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Economic Analysis of Infrastructure Investment and Irrigation Budget Issues in a Southwestern U.S. Water Utility

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DISSERTATION

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Dedication

This is for everyone who believed in me along the way and gave me encouraging words and advice. There is absolutely no way I could have done this without you.

My family: Trisha, James and Cathy, Sally and David, Barby, Jeff and Sarah, Dustin and Carey, Brian and Robyn, Kylie, Christine and Robert, David and Jenny

My friends: Sharon and Gordon, Heidi, Amy and Lee, Debi and Jim, Becky, Courtenay, Leslie, Angely and Jorge, Jeremy, Misty, Kelly, Megan

Most of all, this is for my son, Mateo, who has been a part of the entire process. Bug, we did it!

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ABSTRACT

The three chapters of this dissertation investigate two policy issues faced by water utilities: infrastructure investment and water budget programs. Water utilities have infrastructure that is deteriorating at an increasing rate, necessitating higher rates of investment from ratepayers. At the same time utilities must improve their management of existing water supplies in order to postpone the need to procure water supplies with a higher marginal cost. Water budgets are a way to manage scarce water resources more efficiently.

The first chapter focuses on customer preferences for infrastructure investments. Individuals are willing-to-pay to have fewer outages at home, shorter average outage lengths, greater advance notification, more urban greenspace

irrigated with reuse water, and greater use of renewable energy. The correlated attributes model indicates evidence of adaptive behavior towards longer outages and that individuals who prefer high levels of reuse infrastructure investment also prefer high levels of investment in renewable energy. These results are useful to policymakers who need to raise rates to fund the infrastructure investment gap.

The second chapter studies the impact of model assumptions about the marginal utility of income (MUI) by comparing MWTP distributions from preference-space and WTP-space mixed logit models. In preference-space models, the MUI, whether heterogeneous or fixed, is the denominator of the MWTP ratio. WTP-space models estimate the MUI separately from the attribute coefficients that represent the MWTP. The resulting MWTP distribution using WTP-space estimates has a tighter distribution and no extreme outliers. From a behavioral standpoint, the distribution closely resembles a preference-space fixed cost model.

The third chapter examines the water budget program for irrigation-only customers. Water budgets are a new conservation tool that combine aspects of quantity restrictions with increasing price blocks to encourage efficient water consumption. Excess consumption receives a per-unit surcharge. Private and public sector accounts have significantly different consumption behavior. Price elasticity of demand is estimated as -0.845. Accounts in the 85th and 95th percentiles of water budget use, parks, and multi-family accounts are among the most inelastic. Commercial and home owner associations are the most price responsive. Policy recommendations include focusing on accounts in the middle use tier between 100 and 150% of water budget use and raising the highest surcharge rate.

These papers contribute to the literature by examining new infrastructure investments to increase the use of reuse water irrigating greenspace and renewable energy use. The studies also examine the differences between correlated and uncorrelated attributes models. The final paper contributes by focusing on non-residential water consumption and estimates elasticity of demand for a customer class that only has outdoor water use.

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Chapter 1

Introduction

1.1 Overview

Infrastructure investment and optimal management of water resources are issues for urban water utilities nationwide. Water utilities are facing declining revenue due to conservation at a time when they need greater investment in failing drinking water distribution infrastructure, to comply with environmental regulations, find new sources of water supply and invest in new technologies to optimally use the water they do have. As a natural monopoly industry, water utilities are regulated and cannot set prices in response to market conditions or investment needs. Private water utilities are regulated by state commissions and public or municipal water utilities are self-regulated by a water board. Regulators or rate boards, who set water prices, are typically elected officials who have different incentives than water utility managers. Regulated rate increases have not always kept pace with inflation. As a result, water utility managers cannot reliably use water rates as a tool to encourage optimal water use behaviors or to adequately fund current infrastructure investment needs.

This has been referred to as the infrastructure gap (EPA, 2002).

Federal agencies and industry organizations have been sounding the alarm for the past fifteen years about the state of the nation's infrastructure and the dangers in delaying investment. The American Society of Civil Engineers (ASCE) graded the state of drinking water infrastructure nationwide as a 'D' in the 2013 Report Card for America's Infrastructure (ASCE, 2013). The American Water Works Association warns that delaying infrastructure investment is one possibility, but will result in pipes being stressed beyond their useful lifecycle, more frequent and unplanned breakages, and a repair cost that exceeds the replacement cost. This will be an unsustainable use of water utility resources and could have an adverse impact on public health (AWWA, 2011). The Environmental Protection Agency estimates $385 billion is needed in infrastructure investments through 2030 (EPA, 2013). Investment needs will be sharply higher in the future. Annual investment needed is projected to double from $30 billion to $50 billion by the mid-2040s (AWWA, 2011).

There seems to be little disagreement that ratepayers will pay for the majority of investment costs. According to the ASCE, congressional appropriations to the EPA for infrastructure declined from 2008 through 2012 to an annual average of $1.38 billion (ASCE, 2013). Assuming this is the annual appropriations over the next 20 years, this would only cover 8% of the infrastructure needs identified by the Environmental Protection Agency. Water rates have typically been low in most communities and reflect the average cost instead of the marginal cost of treatment and transport; thus rates do not incorporate the opportunity cost of finding new resources. This has negative implications for both infrastructure investment and optimal resource use. Utilities now will have to impose higher rates or taxes on their customers to pay for the majority of their infrastructure gap.

Optimal management of water supply resources, especially in the face of drought conditions and population growth is an issue for water utility managers. Water utility managers can either procure additional water supplies or maximize the use of their current supply. For water utilities that have already procured all their least costly supplies, accessing new supplies may have a much higher marginal cost. It is less costly to sustainably manage current supplies and reduce water waste.

Demand-side management programs are one tool water utilities use to stretch scarce water supplies, employing both price and non-price conservation programs to achieve their demand reduction goals. Quantity restrictions that mandate a percentage reduction in demand are an example of a non-price conservation policy, while pricing policing work to reduce demand by charging higher rates for higher volumes of use. Water budgets are a new demand-side conservation policy that combine aspects of both types of programs.

This dissertation examines infrastructure investment and water budget programs in the context of the water utility (ABCWUA) serving Albuquerque, New Mexico which is a major metropolitan city in the southwestern United States. Albuquerque is located in the high desert region of central New Mexico where annual precipitation is only nine to ten inches. An underground aquifer was the primary source of water supply for ABCWUA until 2008 when the San Juan Chama (SJC) project was completed. Water is transported through a series of tunnels, diversions, and dams from southern Colorado's San Juan River (part of the Colorado River Basin system) to the Chama River in New Mexico, which is a tributary of the Rio Grande River. Now surface water comprises 80-90% of ABCWUA's water supply. ABCWUA instituted a series of conservation programs to reduce daily per capita water demand to 155 gallons per day as a part of the permit requirements for the SJC project. As a condition of taking surface water from the Rio Grande, ABCWUA must return fifty percent to the river downstream after treating it to environmental standards. This emphasizes the need to account for the consumptive use in their service area to sustainably manage their water supply.

Albuquerque is a representative city in terms of facing failing infrastructure, an infrastructure investment gap, rapid population growth, and changing weather patterns. Between 1990 and 2010 the population increased by 40% to approximately 550,000, although population growth is currently flat.[1] and there have been recurring years of drought in 2006, 2011, and 2013 where large percentages of New Mexico were classified as experiencing extreme to exceptional drought.[2]

In their 2011 Asset Management Plan, ABCWUA acknowledged a backlog of infrastructure repairs and an annual infrastructure gap of approximately $35 million. They projected an annual infrastructure investment need of $76 million over the next century to fully address deteriorating water and wastewater infrastructure (ABCWUA, 2011). There were no operational rate increases between 2004 and 2012 when the governing board of the utility voted for a series of rate increases over the next six years, intending to help with the infrastructure backlog. However, inflationary rates outstripped rate increases.[3] The three main chapters of this dissertation will use various econometric models to address these two issues of infrastructure investment and optimal water resource management using a water budget.

[1]U.S. Census Bureau, American FactFinder website, accessed on April 30, 2015 at http:factfinder.census.gov

[2]Data from U.S. Drought Monitor maintained by the National Drought Mitigation Center at the University of Nebraska-Lincoln. Available at http:droughtmonitor.unl.edu

[3]Between 2000 and 2011, Inflation was approximately 64% while rate increases were around 16%.

