be directly related to impacts, then the total willingness to pay for a policy x_k is the sum of willingness to pay for each individual impact, $WTP(x_k) = \sum_m WTP(z_m)$ as in Blamey, Gordon and Chapman (1999). Accordingly, the total willingness to pay for a given bundle *j* is the sum of willingness to pay for each included policy, or $WTP_j = \sum_k WTP(x_k)$.

Using impact survey results, total willingness to pay for policies and portfolios as may be calculated, and policy portfolio preferences ranked based on these WTP values. Next, actual policy survey rankings may be compared to the WTP-based rankings; WTP rankings may also be compared to actual policy portfolio costs. This allows the following questions to be addressed: first, is there consistency in preferences across surveys, meaning portfolios with the largest willingness to pay values (impact survey) are also ranked highest in the policies survey? Second, are total willingness to pay values for a policy bundle compatible with the actual portfolio costs? Large differences across the two survey results would mean both that households will benefit from having information that allows them to weigh the trade-offs of policies, and that policy-makers will greatly benefit from a better-understanding of what factors, outside of the direct impacts of policies, are driving policy preferences.

3.5 Methods

3.5.1 Models for analysis of best-worst data

Aggregate-level choice data may be analyzed using a "max-diff" multinomial logit (Marley and Louviere, 20015). Results nearly identical to those achieved via the "max-diff" model can be obtained by taking the square root of the ratio of the total number of times an option is chosen as most and least preferred. Doing so gives an option a "score" reflecting the relative importance of options (Marley and Pihlens, 2012), across all respondents.

Using individual-level observations, the sequential best-worst multinomial logit (SMNL) (Lancar and Louviere, 2008) may be used to represent the decision-processes in which best and worst choices, followed by second-best and second-worst, are chosen sequentially. Under the assumption that errors are Gumbel distributed, a given respondent's best-worst choices are expressed as a series of multinomial probabilities where the scale parameter λ is positive/ negative for best/worst choices. For an individual *i* facing a choice set with three options, the probability of choosing an option "A" as most preferred and option "B" as least preferred from options A, B, and C is given as follows

$$\Pr(A,B,C)=\frac{\exp(\lambda x_{iA}'\beta)}{\sum_{J=A,B,C}^{J}\exp(\lambda x_{ij}'\beta)}*\frac{\exp(-\lambda x_{iB}'\beta)}{\sum_{J=B,C}^{J}\exp(\lambda x_{ij}'\beta)}, \tag{3}$$

Where the scale factor is positive if an alternative *j* is chosen most (least) preferred by individual *i* on a given choice occasion. In the case of best-worst choices over attribute bundles, estimated coefficients can be used to calculate each attribute's contribution to overall utility. When best-worst choices are made across individual attributes, estimated coefficients will represent the relative importance rankings of each attribute.

3.5.2 Heterogeneity in Preferences: Random Parameters Logit

Conditional logit models frequently violate IIA, the assumption that an individual's choices are not correlated across choice sets. The random parameters logit accounts for the fact that unobserved individual-specific variables may cause one's choices to be correlated by allowing the model parameters to vary across individuals (Revelt and Train, 1998). That is, it is assumed that there is a unique set of parameters β_i for each individual *i*, and across the population of consumers the parameters follow the density $f(\beta_i \mid \theta)$, where θ are the true parameters (mean and variance) of the distribution of β_i. The probability, conditional on β_i, of an individual choosing an alternative A as most preferred and B as least preferred is the product

$$\mathrm{P}_{i,ABC}(\beta_i) = \frac{\exp(\lambda x_{iA}{}'\beta_i)}{\sum_{J=A,B,C}^{J} \exp(\lambda x_{ij}{}'\beta_i)} * \frac{\exp(-\lambda x_{iB}{}'\beta_i)}{\sum_{J=B,C}^{J} \exp(\lambda x_{ij}{}'\beta_i)} \tag{4}$$

where the scale factor is again negative for worst choices. The unconditional probability is the integral over all possible values of β_i,

$$Q_{i,ABC}(\theta) = \int P_{i,ABC} \mid \beta_i f(\beta_i \mid \theta) d\beta \,. \tag{5}$$

If individuals face a series of choice sets, and choose their most and least-preferred option in each, then (unconditional) probability of observing the series for an individual is expressed as a product of the probabilities in (1) on all choice occasions, and the unconditional probability is again the integral of this product over all possible values of β_i. For a detailed description of the random parameters logit model, see Revelt and Train (1998).

Estimates for both β and θ must be found using simulation methods, as the integral for likelihood function does not have an analytical solution. Though increasingly popular due to its flexibility and widespread availability of software implementing the simulation, the random parameters logit (RPL) requires the researcher to determine which coefficients should be random and to specify the distributions of random coefficients β_i (Haan, Peter, and Arne Uhlendorff, 2006).

3.5.3 Survey Design and Choice Tasks

Any choice experiment must be designed to include all relevant attributes (in this context, policies or impacts) without overwhelming respondents with so much information that they ignore certain attributes, or respond at random. Here, viable policies were identified using the Colorado Water Conservation Board's "Water Supply Future Portfolio and Trade-off Tool." Table 1 shows identified policies and associated impacts. The tool identifies supply projects, non-price conservation,[18] and agricultural water transfers as options for meeting future demand. This budgeting instrument estimates that non-price conservation and supply projects could be used to meet at most approximately 30% of the 710,000 acre/foot gap in water supplies under a "high success" scenario. Given that price increases are also used to induce conservation behavior, price increases were also included in the survey, and it was assumed that they could be

[18] Non-price conservation policies relate mainly to "indoor" water usage (i.e., non-landscaping uses) and include "water audits," rebates for water-efficient appliances, water audits, and messaging/media campaigns.

used to achieve water savings similar to those of non-price conservation, or roughly 30% of the water supply gap.