1.2 Chapter Two

Chapter 2 focuses on customer's willingness-to-pay for infrastructure investments by estimating a six multinomial and random parameters logit (RPL) models. In particular, this chapter compares the impact on preferences and MWTP from using uncorrelated and correlated attributes RPL models. The study contributes to the water utilities literature by examining preferences for reuse water distribution infrastructure and renewable energy use in addition to drinking water distribution infrastructure. Chapter 2 updates a previous similar study but allows cost to be random and analyzes the differences between estimating uncorrelated and correlated RPL models. From a policy standpoint, practitioners should estimate both models for a complete understanding of preferences while understanding the cause of possible differences in MWTP estimates.

Data used in the analysis are from a choice experiment survey done with a random sample of residential customers of ABCWUA. Water utility infrastructure has very high investment costs and a long planning horizon. Choice experiments present individuals with hypothetical infrastructure investments presented as a choice between alternative investment packages whose descriptive characteristics vary. By choosing one alternative over another, the individual is indicating their preference for that combination of characteristics. As long as cost is one of the alternative's varying characteristics, willingness-to-pay can be estimated, which utilities can use in a benefit-cost analysis during their planning process.

Choice experiments (CE) are a popular method for environmental valuation. The theoretical basis for analysis is the random utility model, which assumes that individuals choose the alternative with attribute levels that maximizes their well-being. Early adopters of CE surveys focused on the benefits from estimating trade-offs between attributes, the marginal utility from a small change in attribute level, and valuing complex scenarios (Adamowicz et al., 1994; Hanley et al., 1998). A basic multinomial logit model was used and heterogeneity was often modeled either through interaction terms between demographic characteristics and attributes or by estimating models for different subgroups and testing for equality of coefficients.

As choice experiments have become more commonly used, econometric methods used for analysis have increased in sophistication. RPL models allow latent preference heterogeneity for attributes, which is indicated through the significance of the standard deviation parameter. Often researchers have assumed that an individual's preferences for attributes were independent. Estimating a correlated attributes structure allows preferences for one attribute to be influenced by preferences for another. Various economists recommend this estimation strategy as more theoretically sound (Scarpa et al., 2008; Hole & Kolstad, 2012). A correlated attributes structure has been shown to improve fit and provide more conservative mean and median estimated MWTP (Colombo et al., 2007; Hess & Rose, 2012; Hole & Kolstad, 2012).

I compare RPL model specifications with correlated and uncorrelated attributes using a normal distribution for the random attributes. Consistent with the literature we find more conservative mean and median MWTP estimates. Results indicate that the correlated attributes models have a greater variance in the MWTP distribution and a greater number of individuals display negative preferences, which causes the more conservative mean and median MWTP estimates. Estimated MWTP values are not significantly different between the two models. Of interest to water utility managers and policymakers are the aggregated MWTP values. When median figures from the uncorrelated model are used to calculate aggregated WTP, the estimated additional monthly amount on the water bill for infrastructure investment is higher in comparison to using median figures from the uncorrelated model. The monthly amounts using estimates from both models are within range of respondents' self-reported level of hardship they would experience in the event of extra monthly amounts charged to a dedicated Infrastructure Fund.

1.3 Chapter Three

Chapter 3 estimates four preference-space and WTP-space mixed logit models to compare each model's assumptions of the marginal utility of income on the resulting MWTP distributions. The marginal utility of income represents the value of an extra dollar to an individual. It is an essential component of marginal willingness-to-pay estimates. In standard preference-space mixed logit models, it is estimated as the coefficient on the cost attribute and then used in the denominator when the MWTP ratio is calculated. In WTP-space models, the MWTP are estimated directly as the coefficients on the non-cost attributes, while the marginal utility of income is estimated separately.

This chapter contributes to the discussion in the growing WTP-space literature about model fit versus preference-space models. An income-validity test is used to compare the characteristics of the distribution of MWTP to MWTP distributions derived under different MUI assumptions in preference-space. Findings indicate that the MWTP distribution from the WTP-space model is notably similar to the distribution from the preference-space model with a fixed cost. Under fixed cost assumptions, heterogeneity of MWTP is reduced. A basic weighting scheme is tested to examine the distribution of social benefits of infrastructure investment.

Preference-space models refer to the standard mixed logit method where estimated coefficients represent an individual's preferences for an attribute. WTP-space models are a re-parameterization of the underlying utility equation in the preference-space model. The two types of models are considered formally equivalent (Train & Weeks, 2005). However, due to the difference in how the marginal utility of income is included, there may be an impact on the resulting MWTP distribution. This has not been investigated.

WTP-space models are a more recent econometric development. Several researchers consider them an improvement because the resulting MWTP distribution does not exhibit the extreme outliers common to MWTP distributions estimated in preference-space. The standard deviations are tighter. Researchers suggest that as a result, the MWTP estimates are more realistic. However, the model fit is typically worse for WTP-space models than preference-space models (Train & Weeks, 2005; Sonnier et al., 2007; Scarpa et al., 2008; Hole & Kolstad, 2012; Scarpa et al., 2012). There is not a clear consensus that one method is preferred.

Three mixed logit preference-space models are estimated under different distributional assumptions for the cost parameter and compared with a mixed logit WTP-space model to understand the behavioral implications of the WTP-space model. Results follow previous studies and find that model fit is better for the preference-space models in comparison to the WTP-space model. However, the distribution from the WTP-space model has no extreme outliers and is much tighter with more conservative MWTP estimates. Findings show that the WTP-space model fails an income validity test; there is little difference in MWTP between low and high income individuals.

1.4 Chapter Four

Chapter 4 addresses the issue of optimal management of water supply resources through ABCWUA's water budget program for irrigation-only customers. The primary contribution to the literature is estimating elasticity of demand and the characteristics that impact the water consumption decision for a non-residential customer class. In addition, water budgets are a relatively new long term conservation program. Baerenklau et al. (2014) studied the impact of a residential water budget program. That paper is the only one focusing on water budgets, to my knowledge.

Water budgets combine aspects of quantity restriction and increasing block rates conservation policies yet preserve customer ability to allocate their water demand to their highest use (Mayer et al., 2008). Quantity restriction and pricing policies by themselves demonstrate equity issues with regards to which customer classes are more affected by conservation requirements. Low income customers are forced to conserve under pricing policies as they cannot afford high marginal rates, while high use customers can bear a greater burden under quantity restrictions Renwick & Archibald (1998); Duke & Ehemann (2004); Duke et al. (2002); S. Olmstead & Stavins (2008). Water budgets allot a specific amount of water to each customer based on their specific characteristics. Water consumption that exceeds the allotted budget amount, is charged at an increasingly higher amount depending on the number of surcharge blocks.

A percentage of water utilities use or are switching to using surface water as a primary or supplemental water supply.[4] With surface water, a utility diverts water from a river, treats it to potable quality, distributes it and then cleans it in a treatment plant before returning the water to the river downstream. In

[4]Examples include the water utilities that service Albuquerque (NM), Fresno (CA), Chicago (IL).

arid regions, legal requirements often specify how much water a utility must return to the river at the end of the service cycle. The difference between what the utility diverts and what it returns at the end of the service cycle is consumptive water use. Irrigation and other outdoor water demands are a part of consumptive use. Optimal management of sustainable consumptive water demand is one aspect of managing scarce water supplies. Conservation policies often target outdoor water demand because its consumptive use nature. Literature has focused primarily on conservation policies for residential demand. I am aware of only one study that addresses water budget conservation policies and it focuses on the residential water budget (Baerenklau et al., 2014).

Data are an unbalanced panel from 2008 through 2013 on 1,107 irrigation-only accounts. ABCWUA and SmartUse provided information on annual water consumption, water budget allotments, account types, location coordinates, and landscape details. Additional data for analysis were gathered from outside sources and mapped to account locations using GIS-techniques.

I address two research questions in this chapter: what characteristics affect water consumption levels and what is the elasticity of demand? For the first research question, I estimate a random effects and an ordered logit model. The random effects model looks at the impact of the past year's water budget use on this year's water budget use. The ordered logit model examines the characteristics that impact the probability of being in a particular consumption level and receiving a surcharge. Findings show that past water consumption has a partial impact on current consumption, implying the ability for accounts to change their irrigating behavior. Of the accounts that exceed the water budget and receive a surcharge, the accounts who only exceed up to 150% of their budget are the most likely to change their behavior. Public/private sector and landscape size impact different consumption decisions.