In order create a direct link between the policies and impacts surveys, the estimated costs (per household per month) of meeting the gap via the identified policy options were calculated. State documents provide estimates of the cost ($/acre-foot) of water achieved via supply projects, and non-price conservation. These costs were multiplied by estimated water provided by projects in each category to obtain a range of potential total costs of each option. Costs were then divided by estimates of Colorado's 2050 population to obtain household-level costs of each policy, and these household costs were divided by twelve to find the expected per-bill cost for residents[19]. These calculations lead to estimates of required increases in base charges of $33 for supply projects and $35 for non-price conservation. Based on these estimates, our experimental design adopted $15 and $30 as two plausible levels of increase in base charges resulting from new supply projects. Potential price increases were determined by calculating the percentage increase in price required to achieve similar reductions in water use as those achieved via non-price conservation. Assuming a price elasticity of demand of -0.5 commonly found in the water demand literature (Arbués, Garcıa-Valiñas, and Martınez-Espiñeira, 2002), this required price increase is 26%. As such, 25% and 50% were chosen as levels of price increases, given the reality that some municipalities within the state already have plans to phase in rate increases of over 50% over the next decade in areas where the difference between existing supplies and required future water demand is relatively larger than is the case for the state as a whole.

With regards to agricultural water transfers, the portfolio and trade-off that roughly 30% of the state's agricultural land would need to be fallowed in order to meet the entire gap via

[19] Based on discussion with local water utilities, it was assumed that new residents of the state would pay 40% of the costs of new supplies, with additional costs passed on to new residents.

agricultural water transfers; as such, we select 15% and 30% as plausible levels for agricultural water transfers in the impact survey.

The above-mentioned policies can be used to increase supplies or decrease households' average water demands in the long run; however, utilities also commonly use short-term watering restrictions to decrease demand during drought, and frequent use of restrictions and other demand-management policies (price increases and conservation messaging) may change social norms for water use. As such, variables related to the "greenness" of the community were included in the impact survey. Though it is not possible to directly quantify the extent to which such changes will occur, levels for changes in private (15% of 30% reductions in water usage) and public (30% and 70% reductions in usage) landscaping were chosen based on Denver Water planning documents[20], which identify viable options for saving water by adopting landscaping with low water requirements (e.g. xeriscaping).

Given our intent of relating water policies to their impacts quantitatively, only quantifiable impacts were included in the survey. Admittedly, some policies may induce other impacts that are not quantifiable at the present time, such as the environmental and recreational uses of water. Nevertheless, the comparison of actual policy preferences to impact-derived preferences here is based upon the best information available at the time to policy-makers.[21]

---

[20] The Restoration Group, Inc. and HydroSystems KDI, Inc. "Sustainable Landscape Conversion Design and Irrigation." Prepared for Denver Water, August 31, 2011. Available < http://www.denverwater.org/docs/assets/C826C619-BE09-A674-64DD2562ABF06D52/SustainableLandscapeConversion.pdf>.

[21] Households were also given a question where they ranked the water uses, including recreational and environmental allocations, which should receive priority during scarcity. Municipal and Industrial and agricultural uses were ranked highest by respondents, and less than 20% of respondents believed environmental uses should receive priority, suggesting these non-quantifiable impacts may not have a large effect on overall policy preferences.

3.5.4 Choice Tasks

Attributes, levels, and variable names used in the two surveys appear in Table 2**.** Choice sets were based on an orthogonal, fractional factorial sequential design (Scarpa and Rose, 2008). In the policies survey, respondents were presented with eight choice sets and were asked to identify the most and least preferred options out of three alternative policy portfolios. Each portfolio presented a combination of levels of supply projects, non-price conservation, price increases, and agricultural transfers to meet 100% of the state future water needs. Owing to the balanced design adopted, each individual policy level and each specific combination of policies appeared the same number of times in the survey.

In the impact survey, the fractional factorial design resulted in eight choice sets each containing the 5 identified impacts, at varying levels. Question order was randomized, and respondents were asked to make double-round choices by first picking their most and least-concerning impacts, followed by their second-most and second-least-concerning impacts from remaining options. Sample choice sets for the policies and impact surveys can be seen in Figures 1 and 2, respectively.

3.5.5 Data and Empirical Specification

Each survey was administered to a representative (in terms of age, income, and geographic location) sample of Colorado households using the online survey company Qualtrics. Funds to carry out the survey were provided through a grant from the Colorado Water Conservation Board.

Models for both surveys were estimated for both aggregate and individual-level data. At the aggregate level, max-diff scoring methods (Marley and Philens, 2012) were used to obtain a sample-wide ordering of policy portfolios and impact levels in terms of their importance. Scores are calculated as the square root of the ratio of the number of times a portfolio was chosen most and least-preferred, or the ratio of the number of times an impact (at a given level) was chosen as most- and least-concerning. Using individual-level data, the sequential best worst multinomial logit (SMNL) was estimated, first assuming fixed parameters, and then adopting a random parameter specification (Revelt and Train, 1998) to assess the degree of heterogeneity in preferences. In the policies survey, the empirical specification assumes utility from a portfolio *j* is a (linear) function of the each of the policies that could be used to decrease the volume of agricultural water transfers, parameterized as follows:

$$\mathbf{x}_j{}'\boldsymbol{\beta} = \beta_1 Supply_j + \beta_2 Conserve_j + \beta_3 Price_j \tag{6}$$

In the model for the impact survey, utility is made to be function of the *k* all impacts that may be associated with policy *j,*

$$\begin{aligned}\mathbf{z}_k{}'\boldsymbol{\theta} &= \theta_1 LowAg_k + \theta_2 HighAg_k + \theta_3 LowBase_k + \theta_4 HighBase_k + \theta_5 LowPrice_k \\ &+ \theta_6 HighPrice_k + \theta_7 LowPublic_k + \theta_8 HighPublic_k + \theta_9 LowPrivate_k + \theta_{10} HighPrivate_k\end{aligned} \tag{7}$$