To address the second research question, I estimate a 2SLS instrumental variables model. I find that overall demand is inelastic, -0.845. When I examine the elasticity for different account groups, parks/golf courses, multi-family, and education accounts emerge as having the most inelastic demand, while commercial, HOA, and government accounts have the most elastic demand. If elasticity is estimated based on the accounts' percentile of water budget use, accounts in the highest percentiles have very inelastic demand. These are the accounts in the 95th percentile or higher. Accounts in the 85th to 95th percentiles also have very inelastic demand but not quite like the 95th percentile group.

1.5 Summary

To summarize, this dissertation examines two issues faced by water utilities today: infrastructure investment spending and optimal management of water supplies. Chapter 2 estimates utility customers' MWTP for three types of investments using a correlated attributes random parameters logit model to more completely understand ratepayers' preferences. Findings show that while this econometric specification fits the data better, it comes at the cost of a larger variance in the MWTP distribution and an increase the the percentage of ratepayers with negative preferences. There are not significant differences between the correlated and uncorrelated MWTP values.

Chapter 3 examines the impact on MWTP estimates of estimating a WTP-space mixed logit model and compares the results with a standard preference-space mixed logit model. WTP-space models are regarded as being an improvement over preference-space models because of smaller standard deviations and a lack of MWTP outliers. However, findings suggest that this might be a result of the separate estimation of the marginal utility of income coefficient. MWTP distributions from the WTP-space model and preference-space model with fixed cost are quite similar.

Finally, Chapter 4 analyzes the water budget program for ABCWUA's irrigation-only customers. Results indicate that there are significant differences between the average water consumption behavior of public and private sector accounts over time. Accounts that have water consumption behavior either within their water budget (efficient) or greater than 150% of their water budget (extreme) are highly likely to repeat the same behavior the following year. Those accounts that have excess water consumption between 100% and 150% of their water budget are more likely to change their consumption pattern. Various elasticities of demand are calculated. Chapter 5 summarizes the dissertation, noting the gaps in the literature, contributions, policy recommendations, and make suggestions for future research.

Chapter 2

Preferences for water utility infrastructure investment using correlated and uncorrelated random parameters logit models

2.1 Introduction

U.S. water utilities face many challenges, but a key one is inadequate investment levels for pipe infrastructure; this could lead to an unreliable water supply (ASCE, 2013). As a result, many water utilities in the U.S. face rapidly deteriorating infrastructure. In 2013, the national state of drinking water infrastructure was rated as a 'D' by the American Society of Civil Engineers (ASCE, 2013). In 1999, the U.S. Environmental Protection Agency (EPA) estimated $225 billion to repair drinking water infrastructure nationwide through 2030; in 2011 the estimate was revised upwards to $384 billion (EPA, 2013).

Challenges in infrastructure funding are partially a result of declining federal funding. Today's drinking water pipe infrastructure was installed 60 to 120 years ago at a time when the federal government largely subsidized installation costs. However, congressional appropriations to the Environmental Protection Agency (EPA) for infrastructure declined from 2008 through 2012 to an annual average of $1.38 billion (ASCE, 2013). If this trend continues over the next 20 years, annual appropriations would cover approximately 8% of the EPA's revised estimate. Future infrastructure projects will likely be paid for by ratepayers through a combination of higher water rates and/or taxes.

The goal of this study is to compare preferences and estimated MWTP for water utility infrastructure investments between correlated and uncorrelated random parameters logit models. Data are from a choice experiment survey conducted with ratepayers in a large southwestern U.S. metropolitan area. Specifically I compare any econometric improvement from estimating a random parameters logit (RPL) model with correlated attributes to the impact on the estimated MWTP distribution necessary to policymakers and water utility managers.

Previous CE surveys in the water utility literature have focused on service levels (Hensher et al., 2005; Willis et al., 2005), water quality (Scarpa et al., 2012; Tarfasa & Brouwer, 2013), drought restrictions (Hensher et al., 2006), and future water supply policy options (Blamey et al., 1999). Blamey et al. (1999) used their survey attributes to refer to possible infrastructure projects. However, to my knowledge, this study is the first to describe the CE scenario in terms of the increased investment in water utility infrastructure projects due to deteriorating pipes and environmental concerns.

Researchers incorporate heterogeneity in water utility studies to allow for possible variation in customer preferences over service levels and to improve the precision of MWTP estimates.[1] Most water utility studies use classical heterogeneity (Blamey et al., 1999; Willis et al., 2005). More recent water utility studies have allowed for unobservable heterogeneity (Hatton MacDonald et al., 2003; Lanz & Provins, 2012; Tarfasa & Brouwer, 2013). Only Scarpa et al. (2012) have incorporated correlated attributes in their study of tap water quality.

Many studies have shown correlated attributes to be an econometric improvement with regards to data fit (Colombo et al., 2007; Scarpa et al., 2008; Hess & Rose, 2012). However, estimated MWTP values are not always significantly different from uncorrelated specifications (Colombo et al., 2007; Scarpa et al., 2012).

This paper provides two contributions to the literature. First, it adds to the water utility literature by looking at preferences for water utility infrastructure investment using a RPL model with correlated attributes. I use a unique dataset from a southwestern U.S. city facing a $35 million annual gap in infrastructure investment. MWTP values are estimated for investment scenarios to consider the investment amount that could be gathered through a five-year Investment Fund charge on ratepayers' monthly water bills. Second, this study adds to the body of literature using correlated attributes models by examining the effect of a correlated attribute specification on the entire MWTP distribution, including extreme outliers and the determinants of MWTP.

Results are robust across all models and indicate that consumers would rather invest in drinking water distribution infrastructure over reuse water distribution infrastructure or renewable energy. Income, education, outage experience and water conservation attitudes strongly influence preferences; how-

[1]This is important since water utility customers are not able to reveal their preference for service levels through their purchasing patterns or selection of a water provider.

ever, latent influences more strongly influence preference heterogeneity for all attributes as seen in the magnitude of the standard deviation. The greatest preference variation exists around investing in renewable energy use by the water utility. The correlated attributes model shows that customers who prefer greater investment in reuse water infrastructure also strongly prefer greater investment in renewable energy use by the utility. The correlated RPL increases the heterogeneity in MWTP through a greater variation in the distribution, including more extreme MWTP outliers with a greater percentage of negative preferences. As a result, the correlated model gives more conservative median MWTP values.

My findings indicate that MWTP estimates from the specification allowing for correlation of attributes are not significantly different from MWTP estimates from an uncorrelated attributes specification due to the increased variance across the MWTP distribution. In my study, median MWTP from a correlated attributes model are between 11-42% less than the median MWTPs from the uncorrelated model. One potential investment scenario indicates that customers are willing-to-pay a monthly amount between $4.95 and $6.50 as an additional charge on their monthly water bill into a dedicated Water Infrastructure Fund for a period of five years to avoid deteriorating distribution infrastructure. These amounts represent aggregated scenario totals using median MWTP values from correlated and uncorrelated models, respectively. The issue of extreme outliers from the correlated attributes model can be avoided yet similar insight towards preferences can be gained from estimating an uncorrelated attributes model with a second stage regression to look at the determinants of MWTP. However, correlated and uncorrelated attributes models are found to be complementary and estimating both can enhance understanding of preferences.

2.2 Literature Review

2.2.1 Water utility literature

Australia, New Zealand, and England lead the United States in using consumer preferences in their water utility regulation processes. In both countries, stated preference methods are used to value water utility attributes in order to justify rate requests to the appropriate regulatory agencies or for cost-benefit analyses of investment projects.

In the mid-1990s, the Council of Australian Governments initiated a series of water utility reforms that changed decision-making regarding levels of customer service and how they are reflected in the price (Hatton MacDonald et al., 2003). As a result, Australian regulatory process requires regulated water utilities to support rate increase requests by demonstrating cost-effective investment decisions that result in improved customer service and are an appropriate level of customer service that reflects consumers' willingness-to-pay (Hatton MacDonald et al., 2003; Hensher et al., 2005). Due to Australia's severe drought of 2003-2012, many choice experiment (CE) and contingent valuation (CV) surveys investigated issues of drought restrictions and water supply (Cooper, Burton, & Crase, 2011).

In the United Kingdom private, regional monopolies provide water and sewage services under public regulation. Various governmental organizations[2] regulate water service standards, drinking water quality, and other water supply issues. Every 5 years, the Office of Water Services (OFWAT) sets prices based on a business plan submitted by the regional suppliers. Water utilities that indicate they will exceed the minimum standards must justify addi-

[2] The Office of Water Services, European Union, UK Drinking Water Inspectorate, and the Environment Agency (Willis et al., 2005)

tional investments using information on customers' preferences (Willis et al., 2005). Specifically, Yorkshire Water utilized CV and CE surveys to conduct a cost-benefit analysis of investment options 40 years out. Their goal was to understand their customers' values of aspects of drinking water quality, drinking water supply, sewerage factors, and additional factors such as renewable energy and meter reading services (Ltd., 2009).

In this literature CE and CV surveys have been used to calculate willingness-to-pay (WTP) estimates for attributes that describe characteristics of urban water supply security, disruptions to water service (Hatton MacDonald et al., 2003; Willis et al., 2005; EFTEC, 2007; Ltd., 2009), source of municipal water supply (Haider & Rasid, 2002), appropriate levels of water utility service (Hatton MacDonald et al., 2003; Willis et al., 2005), water supply options under a population growth scenario (Blamey et al., 1999), and avoiding drought or water restrictions (Hensher et al., 2006; Cooper, Burton, & Crase, 2011).

2.2.2 Preference heterogeneity

Within the water utility literature, classical heterogeneity has most often been used to identify influential characteristics in valuing service level improvements.[3] Various studies have shown income, age, household size, gender, household characteristics, and ethnicity are influential (Hatton MacDonald et al., 2003; Willis et al., 2005; Scarpa et al., 2012; Tarfasa & Brouwer, 2013). This information can be incorporated into business plans, educational campaigns, or to design subsidies. Unobservable heterogeneity as modeled in the RPL is less useful in this context; it provides information on the magnitude of variation in

[3]The infrastructure investment required to achieve various service levels is not explicitly discussed.

preferences but not the underlying cause.

However, in the larger environmental valuation literature the RPL model has become the more common analysis method for choice experiments.[4] Observable characteristics can be interacted with random attributes, which can result in a better statistical fit (Greene & Hensher, 2007). Several water utility studies that have used an RPL model have also included interaction terms to model observed heterogeneity (Hatton MacDonald et al., 2003; Tarfasa & Brouwer, 2013).

Researchers often estimate uncorrelated RPL models that assume individuals' choices and, specifically, the descriptive attributes of an alternative are independent (Balcombe et al., 2009). Uncorrelated models are easier to estimate and model identification is less problematic than with correlated models.[5] However, some researchers have challenged the assumption of independent attributes as unrealistic to decision-making.[6] Scarpa et al. (2008) notes that a correlated attributes structure should be estimated because the confounding, non-constant scale parameter across individuals leads to correlation. The covariance matrix incorporates both scale and standard deviation terms as the off-diagonal terms are a product of the variance of attribute k and the interaction of the two attributes, k and m (Hensher & Greene, 2003). Estimating a correlated attributes specification (*'correlated attributes'*) improves understanding of relationships between individuals' preferences for attributes (Colombo et al.,

[4]Examples include health (Hole, 2008; Hole & Kolstad, 2012), recreation (Scarpa et al., 2008) and transportation (Hess, 2010) economics.

[5]Including a correlation structure increases the number of estimated parameters and introduces issues of model identification and parameter restrictions. The likelihood function can fail to converge due to a flat region at the maximum (Ruud, 1996) or it may converge but have large standard errors or a nearly-singular Hessian matrix, indicating fragile identification (Keane, 1992).

[6]Correlated error structures can be estimated to consider the issue of non-independence across alternative choices, however that is a separate model type that is not discussed in this paper.

2007; Scarpa et al., 2012).

The consensus is that correlated attributes represent an improvement over the uncorrelated attributes with regards to the data fit (Colombo et al., 2007; Scarpa et al., 2008; Hess & Rose, 2012). Hole & Kolstad (2012) consider specifying a random cost parameter and a correlated covariance matrix to be more influential in improving model fit than the difference between WTP-space and preference-space models and Hess & Rose (2012) advocates for a correlated attributes model as a better way to jointly estimate scale and preference heterogeneity.

However, results vary regarding the impact of correlated attributes on estimated coefficients or the statistical moments of the MWTP distribution. Several studies find that models that allow correlated attributes result in a larger magnitude of the estimated mean and standard deviation coefficients compared to those that don't (Colombo et al., 2007), although Scarpa et al. (2008) find only a slight increase. Conversely, Hole & Kolstad (2012) find the correlated attributes result in more conservative estimated mean WTP values. Even when the correlated attributes fit the data better, there are other impacts such as changing significance levels of influential socio-economic characteristics (Colombo et al., 2007) and estimated welfare measures from both models are not always significantly different (Colombo et al., 2007; Scarpa et al., 2012).[7] Finally, the benefit of specifying correlated versus uncorrelated attributes could be situational. An uncorrelated attributes model performed better in a benefit transfer situation when results were compared against a benefit transfer using MNL estimates (Colombo et al., 2007).

This paper will contribute to the discussion over the benefits of estimating

[7] Distributional assumptions for the random parameters can affect the significance of estimated covariance terms (Hole, 2008).

a correlated attributes structure. I compare the impact of specifying correlated and uncorrelated attributes on preferences for water utility infrastructure projects, on MWTP heterogeneity, and on aggregated MWTP for infrastructure investment scenarios. Central statistical moments such as the median MWTP estimates are often used to measure policy benefits because they are often more robust to outliers than mean MWTP. However this minimizes the information contained in the MWTP distribution. Strong outliers at either end of the distribution can influence the median upwards or downwards, possibly over- or under-estimating aggregate policy benefits in the absence of significantly different MWTP values between models.

2.3 Econometric Theory

Both multinomial and random parameters logit models are based on the random utility maximization described by (McFadden, 1974). When individuals make a choice between alternatives of a good, they choose the one that maximizes their utility, U_{in}, represented as $U_{in} = V_{in} + \varepsilon_{in}$. The alternatives are described by a deterministic component, V_{in}, made up of observable attributes, X_{in}, and a stochastic term, ε_{in}, that includes the latent influences on decision-making. The random element is assumed to follow a Type I extreme value distribution; logistic regression is used. The conditional likelihood, L_{in}, of individual n making the choice, y_{in} of alternative i out of all possible choices j is:

$$P_{in}(\beta) = \frac{exp^{\sum \beta X_{in}}}{\sum_{j \in C} exp^{\sum \beta X_{jn}}} \tag{2.1}$$

The conditional likelihood of a choice is a function of the βs, which represent the impact on utility of a marginal change in the attribute. For the basic multinomial logit (MNL) model, maximum likelihood methods are used to analytically solve $L_{in} = \prod_{n \in N} \prod_{i \in I} P_{in}^{y_{in}}$ which gives the likelihood of all the choices I made by survey respondents N. Taking the log gives the unconditional likelihood of choices given the estimated values of β, which are homogeneous across the survey population.

The RPL model decomposes the error term from the MNL model term into $\varepsilon_{in} = \eta_n + \epsilon_{in}$.[8] The error term, ϵ_{in}, is still assumed to follow a Type I extreme value distribution. Individual preferences for an attribute follow a population distribution $\beta_n(\theta)$; the distribution $\theta \sim (b, \Sigma)$ is described by the parameters b and Σ. These parameters describe the population mean and variance, respectively. An individual's unique preference is written $\beta_n = b + \eta_n$, where η_n represents the individual's standard deviation. Now the conditional likelihood of an individual's choice as seen in Equation 2.1 is a function of the parameters of the population distribution: $P_{in}(\beta_n|\theta) = \frac{exp^{\beta_n X_{in}}}{\sum_{j \in C} exp^{\beta_n X_{jn}}}$. This expression is integrated across all possible values of the parameters of the population distribution.[9] The unconditional likelihood of the random parameters model is:

$$L_n(\theta) = \int P(y_n|\beta) f(\beta|\theta) d\beta \tag{2.2}$$

2.3.1 Independent vs. correlated attributes in RPL models

Specifying a correlated attributes structure involves the variance parameter of the population distribution, $\theta(b, \Sigma)$. If independence is assumed, zeros are in the off-diagonal spaces of the variance-covariance matrix, Σ. Assuming a simple model with independent random attributes, the variance-covariance ma-

[8]This decomposition shows how unobservable heterogeneity might be missed in a classical heterogeneity MNL model (Hensher & Greene, 2003).

[9]This integral does not have a mathematical solution; simulation is used.

trix, Σ, appears:

$$\Sigma = \begin{bmatrix} \Sigma_1 & . \\ 0 & \Sigma_2 \end{bmatrix}$$

An individual's standard deviation term, $\eta_n = \Sigma\mu_n$, is a product of the standard deviation from the variance matrix, σ, and a draw from the standard normal deviation, μ_n. In a correlated attributes structure the variance-covariance matrix is Ω. A lower-triangular Cholesky matrix with non-zero off-diagonal elements is estimated such that $\Omega = TT'$.

$$T = \begin{bmatrix} \omega_1 & . \\ \omega_{12} & \omega_2 \end{bmatrix}$$

The individual's standard deviation term is still written $\eta_n = T\mu_n$, but now incorporates the effect of the off-diagonal term ω_{12} as well.