The data is "expanded" for estimation such that each best and worst choice is an observation. An impact level is coded as a dummy variable equal to one if included in the choice set and chosen as most-concerning, whereas the included attribute levels chosen as least concerning are coded with negative values. The dummy variable for the high level of agricultural water transfers (30% decrease in agricultural land) is omitted from the specification for identification purposes; thus ordering of estimated coefficients from smallest to largest represents the extent to which an impact and level is more (or less) concerning than high-level agricultural water transfers. In estimating the non-random SMNL model, standard errors were clustered at the individual level. In the RPL model, all coefficients were assumed to be random and to follow a normal distribution, save for the low base charge impact, which was fixed.[22] Fixing the price/income coefficient in a random parameters model means willingness to pay estimates for follow the same distribution as the parameters of interest (Sillano, Mauricio and de Dios Ortúzar, 2005). The random parameters model was estimated using the user-written program *mixlogit* in Stata (Hole, 2007).

3.5.6 Methods for Comparing Policy and Impact Results

Table 4 shows each portfolio and its direct impacts, which will be used for cross-survey comparison. Results from the two surveys are compared as follows: first, WTP values are calculated for each impact using both the aggregate and individual-level data. At the aggregate level, the max-diff score results are used to find a WTP-type value that reflects the implied cost of each impact at the aggregate level--or, in dollar terms, how much worse (or better) and impact is relative to high levels of ag dry-up. This is accomplished by normalizing scores relative to a single impact and level (here, the $15 base charge), which will have a score of 1. If, for example, the normalization gives HighDryUp a score of 5, this means *HighDryUp* is 5 times as concerning as the $15 charge (*LowBase).* Multiplying value by $15, we would find that the implied cost of *HighDryUp* is $75. As such, the benefits provided by use of the $15 base charge, relative to use of *HighDryUp,* would be $70-$15=$55, essentially the implied cost of low base charges.

Willingness to pay values are also calculated using the RPL model, which allows for estimation of both the mean and standard deviation of WTP. In general, willingness to pay is the marginal utility of the variable of interest divided by the marginal utility of money (Louviere and Islam, 2008). Here, this calculation is complicated by the fact that the marginal utility of money

---

[22] Results are insensitive to whether θ_3 is a fixed or a random coefficient, so we specify the parameter as non-random to facilitate willingness to pay calculations.

is captured by the coefficient associated with a (low-level) increase in base charges ($15). Furthermore, all coefficients in the impact survey are estimated relative to the omitted high-level of water transfers, and respondents choose their most and least-concerning impacts.

In this framework, the willingness to pay calculation becomes

$$\frac{\theta_x}{\theta_{LowBase}} * ImpliedCost(LowBase) \tag{4}$$

where x is the impact of interest. The ratio $\frac{\theta_x}{\theta_{LowBase}}$ is multiplied by the implied cost of low base charges so that the unit for the WTP calculation is dollars, relative to *HighDryUp*, consistent with the estimation of all coefficients relative to *HighDryUp.* Accordingly, positive values for WTP calculations will reflect the dollar value of benefits provided by each impact, relative to fallowing 30% of agricultural land. Additionally, the benefits calculations are used to find the maximum a household would be willing to pay through an impact in order to avoid high levels of fallowing. For instance, if it is found that the benefits associated with a $30 base charge are $5.00, this would mean the household would be willing to pay the $30 charge plus another $5.00 in base charges to avoid the 30% reduction in irrigated agricultural land.

As seen in Table 4, portfolios 1-3 directly correspond with individual impacts. Thus, rankings of WTP for these impacts are compared to rankings for associated portfolios in the policies survey.[23] Additionally, we determine which portfolios are affordable for households by

[23] In the impact survey it was specified that each individual impact could be used to as an alternative meeting 30% of the water supply gap via ag transfers. As such, rankings for portfolios with more than one impact are not necessarily comparable to the sum of willingness to pay for individual impacts; for instance, it can't be said that the WTP for base charges can be doubled for a portfolio with two policies that would increase base charges, as this large overall base charge increase would surely have been ranked lower, relative to water transfers.

comparing predicted costs to the households' maximum willingness to pay for impacts. Any portfolio with a maximum cost less than its actual estimated cost is a viable policy option.

3.6 Results

Results are presented first for the aggregate policy and impact "score" models, followed by individual-level RPL results. Policy portfolios rankings are then compared to impact-implied rankings, followed by discussion of which policy portfolios are actually feasible given the results for WTP (savings) associated with each impact.

3.6.1 Aggregate Results: Policy and Impact Max-diff Score Models

Table 5 shows standardized scores for the policy portfolios. The most-preferred portfolio meets 30% of future demands via supply projects and 30% through non-price conservation, meaning 40% of demand would be met by agricultural water transfers. This portfolio has a standardized score of 494 versus 100 for the 100% ag transfer portfolio, meaning it is roughly five times as preferable. The second-best portfolio uses all policies, including price increases, to further decrease agricultural transfers. The least-preferred portfolio would meet 30% of demand via price increases and 70% with water transfers; the only option considered worse than meeting 100% of demand via water transfers. Overall, Coloradoans seem to support a multi-policy approach aimed at decreasing water transfers and prefer new supply projects relative to non-price conservation.

Table 6 shows overall ordering of impacts from most to least-concerning based on standardized scores. Changes in irrigated land are the most concerning impacts, with respondents believing that low-level of dry-up are 76% as concerning as high levels. High-level price increases (50%) and base charges ($30) are then 58% and 53% as concerning as high levels of dry-up. Changes in private and public landscape are the least-concerning impacts, as both high and low levels for these attributes are less than 20% as concerning to residents as are large-scale agricultural water transfers. Lastly, Table 6 also shows the implied benefits calculated for each impact (Equation 4). All values are positive, meaning they reflect welfare gains provided by each impact if used instead of *HighDryUp.* Changes in landscaping provide the highest benefits, with *PrivateHigh* providing $82.65 in benefits, relative to *HighDryUp.* Change in price increases and base charges provide smaller, but still significant, benefits, with *HighBase* (portfolios 1 and 2) and *LowPrice (*portfolio 3) achieving $45.21 and $32.14 in benefits, respectively.