2.3.2 Including the impact of observable attitudes and characteristics

To incorporate preference variation into the MNL model, classical heterogeneity methods are used. Observable characteristics are included through interactions with the attributes, $V_{in} = \beta' X_{in} + \varphi'(z_{in})$. Here z_{in} represents the vector of attribute socio-economic interactions and φ is the vector of coefficients.

2.3.3 Marginal willingness-to-pay (MWTP) estimates

In the MNL model, MWTP for attribute k is calculated as the ratio of the coefficients for attribute k and the $Cost$ attribute:

$$MWTP_k = -\left[\frac{\partial U_i/\partial x_k}{\partial U_i/\partial x_{Cost}}\right] = -\left(\frac{\beta_k}{\beta_{Cost}}\right) \tag{2.3}$$

Observable socio-economic and demographic characteristics are additively included in the equation for MWTP.[10] Confidence intervals around the MWTP are simulated for the MNL estimates using the Krinsky-Robb method (Krinsky & Robb, 1986).

From the RPL model, individual-specific coefficients are estimated conditional on their observed chosen alternatives from the choice questions they faced. Coefficients represent the mean and standard deviation for the percentage of individuals from the overall population who would choose the same. The procedure is described in Train (2009) and coded into Stata 13 for the RPL model by Hole (2007). Greene et al. (2005) consider estimating conditional parameters to more realistically approximate underlying individual preferences.[11] Individual MWTP values can be calculated using Equation 2.3.

Reported confidence intervals for the MNL models use the mean and standard deviation coefficients from the entire population as the point estimates for the Krinsky-Robb simulation over 1000 draws, in this case. The values are ordered and 95% MWTP confidence intervals are reported as the 26th and 975th values. This represents the interval within which I am 95% certain the the true mean MWTP value lies. In contrast, the confidence intervals reported in the RPL model represent the individual-specific conditional MWTP for the individuals at the 5th and 95th percentiles.

[10] $MWTP_k = -\left(\frac{\beta_k + \varphi_g S_n}{\beta_{Cost} + \varphi_{Cost*Inc} Income_n}\right)$

[11] They find approximately 12% of the estimated MWTP values from overall population parameters are outside of the MWTP distribution estimated using individual parameters and suggest estimating individual-level parameters may resolve the issue of unrealistically large MWTP values.

2.4 Survey and Sample

2.4.1 Survey Instrument

The survey application was done with the Albuquerque Bernalillo County Water Utility Authority ('the water utility'), which serves approximately 550,000 customers living in metropolitan Albuquerque, New Mexico. In its recent asset management plan, the water utility acknowledged a $35 million infrastructure funding gap between current investment levels and annual investment needed to address deteriorating infrastructure over the next century. The status quo level of capital infrastructure investment is $41 million annually. Without increased investment, the water utility projects a $300 million backlog in infrastructure projects by 2025, reaching $850 million backlog by 2041 (ABCWUA, 2011). The CE survey was designed to understand customer preferences for infrastructure projects and incorporate them in to the planning process.

The water utility provided a random sample of 1,900 residential water customers.[12] Residential customers were surveyed because they directly receive and pay the water bill; they were primarily homeowners.[13] The survey was extensively tested in 8 focus groups and 18 debriefing interviews with the final survey consisting of 30 questions divided into in four sections.

The first section described the six attributes; the attributes are described in Table 2.1. For each attribute except *Frequency*, the status quo level for all utility customers was presented. For the *Frequency* attribute, respondents were asked how many outages they had experienced at home in the past five years.

[12] An additional 200 residential customers received a mailed pre-test prior to mailing the first survey packet.

[13] Hensher et al. (2005) did not find any significant distinction between renter and owner preferences in single-family housing.

That resulted in an individual status quo.[14] There were six levels for the *Cost* attribute ranging from $0 to $15 per month. Each attribute description also included a relevant question that engaged respondents to relate the attribute to their personal experience.

The second section consisted of four CE questions. Each choice question consisted of a choice between two water utility infrastructure investment packages (See Figure 2.1).[15] A generic choice design was used that allowed for possible attribute interactions between three attributes: *Frequency*, *Length*, and *Notify*. The Choiceff macro was used to generate an efficient design (Kuhfeld, 2010). Each non-cost attribute had three levels to allow for possible non-linearity in the attributes (Kuhfeld, 2010). The full design of 32 choice questions was blocked into 8 survey versions of 4 choice questions each.

The third section involved questions about attitudes towards water conservation, wastewater contaminants, and distribution pipe maintenance on private property. The final section asked demographic questions, including ones about the number of children, percent of property watered in an average summer month, and presence of sensitive populations at home so that I could test if these characteristics were influencing preferences.

Survey administration followed best practices where each survey respondent received up to five contacts (Dillman, 2007).[16] Surveys were available in English and Spanish as well as on-line; eleven percent of recipients responded on-line.

[14]The median of all respondents' outage experience was used as the overall status quo level for analysis.

[15]Respondents were not given a status quo or 'no choice' alternative because the state of distribution infrastructure is not static and a choice of investing zero extra dollars leads to deteriorating distribution infrastructure and lower service levels.

[16]Contacts include a pre-notice letter, an initial survey packet, a reminder postcard and two replacement packets.

2.4.2 Survey Respondents

The response rate was calculated conservatively at 45.8%, according to guidelines set out by the American Association of Public Opinion Research (AAPOR), by assuming all survey addresses were eligible respondents even if their surveys were returned as undeliverable or unclaimed by the post office (AAPOR, 2009).[17] Responses were spread evenly across the eight survey versions.

Table 2.2 provides descriptive statistics. A percentage of survey respondents did not answer various demographic questions used in the analysis; their observations were dropped, leaving 770 households with complete demographic information.[18] The average age of respondents was 53 and 54% were female. The average respondent was more likely to be non-Hispanic (67%). Twenty-nine percent of respondents had a Bachelor's degree, with a few years of college the second most prevalent education level (21%). Respondents had lived at their current address an average of 14 years and had lived in New Mexico an average of 32 years. An overwhelming majority of respondents watered less than half of their property in an average summer month (82%), while three percent didn't water their property at all. Thirty-one percent had children living at home.

Water infrastructure is deteriorating quicker in central Albuquerque as seen in Figure 2.2. Darker colors represent tracts with more pipe breaks reported by the water utility. In the five years prior to the survey, the average respondent lived in a Census tract that experienced 13.4 pipe breaks. Twenty-nine percent lived in Census tracts with zero to five pipe breaks, while fifteen percent lived in Census tracts that experienced 25 breaks or more. Approx-

[17] If I had considered that unknown recipients were not, in fact, eligible responses then the calculated response rate was 48.2% according to AAPOR.

[18] I estimated simpler models that did not use any respondent characteristics. Results were not measurably different.

imately 32% self-reported having experienced at least one outage at home in that time period.

A water conservation support index was created to measure towards four methods of encouraging water conservation: rebates, education, higher rates for higher use, and watering restrictions. Thirty-nine percent had strong water conservation attitudes.[19] Demographics of the survey respondents are compared for two Census populations: owner-occupied housing units only and all residents within the Albuquerque/ Bernalillo County metropolitan area.[20] Overall, the ABCWUA survey homeowners were representative geographically, by age, and by income to Albuquerque/ Bernalillo County homeowners. However, the average survey respondent was more likely to be female, more educated, and non-Hispanic than the average Albuquerque homeowner.[21]

2.5 Empirical model specifications

Empirically I estimate six models.[22] Model 1 is a baseline model that estimates attribute main effects. I estimate three specifications of Model 1: a multinomial logit (MNL1) and two random parameters logit (RPL), one with uncorrelated attributes (RPL-N1u) and one with correlated attributes (RPL-N1c). Model 2 incorporates observable and stated heterogeneity through socio-economic characteristics and attitudinal responses. The same three specifications are es-

[19]The index ranged from 3 to 12. Strong water conservation attitudes meant an index score of 11 or 12 and that at least three methods were considered very acceptable.

[20]Comparison across several Census products is necessary because geographically, while ABCWUA's service area encompasses most of the City of Albuquerque, it excludes parts of the city while including parts of unincorporated Bernalillo County.

[21]Statistical tests were done in comparison with the metropolitan population as well. Results were similar except that age and income were also rejected. Survey respondents were also wealthier and older than the average Albuquerque resident.

[22]All models were estimated in Stata 13.0.

timated: a multinomial logit (MNL2), an RPL with uncorrelated attributes (RPL-N2u) an RPL with correlated attributes (RPL-N2c).

The baseline model (MNL1) reflects the tastes of a representative water utility customer. Despite the limitations and restrictive assumptions of the MNL, it remains a good starting point in estimation and for comparison with subsequent, more complicated models. Estimates can easily be aggregated across the utility service population. The RPL models assume a normal distribution for the five random attributes and a full covariance matrix is estimated for the correlated attributes specification. I am interested in the effects of including correlated attributes and observable heterogeneity.

MNL1 is linear-in-parameters, as is standard in the literature. I estimate main effects for each attribute in the survey and one interaction term between the frequency and length of outages, $\widehat{F * L}$.[23] The deterministic portion of the utility equation for individual n choosing alternative i is:

$$V_{in}^{MNL1} = \beta_1 Freq_i + \beta_2 Length_i + \beta_3 Notify_i + \beta_4 Reuse_i + \beta_5 Green_i + \beta_6 Cost_i + \beta_7 \widehat{F * L} \tag{2.4}$$

I expect the following signs for the attributes: negative for $Freq$, $Length$, and $Cost$, but positive for $Notify$, $Reuse$, and $Green$. Consistent with the literature, this implies that the average customer prefers to avoid additional outages, longer outages, and a higher water bill, but prefers increased use of renewable energy by the water utility, increased use of reuse water to irrigate green spaces, and additional advance notification of planned outages.

Classical heterogeneity includes interactions between individual character-

[23]Often an alternative-specific constant (ASC) term is included to capture latent preferences towards non-status quo alternatives. A significant ASC would be unexpected in a generic model, as it would indicate a preference for Alt A or B, all else equal. I did estimate a specification with an ASC but as expected, the term was insignificant, similar to (Hole, 2008).

istics and attributes. MNL2, RPL-N2U, and RPL-N2C include four characteristics interacted with attributes: *Income*, *NoCollege*, *OutExper*, *Conserve*. Income level is interacted with infrastructure costs ($Cost * Income$)[24], a strong water conservation attitude is interacted with irrigation with reuse water ($Reuse * Conserve$) and renewable energy use by the utility ($Green * Conserve$), past experience with outages at home is interacted with outage frequency in the future ($Freq * OutExp$), and educational attainment is interacted with outage length ($Length * NoCollege$). These terms are included linearly with the indirect utility equation from Equation 2.4. Observable characteristics were selected based on the literature and an iterative process with this data.[25]

The RPL specifications were based on MNL1 and MNL2 with all of the attributes specified as random except $Notify$ and the $Freq * Len$ interaction term.[26] I assume a normal distribution for the five random attributes to minimize the issue of unrealistic MWTP estimates, while acknowledging the potential issue with incorrect sign for the attributes $Freq$, $Length$, and $Cost$.[27]

For the two correlated RPL specifications, I consider the trade-off between an increased number of parameters to estimate, model identification issues, and the potential information gained with regards to preferences from estimating a full covariance matrix. Various researchers have estimated a restricted

[24] Similar to (Greene & Hensher, 2007).

[25] I divided the full dataset into sub-datasets and estimated the model given in Equation 2.4. I tested for differences in scale using the test described by Swait & Louviere (1993). Potential characteristics were tested further. During this process I also considered various interactions for $Notify$; none were found to be significant.

[26] There were convergence issues for specifications with all random attributes or a lognormal cost attribute. This is consistent with previous literature Ruud (1996); Revelt & Train (1998).

[27] Choosing which variables to specify as random and the appropriate distribution is an issue with RPL models. The normal is popular due to its tractability but the assumption of symmetry can lead to theoretically incorrect signs for variables where preferences should be all positive or negative (Hensher & Greene, 2003; Hess, 2010). The lognormal can have difficulty converging but results in the correct signs for variables such as cost (Hess, 2010), although some studies do use assume a normal distribution for cost (Hole, 2008). Balcombe et al. (2009) argues that the normal distribution does not make assumptions about the sign on individuals' preferences.

covariance matrix because the full matrix is too computationally demanding (Train, 1998; Hole & Kolstad, 2012; Scarpa et al., 2012). I estimate a full covariance matrix for the five random attributes while keeping $Notify$ and the demographic interactions fixed; this approach adds an additional 10 parameters to be estimated but provides information on relationships between individuals' preferences over investment combinations.[28]

2.6 Results

Parameter estimates from MLE for the three models in model specification 1 are reported in Table 2.3. The estimates for the three models in model specification 2 are reported in Table 2.4 I first examine preferences for infrastructure investment and secondly, look at how a correlated attributes structure impacts both preferences and the MWTP distribution. In general, preferences are robust across all specifications and substantial heterogeneity, both observable and unobservable, exists. Signs are as expected and coefficients are all statistically significant at the 1% level. Overall the magnitude and order preferences between models is consistent. As measured by the magnitude of the coefficients and estimated MWTP of $Length$ and $Frequency$ compared to $Reuse$ and $Green$, the average customer has stronger preferences for improvements to drinking water distribution infrastructure. She has approximately equal preferences towards investing in reuse water infrastructure to irrigate urban greenspace and investing in increased use of renewable energy to treat water. Allowing a correlated attributes specification does not substantially change the magnitude or ranking of preferences when looking at attribute coefficients.

[28]Only $Green - Reuse$ showing significant levels of correlation in N1c and N2c. I restricted all covariances involving $Length$, $Freq$, and $Cost$ to be 0, re-estimated the N2 model, and did a likelihood-ratio test. The LRT statistic was 28.451 against a X_9^2 statistic of 16.92. I reject the null hypothesis of covariance parameters equal to zero and use the full covariance matrix.

Initial discussion of preferences is based on the specifications from the baseline model (MNL1), which only estimated main effects. Because all attributes were centered on their status quo level for estimation (given in Table 2.1), coefficients are interpreted as an indication that the average customer's is better off or worse off from a one-unit or one percent change from the status quo.[29] The attributes $Cost$, $Length$, $Freq$, and $Freq * Length$ have negative signs indicating the average customer is worse off with increases in infrastructure investment costs, average outage length, and the number of future outages at home.[30] The attributes $Reuse$, $Green$, and $Notify$ all have positive signs. The average ratepayer is better off from increasing levels of Albuquerque greenspace irrigated with reuse water, energy used by the utility generated from renewable resources, and advance notification of outages due to planned maintenance provided by the utility. The same basic results are seen when accounting for classical heterogeneity and latent, random heterogeneity with correlated and uncorrelated attributes.

My results are comparable to other water utility studies that have studied similar attributes. In Hatton MacDonald et al. (2003); Hensher et al. (2005) and Willis et al. (2005), longer and more frequent outages and higher costs negatively impact customer well-being. Blamey et al. (1999) also finds a positive effect to ratepayers from irrigating with reuse water. Hensher et al. (2005) find that advance notification is positive only if provided within a week of the planned outage.

Model MNL2 includes self-reported heterogeneity characteristics interacted

[29]For the attribute $Freq$, 0 outages were used as the status quo level for the analysis based on respondents' self-reported level of outages experienced at home. The mean number of outages experienced by respondents prior to the survey was 0.63, while the median number was zero.

[30]The interpretation of the negative $Freq * Length$ term is that individuals also consider these attributes together and that outages at home that are longer and more frequent leave the customer even worse off.

with attributes, showing that there exists explainable variation in preferences. Interaction coefficients are all positive and highly significant at the 1% level. Having a higher income diminishes the negative impact of higher costs. Individuals with a high school diploma or less experience less of a negative impact with longer average outages than those with at least some years of college. Individuals who self-reported having previously experienced an outage at home were less negatively impacted by longer outages than those who had not previously experienced an outage, suggesting that they had acquired skills in dealing with outages or found out it was not as bad as expected. This result is similar to Hensher et al. (2005) who conclude that ratepayers employ adaptive strategies after experiencing outages.[31] Strong water conservation attitudes increase the positive impact from increases in the use of reuse water for irrigation and renewable energy use. The sign on these interactions is generally as expected, signaling the validity of the estimated results.