SMNL and RPL Models

Table 7 shows estimated coefficients and standard errors (in parentheses) for both the SMNL and RPL models estimated for the policies survey. All coefficients are statistically significant at the one percent level of confidence. In both models, a positive coefficient means that including the associated policy increased the probability that a portfolio would be chosen as most-preferred.

Results for the SMNL show inclusion of both supply projects and non-price conservation increased the likelihood of choosing a portfolio as preferred, while price increases decreased it. For the RPL model, both the mean and standard deviation of coefficient estimates are presented. The model has a superior pseudo log-likelihood value and finds statistically significant standard deviations for all estimated coefficients. In fact, standard deviations are larger than coefficient estimates for all policies, implying that the overall ranking of policies varied largely across respondents.

Results for the impact survey SMNL and RPL models are presented in Table 8. For both models, a negative coefficient implies that an impact was less concerning to respondents than the (omitted) *HighAg* variable. All coefficients are statistically significant at a one percent level of confidence and may be directly interpreted in terms of magnitude. As expected, overall rankings of impact importance mirror the aggregated-data results. In both models, the signs of all coefficients are negative, implying all other impacts are less concerning than *HighDryUp. LowAg* is the second most-concerning impact, followed by *HighPrice, HighBase, LowPrice, and LowBase.* The landscaping-related variables are the least-concerning impacts in both models. While the RPL mean coefficient estimates are similar to SMNL coefficient results, the estimated standard deviations in the RPL are large and statistically significant. For *LowAg, HighPrice,* and *HighBase,* the standard deviations are larger than coefficient estimates, implying that some respondents believed these variables to be more concerning than agricultural water transfers. Standard deviations are smaller relative to estimated coefficients for landscaping variables, as the majority of households found these to be the least-concerning impacts.

As with the aggregate model, benefits associated with each impact, relative to *HighDryUp*, are calculated and presented in Table 8, along with the standard deviation of savings calculated in the RPL model. Again, these savings are the WTP calculations that show how much better or worse (in dollar terms) each impact is than a case where demand is met only through ag transfers.

Results for the SMNL model are nearly identical to those found using the aggregate-level data. As such, we focus the discussion on the RPL model, which allow for characterization of heterogeneity in the savings provided by impacts. Again, landscaping variables provide the highest savings relative to ag dry-up and range from \$65.33 (*HighPublic*) to \$88.12 (*LowPrivate*) in the RPL model. *LowDryUp* provides the smallest savings, (\$5.19) and has extremely large standard deviation (\$47.18), implying a great deal of heterogeneity in the savings individuals receive from low levels of dry-up, relative to high levels. *HighPrice* also exhibits strong heterogeneity with an estimated savings of $13.18 and standard deviation of $52.86. *HighBase* and *LowPrice*, which correspond individually to portfolios 1-3 (Table 4) provide savings of $25.88 (st. dev. $34.15) and $43.65 (st. dev. $33.94), respectively. Overall, RPL results show that all impacts provide positive mean savings relative to high-level dry-up; however the distribution of savings estimates is also extremely large for impacts with direct monetary impacts on households, implying a great deal of heterogeneity in the savings associated with each impact.

Lastly, the maximum costs households would be willing to face, in the form of either price increases or base charges, may be calculated using the estimated savings results. Here, we find that the impact *HighBase*, associated with an increase in base charges of $30, provides a savings of $25.88 relative to high levels of dry-up. Thus, the most households would be willing to pay (in the form of base charges) to avoid fallowing 30% of agricultural land is $55.81 per month.

LowPrice (25% increase in price) provides $43.65 of savings relative to *HighDryUp.* Based on households' reported water bills (Table 3), a 25% in use amounts to $10/month for the average household. Thus, the maximum households would be willing to pay in the form of price increases is approximately $53.65. Again, the large standard deviations for these results imply that benefits associated with each impact vary greatly around mean values.

3.6.2 Comparing Policies and Impact Results

Table 9 shows the comparisons between policy portfolio and impact benefit results. Again, the portfolios that would meet 30% of demand via supply projects or non-price conservation (and 70% through ag transfers) can be directly associated with the impact *HighBase.* The 30% Price Increase portfolio corresponds to the *LowPrice* impact. In the policies survey, the 30% supply portfolio is the most-preferred portfolio of the three, and the 30% price portfolio is actually less preferred than the baseline portfolio, where 100% of demand are met through water transfers. In the impact survey, rankings are reversed: *LowPrice* provides the largest benefits, followed by *HighBase* (30% Supply, 30% Non-price conservation), and all impacts are strongly preferred to agricultural water transfers.

Table 9 also shows predicted costs for portfolios, compared to the maximum costs households would be willing pay in the form of each impact. Portfolio 5 would require $30 increases in base charges each for both non-price conservation and supply projects, respectively. Portfolios 6 and 7 would require $30 increases in base charges and 25% increases in prices. The estimated cost of the "double base charge" portfolio 5 is $60, just larger than the maximum acceptable base charge cost of $55.88. Portfolios 6 and 7 also have total estimated costs of $40, well below the maximum acceptable costs for either price increases ($53.65) or base charges ($55.88). Based on these results, it appears that these portfolios that would use two policies are (at least close enough) to households' maximum acceptable costs to be affordable options for households, especially under scenarios where increased charges/fees might be phased in over time. Only Portfolio 8, which would use all policies to meet demand, has a total estimated cost ($70) that is much larger than the acceptable cost for either base charges or price increases. If it is assumed that a household will not bear more than roughly $53.66 in total additional costs (in relation to any policies used) to preserve agricultural land, this portfolio is not a viable option; however, it was the second-highest ranked policy portfolio in the policies survey. As such, it appears that households underestimated the cost of financing non-price conservation programs and supply projects and overstated willingness to use all policies to avoid agricultural water transfers. Overall, large estimated benefits associated with all impacts (relative to ag transfer) show that there is surprisingly large support for non-transfer policies. However, the actual policy mix used to achieve this goal varies when results from the two survey types are compared.

3.7 Conclusions

Comparisons across the surveys show that households do make different choices when decisions are made across policies as a whole, as opposed to policy-related impacts. In the policies survey, portfolios with supply projects and non-price conservation were strongly preferred to those including price increases; however, impact-results show that modest price increases (25%) that could be used to meet water demand provide the largest benefits, relative to decreases in agricultural water transfers, of all the direct impacts. Thus, it appears that households had an aversion to the idea of price increases in the policies survey, but may not have understood how those price increases would impact their individual water bills in comparison with the increased fees used to fund alternatives like new supply projects. Households also supported supply projects relative to non-price conservation, despite the fact that supply projects—under different assumptions regarding how they are to be funded via charges for new versus current residents of the state—may potentially be even more costly than estimated here. As such, providing information on the costs of alternative policies would prove beneficial to households in helping them to select their preferred policy mix. Additionally, households appear to strongly support decreases in both public and private landscaping as an alternative to water transfers and other policies that would impact water bills; this suggests the state could consider more restrictive regulations for landscaping in new developments and use of non-drought watering restrictions as alternatives to water transfers. It should be cautioned, however, RPL model results show that the variance around mean estimates of impact/policy importance is very large, especially for water-bill impacts. As such, there is a large subset of households for whom agricultural water transfers are the preferred option for meeting future water demands.

Despite the differences in policy rankings across the two surveys, respondents exhibit strong preferences for policies that could be used to mitigate water transfers when asked about either policies or impacts. We find that households would be willing to pay up to $55 per month in the form of flat fees or increases in the marginal price of water. This cost exceeds or approaches the actual predicted costs of all policy portfolios that would use two or fewer policies to decrease agricultural water transfers. Furthermore, because benefits calculations are based on the relative rankings of included attributes, they are not sensitive to the absolute value of the costs included in the surveys. Consequently, even if actual household-level costs of policies differ from calculations presented here, it can still be said that any combination of policies used by water managers with a cost less than $55 per month would be supported. This value is quite large, and reflects strong support for alternatives to agricultural water transfers.

These large maximum acceptable costs are somewhat surprising, as is the consistency between the two surveys. These results suggest one of three possibilities: either that households had better information than expected regarding the cost of policies that would preserve agriculture land; that "consumer versus citizen" and "warm-glow"-type effects were present in both surveys; or that the choice of a policies versus impacts-type survey has less of an effect of overall policy rankings than expected. Regardless of which of these is true, results show that both the policies and impacts surveys adequately captures respondents' support for overall policy goals (i.e., avoid agricultural water transfers), though an impacts-type survey may be preferable when one wants to decide the policy mix that should be used to actually achieve them.

Table 3.1: Relating policies to impacts

	Policies			
	30% of "gap" met via supply projects	**30% of gap met via non-price conservation programs**	**30% of gap met via price increases**	**100% of gap met vial agricultural water transfers**
Quantifiable Impacts	$33 increase in base charge on monthly bill	$35 increase in base charge on monthly bill	25% increase in marginal price of water	30% of agricultural land fallowed

Table 3.2: Experimental design, attributes and levels

Polices Survey	**Level 0**	**Level 1**	**Variable Name**
Supply Projects	0%	30%	*Supply*
Non-Price Conservation	0%	30%	*Conserve*
Price Increases	0%	30%	*Price*
Agricultural Transfers	Complement to 100% (10%, 40%, 60%, 100%)		
Impacts Survey	**Level 0**	**Level 1**	**Variable Names (Level 0, Level 1)**
Agricultural land dry up	15%	30%	*LowDry, HighDry*
Price Increase	25%	50%	*LowPrice, HighPrice*
Base Charge Increase	$15	$30	*LowBase, HighBase*
Reduction in Public Landscaping	30%	70%	*LowPublic, HighPublic*
Reduction in Private Landscaping	15%	30%	*LowPrivate, HighPrivate*

Table 3.3: Demographic and water-use information

Characteristic	Range	%Colorado (2012*)	% Policies Survey	% Outcomes Survey
Income	<$25,000	20.7	12.91	12.56
	$25,001-$50,000	23.4	22.07	21.07
	$50,001-$75,000	18.6	22.86	21.66
	$75,001-$100,000	13.1	22.46	22.55
	$100,001-$200,000	19.3	15.86	17.41
	>$200,000	5.0	3.84	4.75
Gender	Male	51.1	49.66	50.74
	Female	49.9	50.34	49.26
Region	Front Range	82	75.07	72.3
	West Slope and Mountains	13.1	10.74	10.68
	Eastern Plains	3	14.19	17.01
Age	21-30	14.4	9.06	10.48
	31-40	14.1	13.3	12.76
	41-50	14.3	13.99	14.84
	51-60	11.9	26.6	27.5
	61-70	9.1	29.26	25.32
	>71	7.4	7.78	9.1
Education	High School	22.4	7.49	6.33
	Some College	22.8	33.69	36.2
	Bachelor's	23.4	22.96	21.56
	Graduate or Professional Degree	13.2	32.02	31.85
	Vocational or Technical Degree	8.1	3.84	4.06
Type of home	Single Family Home	74.2	75.85	75.87
	Multiple Family Home	25.8	1.08	1.68
	Condominium or Townhouse	N/A	12.61	13.25
	Apartment	N/A	9.46	9.2
Owner or Renter	Own	65.9%	79.01	79.72
	Rent	34.1%	20.99	20.28
Average water bill in winter (Nov. to Feb.)	$0-$24.99	22.56	22.75	
	$25-$49.99	35.47	34.82	
	$50-$74.99	15.86	16.42	
	$75-$99.99	4.73	6.53	
	$100 or more	1.38	1.98	
	Do not pay for water	20	17.51	

Table 3.3 Cont.