The four RPL specifications (N1u, N1c, N2u, and N2c) have similar signs and significance levels on the mean and standard deviation coefficients. The standard deviation coefficients are large in comparison to the population mean. In all RPL models, the ratio of the mean to the standard deviation is less than one for all attributes except $Length$, indicating significant latent heterogeneity. Even N2u and N2c still display quite large standard deviations indicating observable characteristics and attitudes do not account for a significant portion of the preference variation.

In the four RPL specifications, between 5-10% of coefficients for $Freq$ and 1-2% of coefficients for $Length$ are positive (theoretically incorrect) due to distributional assumptions. I interpret this as a sign that the individual is cost-sensitive and prefers adaptive behavior to deteriorating service conditions or

[31] In contrast, Hatton MacDonald et al. (2003) found that previous experience of outages insignificant.

are indifferent, not that they prefer more frequent or longer outages. With an essential good such as water, individuals cannot decide to forgo it in the face of rising costs for improved service. These individuals should have a theoretically-correct sign on $Cost$. Something similar happens with the $Cost$ coefficients although this is another extreme type of customer. One to ten percent of individuals have a positive cost coefficient, which is informative of price insensitive customers, likely high income (Lanz & Provins, 2013). However I expect them to display the correct sign on $Length$ and $Freq$. Both of these customer types will end up with incorrectly-signed MWTP estimates, with the latter more likely reflected in outliers on the positive end of the MWTP distribution due to extremely small, positive cost coefficients. For all three attributes, the two correlated attributes specifications display higher percentages of incorrectly-signed coefficients.

N1c and N2c show the effect of allowing for correlated attributes. The estimated covariance matrices for N1c and N2c are reported in Table 2.5. A positive correlation indicates that individuals who like high levels of one attribute, also prefer high levels of the other attribute (Colombo et al., 2007).[32] Several significant correlations occur in both N1c and N2c, indicating that the observed attitudes or characteristics were not the cause of the initial correlation pattern in N1c. $Green$ and $Reuse$ exhibit strong positive correlation. Individuals who prefer greater investment in reuse water infrastructure also prefer increased investment in the use of renewable energy to treat and distribute water. $Length$ is negatively correlated with $Cost$, indicating that individuals who highly value lower costs on their water bill, are willing to forgo investments in distribution infrastructure that would reduce the average outage length. Other correlations only occur in N2c, such as $Length$ and $Reuse$, which show a weak positive

[32] Train (1998) also interprets positive correlations as individuals placing above average emphasis on those attributes in comparison to other descriptive attributes. He suggests that this implies individuals values those attributes together.

correlation.

Likelihood ratio tests indicate that including respondent characteristics and allowing for a correlated attribute structure both improve the model fit. Overall the best fitting model is N2c, which includes unobservable characteristics and allows for correlated attributes.

Table 2.6 and Table 2.7 report monthly mean and median MWTP for all six specifications. For Model MNL1, MWTP values are calculated using the point estimates from Table 2.3; 95% confidence intervals are calculated using the Krinsky-Robb procedure (Krinsky & Robb, 1986). For the RPL models, individual conditional β's were generated using the procedure described by Train (2009).[33] The estimated MWTP values for all the survey ratepayers forms the MWTP distribution for the survey population. Results from the baseline MNL1 indicate the median ratepayer is willing-to-pay an extra $\$0.17$ per month into a dedicated Infrastructure Investment Fund to increase by 1% the amount of urban greenspace irrigated with reuse water above the current 25%. She is willing-to-pay $\$0.13$ per month for a one percent increase in the amount renewable energy use by the water utility above the current 20% and $\$0.07$ per month for a 1% increase in advance notification of outages due to planned maintenance above the current 70%. She is willing-to-pay $\$0.71$ to avoid a one-hour increase in the average length of an outage across all customers from the current 3 hours and $\$0.78$ to avoid experiencing an additional outage at home over the next five years.[34] The MWTP values for the $Length$, $Freq$, and $Reuse$ at-

[33] An individual's preferences are located somewhere on the distribution of population preferences. When her other choices are also considered, then that provides a narrower distribution of preferences around a section of the population preferences. Bayes' Rule connects the two. The product of the probability of an individual's series of choices conditional on the population distribution and the function describing their conditional preferences is set equal to the product of the probability of an individual's series of choices conditional on their preferences and the function describing the population preferences. Rearranging solves for the individual's conditional preference distribution.

[34] Estimated coefficients represent customers' preferences for a one-percent change in the

tributes refer to paying for the necessary distribution infrastructure to achieve a one-unit change in each attribute so are indirectly comparable although they are described in different units.

As observable characteristics and latent heterogeneity, both correlated and uncorrelated are added, the effect on the distribution of the MWTP can been seen primarily through the mean MWTP. As would be expected, the median is less influenced by outliers. Still, it is apparent that the median MWTP from the RPL models are more conservative than those from the MNL models, even falling outside the 95% confidence intervals for MNL1. This is likely a result of the normal distribution for the random parameters, which now allows for a percentage of the respondents to have negative preferences towards certain infrastructure investments or to be price insensitive. Within the RPL models, the median MWTP from the two correlated specifications is more conservative still, similar to Train (1998). One result of the correlated attributes specification is that a greater percentage of individuals have negative willingness-to-pay values.[35] Furthermore, the distribution of estimated MWTP from the correlated specifications is seen to have a greater variance with more extreme outliers, as will be discussed. This makes the resulting MWTP less useful in policy applications and offsets the econometric improvement from estimating a correlated specification.

The impact on the MWTP distribution from a correlated attributes structure is examined using a quantile approach, as recommended by Scarpa et al. (2012) since quantiles are robust to outliers. Table 2.8 provides the unadjusted

attribute. For instance, $\beta_{Length} = \left[\frac{Length-3}{100}\right]$. MWTP$_{Length}$ is calculated as $\frac{\beta_{Length}/100}{\beta_{Cost}}$. Dividing the coefficient by 100 returns the interpretation to the original units describing the attribute.

[35] Negative MWTP values can be a result of a positive $Cost$ coefficient or a negative numerator coefficient in the MWTP ratio. If it the former, then the individual is price insensitive but has positive preferences towards the attribute. In the case of the latter, the individual has negative preferences towards the attribute.

distributions for the $Length$, and Table 2.9 for the $Frequency$ attributes.[36] Estimated MWTP by quantile is reported for the all models following the method in Campbell et al. (2014), without standard errors or confidence intervals. The distribution is initially characterized by examining the interquartile range (IQR), defined as the central spread between the 25th and 75th percentiles. The IQR is more dispersed for the correlated specifications of both N1 and N2, indicating a less peaked distribution of MWTP values. Gray boxes highlight the negative values from each specification, confirming the greater percentage of negative MWTP values in the correlated specifications.

2.6.1 Impact of correlated attributes on MWTP determinants

I also look at the determinants of estimated MWTP for two attributes, $Freq$ and $Length$, to consider the impact of estimating a correlated attributes specification. This is one method to test validity of the results (Scarpa et al., 2011). Because of the issue with extreme outliers for the correlated specification, I remove 5% of the outliers on each end of the MWTP distributions of N2u and N2c. This allows us to examine the impact of a correlated attributes specification on the determinants of MWTP for the majority of water utility customers.[37] The dependent variable, $MWTP_{nk}$, represents ratepayer n's estimated MWTP for attribute k and is regressed on a vector of explanatory socio-economic variables.[38] Table 2.10 lists the explanatory characteristics and the results of the four regressions.

[36] No extreme outlier values were dropped.

[37] Campbell (2007); Scarpa et al. (2011) use this procedure to look at what characteristics influence MWTP.

[38] $MWTP_{nk} = \beta_0 + \beta_1 Income + \beta_2 Female + \beta_3 Hispanic + \beta_4 NearbyOutages + \beta_5 West + \beta_6 SouthSE$

Results indicate living in an area of Albuquerque with more rapidly deteriorating distribution infrastructure, *NearbyOutages*, increases the estimated MWTP to avoid more frequent outages and longer outages than living in areas where pipe breaks are not as frequent.[39] The results of the OLS regression on the MWTP distributions in N2u and N2c for $Freq$ and $Length$ indicate that an individual living in a high break area has an estimated MWTP to avoid an additional outage that is $\$0.31$ (N2u) and $\$0.51$ (N2c) higher than the estimated MWTP for someone who lives in a low break area. This individual also has an estimated MWTP to avoid a longer outage that is $\$0.21$ (N2u) and $\$0.63$ (N2c) higher than the estimated MWTP of an individual who lives in a low break area. The results indicate that living in a high break area has a greater impact on MWTP in the distribution from the correlated model.