Characteristic	Range	%Colorado (2012*)	% Policies Survey	% Outcomes Survey
Average water bill in summer (May-Aug.)	$0-$24.99	7.98	7.72	
	$25-$49.99	20.1	18	
	$50-$74.99	19.31	21.56	
	$75-$99.99	15.57	15.43	
	$100 or more	17.04	19.78	
	Do not pay for water	20	17.51	

Table 3.4: Comparing policy portfolio and impact results

		Policy Portfolio			**Impacts**
Portfolio #	**Supply**	**Conservation**	**Price**	**Ag Transfer**	
1	30%	0%	0%	70%	$30 base charge
2	0%	30%	0%	70%	$30 base charge
3	0%	0%	30%	70%	25% price increase
4	*0%*	*0%*	*0%*	*100%*	*0*
5	30%	30%	0%	40%	$30 base charge, +$30 base charge
6	30%	0%	30%	40%	$30 base charge + 25% price increase
7	0%	30%	30%	40%	$30 base charge,+25% price increase
8	30%	30%	30%	10%	$30 base charge, +$30 base charge+25% price increase

Table 3.5: Aggregate results, policies survey

Policy Portfolio				# Times Most-Preferred	# Times Least-Preferred	M-L	Standardized
Supply	**Conservation**	**Price**	**Ag Transfer**				
30%	30%	0%	40%	517	65	452	100.00
30%	30%	30%	10%	464	176	288	57.57
30%	0%	30%	40%	253	172	81	43.00
30%	0%	0%	70%	206	169	37	39.15
0%	30%	30%	40%	186	185	1	35.55
0%	30%	0%	70%	178	427	-249	22.89
0%	0%	0%	100%	153	479	-326	20.04
0%	0%	30%	70%	60	524	-464	12.00

Table 3.6: Aggregate results, impact survey

Attributes and Levels	Most Concerning	Least Concerning	√(M/L)	Standardized Ratio Score	Impact Implied Benefits
Ag Transfer, High (30%)	2391	228	3.24	100	0
Ag Transfer, Low (15%)	1965	320	2.48	0.77	$16.29
Price Increase, High (50%)	1294	362	1.89	0.58	$28.92
Base Charge Increase, High ($30)	752	247	1.74	0.54	$32.14
Price Increase, Low (25%)	631	497	1.13	0.35	$45.21
Base Charge Increase, Low ($15)	331	668	0.70	0.22	$54.43
Reduction in Public Landscaping, High (70%)	315	1091	0.54	0.17	$57.85
Reduction in Public Landscaping, Low (30%)	153	1192	0.36	0.11	$61.71
Reduction in Private Landscaping, High (30%)	151	1637	0.30	0.09	$63.00
Reduction in Private Landscaping, Low (15%)	104	1846	0.24	0.07	$64.29

Table 3.7: SMNL and RPL results, policies survey

	SMNL	**SMNL with Random Parameters**
Variable	Coefficient	Coefficient
Supply	0.836 (0.034)	1.46 (0.063)
Std. Dev.	--------	2.046 (0.058)
Conserve	0.748 (0.032)	1.544 (0.057)
Std. Dev.	--------	1.729 (0.060)
Price	-0.180 (0.040)	-0.272 (0.079)
Std. Dev.	--------	2.757 (0.087)
Pseudo Log Likelihood	-12888.514	-9858.530

*= α 0.10, ** α=0.05, *** α=0.01

Table 3.8: SMNL and RPL results, impact survey

	SMNL	**Impact Benefits, SMNL**	**SMNL with Random Parameters (LowBase Fixed)**	**Impact Benefits, RPL**
Variable	Coefficient		Coefficient	
LowAg	-0.393 (0.030)	$15.26	-0.241 (0.055)	$5.18
Std. Dev.	-------		1.483 (0.063)	$47.18
HighPrice	-0.528 (0.066)	$20.52	-0.381 (0.058)	$13.18
Std. Dev.	-------		1.811 (0.055)	$52.46
HighBase	-0.775 (0.061)	$30.19	-0.897 (0.044)	$25.88
Std. Dev.	-------		1.129 (0.053)	$34.15
LowPrice	-1.122 (0.064)	$43.60	-1.394 (0.046)	$43.65
Std. Dev.	-------		1.165 (0.048)	$33.95
LowBase	-1.401 (0.064)	$54.43	-1.796 (0.038)	$54.43
HighPublic	-1.739 (0.061)	$67.56	-2.226 (0.046)	$65.34
Std. Dev.	-------		1.162 (0.050)	$32.94
LowPublic	-2.050 (0.061)	$79.65	-2.628 (0.043)	$77.72
Std. Dev.	-------		0.692 (0.057)	$11.69
HighPrivate	-2.138 (0.068)	$83.04	-2.723 (0.046)	$82.26
Std. Dev.	-------		0.945 (0.056)	$25.78
LowPrivate	-2.336 (0.069)	$90.76	-2.971 (0.044)	$88.13
Std. Dev.	-------		0.525 (0.128)	$15.62
Pseudo Log Likelihood	-32722.80			

*= α 0.10, ** α=0.05, *** α=0.01

Table 3.9: Comparing policy portfolio and impact results

Policy Portfolio				Impacts	
Supply	**Conservation**	**Price**	**Ag Transfer**		
				Standardized Score (Rank)	**Implied Benefits (Rank)**
30%	0%	0%	70%	1.92 (1)	$25.88(2)
0%	**30%**	0%	70%	1.14 (2)	$25.88(2)
0%	0%	**30%**	70%	0.59 (4)	$43.65 (1)
0%	*0%*	*0%*	*100%*	*1 (3)*	*30% of agricultural land dried up (3)*
"Affordability" Comparisons					
				Actual Cost	**Maximum Willingness to Pay**
30%	30%	0%	40%	$60	<$55.88 base charge
30%	0%	30%	40%	$40 ($30 base charge, $10 in price increases)	<$55.88 base charge, <$53.65 price increases
0%	30%	30%	40%	$40 ($30 base charge, $10 in price increases)	<$55.88 base charge, <$53.65 price increases
30%	30%	30%	10%	$70 ($60 base charges, $10 in price increases)	<$55.88 base charge, <$53.65 price increases

Figure 3.1: Sample choice set for policies survey

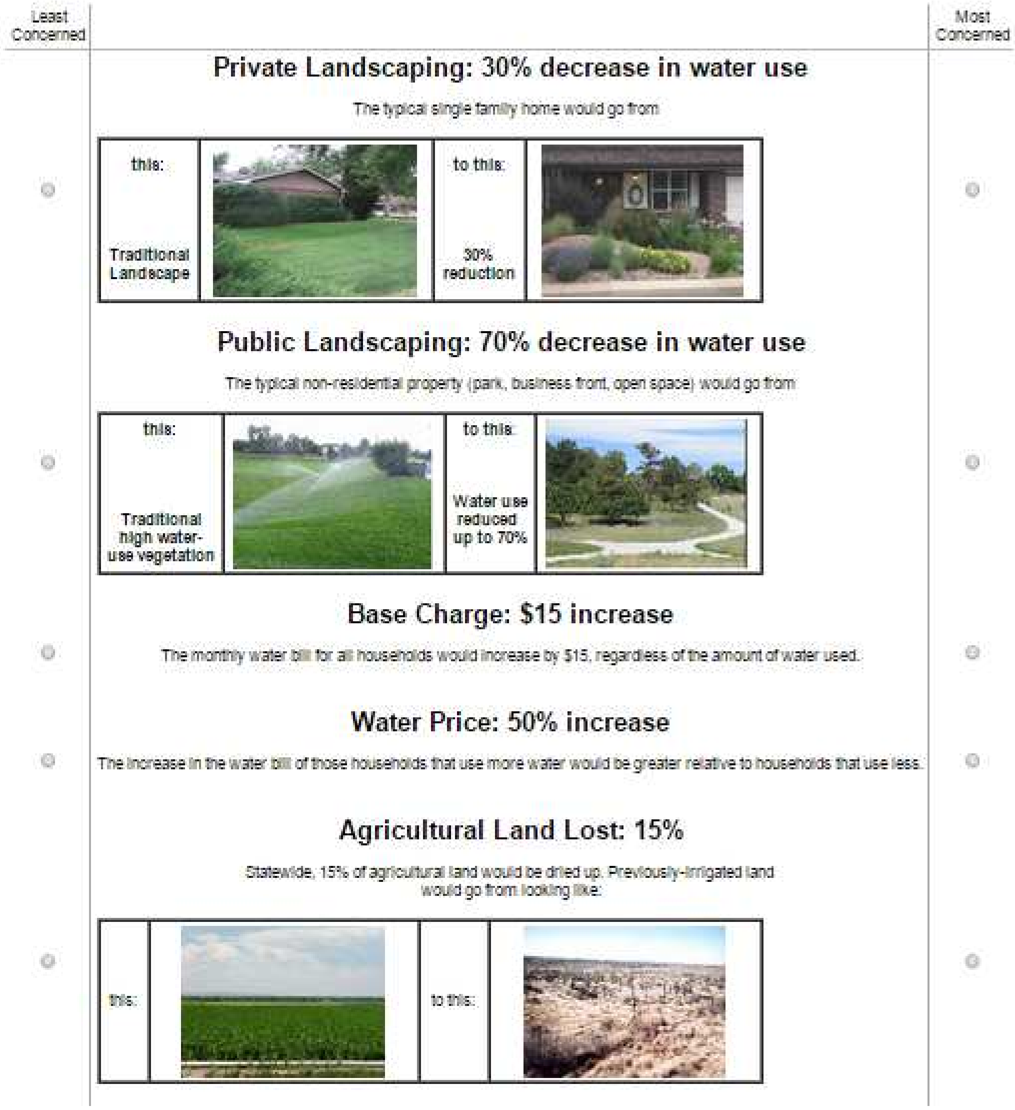

Figure 3.2: Sample choice set for impact survey

REFERENCES

Andreoni, James. "Impure altruism and donations to public goods: a theory of warm-glow giving." *The Economic Journal* (1990): 464-477.

Arbués, Fernando, Marıa Ángeles Garcıa-Valiñas, and Roberto Martınez-Espiñeira. "Estimation of residential water demand: a state-of-the-art review." *The Journal of Socio-Economics* 32, no. 1 (2003): 81-102.

Beasley, Steven D., William G. Workman, and Nancy A. Williams. "Estimating amenity values of urban fringe farmland: A contingent valuation approach." *Growth and Change* 17, no. 4 (1986): 70-78.

Blamey, Russell, Jenny Gordon, and Ross Chapman. "Choice modelling: assessing the environmental values of water supply options." *Australian Journal of Agricultural and Resource Economics* 43, no. 3 (1999): 337-357.

de Best-Waldhober, Marjolein, Dancker Daamen, and André Faaij. "Informed and uninformed public opinions on CO 2 capture and storage technologies in the Netherlands." *International Journal of Greenhouse Gas Control* 3, no. 3 (2009): 322-332.

Boxall, Peter C., Wiktor L. Adamowicz, Joffre Swait, Michael Williams, and Jordan Louviere. "A comparison of stated preference methods for environmental valuation." *Ecological Economics* 18, no. 3 (1996): 243-253.

Fleishman, Lauren A., Wändi Bruine De Bruin, and M. Granger Morgan. "Informed Public Preferences for Electricity Portfolios with CCS and Other Low-Carbon Technologies." *Risk Analysis* 30, no. 9 (2010): 1399-1410.

Flynn, Terry N., Jordan J. Louviere, Tim J. Peters, and Joanna Coast. "Best–worst scaling: what it can do for health care research and how to do it." *Journal of Health Economics* 26, no. 1 (2007): 171-189.

Flynn, Terry N., Jordan J. Louviere, Tim J. Peters, and Joanna Coast. "Estimating preferences for a dermatology consultation using Best-Worst Scaling: Comparison of various methods of analysis." *BMC Medical Research Methodology* 8, no. 1 (2008): 76.

Gilens, Martin. "Political ignorance and collective policy preferences." *American Political Science Association*, vol. 95, no. 02, pp. 379-396. Cambridge University Press, 2001.

Haan, Peter, and Arne Uhlendorff. "Estimation of multinomial logit models with unobserved heterogeneity using maximum simulated likelihood." *The Stata Journal* 6, no.2 (2006): 229-245.

Haider, Wolfgang, and Harun Rasid. "Eliciting public preferences for municipal water supply options." *Environmental Impact Assessment Review* 22, no. 4 (2002): 337-360.

Hanley, Nick, David Bell, and Begona Alvarez-Farizo. "Valuing the benefits of coastal water quality improvements using contingent and real behaviour."*Environmental and Resource Economics* 24, no. 3 (2003): 273-285.

Hensher, David, Nina Shore, and Kenneth Train. "Households' willingness to pay for water service attributes." *Environmental and Resource Economics* 32, no. 4 (2005): 509-531.

Hole, Arne Risa. "Estimating mixed logit models using maximum simulated likelihood." *Stata Journal* 7, no. 3 (2007): 388-401.

Howe, Charles W., and Christopher Goemans. "Water Transfers and Their Impacts: Lessons From Three Colorado Water Markets." *Journal of the American Water Resources Association* 39 (2003): 1055-1065.

Hynes, Stephen, Danny Campbell, and Peter Howley. "A Holistic vs. an Attribute-based

Approach to Agri-Environmental Policy Valuation: Do Welfare Estimates Differ?" *Journal of Agricultural Economics* 62, no. 2 (2011): 305-329.

Keenan, Sean P., Richard S. Krannich, and Michael S. Walker. "Public perceptions of water transfers and markets: Describing differences in water use communities." *Society & Natural Resources* 12, no. 4 (1999): 279-292.

Lancsar, Emily, Jordan Louviere, Cam Donaldson, Gillian Currie, and Leonie Burgess. "Best worst discrete choice experiments in health: Methods and an application." *Social Science & Medicine* 76 (2013): 74-82.

Lancsar, Emily and Jordan J. Louviere. "Estimating individual level discrete choice models and welfare measures using best-worst choice experiments and sequential best-worst MNL." University of Technology, Centre for the Study of Choice (Censoc) (2008): 08-004.

Lusk, Jayson L., Lisa O. House, Carlotta Valli, Sara R. Jaeger, Melissa Moore, J. L. Morrow, and W. Bruce Traill. "Effect of information about benefits of biotechnology on consumer acceptance of genetically modified food: evidence from experimental auctions in the United States, England, and France." *European Review of Agricultural Economics* 31, no. 2 (2004): 179-204.

Loomis, John, Paula Kent, Liz Strange, Kurt Fausch, and Alan Covich. "Measuring the total economic value of restoring ecosystem services in an impaired river basin: results from a contingent valuation survey." *Ecological Economics* 33, no. 1 (2000): 103-117.

Louviere, Jordan J., and Towhidul Islam. "A comparison of importance weights and willingness-to-pay measures derived from choice-based conjoint, constant sum scales and best–worst scaling." *Journal of Business Research* 61, no. 9 (2008): 903-911.

Lee, Julie Anne, Geoffrey N. Soutar, and Jordan Louviere. "Measuring values using best-worst scaling: The LOV example." *Psychology & Marketing* 24, no. 12 (2007): 1043-1058.

Marley, A. A. J., and David Pihlens. "Models of best–worst choice and ranking among multiattribute options (profiles)." *Journal of Mathematical Psychology*56, no. 1 (2012): 24-34.

Marley, Anthony AJ, and Jordan J. Louviere. "Some probabilistic models of best, worst, and best–worst choices." *Journal of Mathematical Psychology* 49, no. 6 (2005): 464-480.

Nunes, Paulo ALD, and Erik Schokkaert. "Identifying the warm glow effect in contingent valuation." *Journal of Environmental Economics and Management* 45, no. 2 (2003): 231-245.

Revelt, David, and Kenneth Train. "Mixed logit with repeated choices: households' choices of appliance efficiency level." *Review of Economics and Statistics* 80, no. 4 (1998): 647-657.

Scarpa, Riccardo, and John M. Rose. "Design efficiency for non-market valuation with choice modelling: how to measure it, what to report and why." *Australian Journal of Agricultural and Resource Economics* 52, no. 3 (2008): 253-282.

Shwom, Rachael, Amy Dan, and Thomas Dietz. "The effects of information and state of residence on climate change policy preferences." *Climatic Change* 90, no. 4 (2008): 343-358.

Sillano, Mauricio, and J. de D. Ortúzar. "Willingness-to-pay estimation with mixed logit models: some new evidence." *Environment and Planning* 37, no. 3 (2005): 525-550.

Train, Kenneth E. "Recreation demand models with taste differences over people." *Land Economics* (1998): 230-239.

Thorvaldson, Jennifer, James Pritchett, and Christopher Goemans. "Western households' water knowledge, preferences, and willingness to pay." *Canadian Journal of Agricultural Economics* 58, no. 4 (2010): 497-514.

Zarnikau, Jay. "Consumer demand for 'green power'and energy efficiency." *Energy Policy* 31, no. 15 (2003): 1661-1672.