Income is also a significant determinant of MWTP to avoid more frequent outages in both the uncorrelated and correlated specifications. I expect this given that the $Cost * Income$ interaction term was significant in the analysis. The estimated MWTP distribution in the N2u specification indicates that as income increases categorically, estimated MWTP increases by $\$0.07$. But the results in N2c are contradictory; the sign on $Income$ is negative meaning that MWTP to avoid one additional outage decreases by $\$-0.08$ as income increases, so that an individual with a total household income of $\$220,000$ has an estimated MWTP that is $\$0.56$ less than an individual with a total household income of $\$18,000$. By dropping the extreme outliers, which usually are a result of near-zero marginal utility of income coefficients for higher income individuals the relationship between income and MWTP appears to be theoretically incorrect and would fail a validity test. This is a trade-off of using the correlated

[39] ArcMap GIS software was used to geocode the location of each individual's address. The water utility provided GIS files of the distribution system with pipe breaks between 1995-2009 already geocoded. I created a half mile buffer zone around each individual's location and did a $Count$ of all the breaks that fell within each buffer zone.

specification. It also could reflect the higher percentage of negative values in the correlated specification. Even with the extreme five percent dropped, approximately ten to twenty percent of MWTP values in the correlated specification are negative and could be related to higher income individuals.

Finally, several characteristics that were weak determinants of estimated MWTP in N2u were female and living in south Albuquerque ($Freq$) and income and Hispanic ($Length$); these were not significant determinants of estimated MWTP from the N2c specification.[40]

2.7 Discussion and Implications

One goal of the study was to examine if estimating a correlated attributes structure would improve general understanding of preferences and how it would impact the MWTP distribution. This has an implicit goal of understanding if more is gained by the improved econometrics than is lost from the cost in modeling. Similar to the literature, I find that the correlated attributes result in an slightly better model fit and offers some insight into ratepayers' preferences for combinations of attributes together.

However, the correlated attributes model also results in an increased spread of the MWTP distribution, a greater percentage of negative MWTP values, and more extreme negative MWTP outliers. Estimating the determinants of MWTP indicates socio-economic groups that have significantly different WTP for service level improvements. However, as a result of the extreme outliers in the

[40] In the initial stages of analysis I tested for preference variation due to demographic and attitudinal characteristics by estimating a main effects model on sub-datasets, calculating 95% confidence intervals using the Krinsky-Robb method and graphing them to display overlaps. Results suggested that Income and Hispanic characteristics had varying preferences, but Gender did not. I tested for varying preferences among regions of Albuquerque and failed to reject the hypothesis of similar preferences, but was using four regions instead of three.

correlated attributes model, ten percent of the MWTP distribution must be dropped in order to analyze the determinants of MWTP. Significant determinants of MWTP are found to be living in an area with deteriorating infrastructure and income, but the sign on the coefficient for income is negative in N2c which is hard to believe. It may reflect that under the correlated attributes structure the individual cost coefficients very near to zero increased reflecting the covariance term in the individual's standard deviation. These are likely high income individuals who subsequently have extreme MWTP for an attribute. These are the observations that were dropped. Alternatively, it could be due to the increase in negative MWTP values even with five percent of the most extreme negative outliers dropped.

When calculating societal willingness-to-pay for policy scenarios, the increase in negative MWTP values results in more conservative median MWTP. I calculate willingness-to-pay for a hypothetical policy scenario that focuses on improving drinking water distribution infrastructure and compare the effect on monthly bills using median MWTP from correlated and uncorrelated specifications.[41]

The Cost attribute in the survey was described as the amount that would be paid into a dedicated Infrastructure Investment Fund over the course of five years. Table 2.11 estimates the amount that would be collected from approximately 179,000 single-family residential customers over the course of the investment fund for a 1% or 1-unit change in the infrastructure project, using median figures from each model. For the random attributes, the correlated estimates are between 11% and 42% smaller than the uncorrelated model estimates. This represents quite a difference if calculating willingness-to-pay for a larger increase such as a 10% increase in reuse water infrastructure or to avoid

[41]The water utility in Albuquerque, New Mexico reports an increased need for infrastructure investment in upcoming decades in their 2011 Asset Management Plan.

a 3-hour increase in the average length of an outage.

These lower estimates when using the correlated MWTP results come from the covariance elements which are included in the standard deviation term in each individual's unique β_n. Many of the covariances were not significant. I calculated a LRT between a model with only the significant covariances and one with all covariances; the LRT statistic failed to reject the null hypothesis that the limited model was an improvement. Thus I report results from model with all covariances. Perhaps if the other model results were used, there would be a smaller percentage of negative extreme outliers. The correlation structure results in a more spread out MWTP distribution. And for some individuals, the correlation moves them from the positive side of the distribution to the negative side. The existence of more extreme outliers indicates that a greater number of individuals have a cost coefficient very close to zero in the correlated specifications. However, an individual's marginal utility of income is dependent on their pattern of choices and so it this issue of more extreme outliers may not be as much of an issue in other datasets. But the analyst should be aware of the possibility.

A policy scenario was created to compare the estimated monthly amount per ratepayer for investment in drinking water distribution infrastructure between uncorrelated and correlated attributes models (see Table 2.12). Policy totals are calculated and the monthly impact on individual ratepayer accounts is calculated for validation with the self-reported hardships. The monthly bill impact assumes equitable division of the policy scenario costs without accounting for any subsidy to low income ratepayers. The hypothetical policy scenario focuses on drinking water infrastructure since preferences were stronger for those investments. The monthly impact on ratepayers under an equity scenario is $\$4.95$ using results from the correlated model and $\$6.50$ with uncorrelated model results. This is well within the bounds of the *Cost* attribute that individuals saw in the survey.[42] These amounts also correspond to individuals' perception of the hardship their household would experience when faced with an increase in their water bill due to infrastructure investment.[43] This suggests these hypothetical policy scenario funds realistically correspond to what individuals could actually pay. In addition, this suggests that a redistribution of the funding for infrastructure investment needs could likely be accomplished based on income levels in an equitable and efficient manner.

Finally, the utility prefers the greater initial investment in Scenario 4 but considers the more gradual investment increase in Scenario 6 more feasible for ratepayers even though it does not totally eliminate the backlog (ABCWUA, 2011). In the first five years of these two scenarios, the extra amount collected is \$45 and \$33.75 million, respectively. While the funding scenarios described in the Asset Management Plan use a different timeframe than the 5-year Investment Infrastructure Fund, the results can still provide guidance in what ratepayers are willing-to-pay to avoid deteriorating drinking water distribution infrastructure and that perhaps the water utility could pursue a funding plan that has a greater increase in investment in earlier years. The hypothetical policy collects between \$53 and \$70 million depending on the model results over the same five year period and keeps the monthly Infrastructure Fund charge at an amount that does not cause undue hardship for the majority. Only 8% of respondents reported that an additional \$5 on their monthly water bill would cause moderate or great hardship. The majority of these individuals are low income, which might provide guidance in designing subsidies for this portion of ratepayers.

[42] The *Cost* attribute ranged from \$0 to \$15.

[43] Only one quarter of low income individuals and seven percent of high income individuals report moderate to great hardship with an increase of \$5 in their monthly water bill.

2.8 Conclusion

In my empirical study of the impact of using correlated models on preferences, I find that ratepayers have robust preferences across uncorrelated and correlated specifications. Significant unexplained preference variation exists as measured by the standard deviation, although income, lacking any college education, previous experience with outages at home, and strong water conservation attitudes do influence preferences for specific attributes. I examine the impact of using a correlated attribute structure on preferences and the entire MWTP distribution. In the best fitting model that includes the influence of observable characteristics, the correlated attributes structure indicates that individuals who are more cost sensitive also display adaptive behavior towards longer outages. Investing in reuse water infrastructure and investing to avoid longer outages in drinking water distribution infrastructure are weakly seen as substitute investments by individuals. Correspondingly, individuals who favor high levels of renewable energy investment, also strongly favor investment in reuse water.

The second goal of the analysis was to examine the impact of a correlated attributes specification on the MWTP distribution. For my data, incorporating a correlated attributes structure increases the spread of the MWTP distribution. Median MWTP values from the correlated models are significantly more conservative than the homogeneous model, however not always significantly different from the uncorrelated versions. Including observable characteristics does not significantly change the estimated median MWTP. However, for the $Length$ attribute the median from N2u with observed heterogeneity was not very different from the median in N2c when correlated attributes were estimated. It could be that estimating observable heterogeneity can be undertaken instead of a correlated attributes.

The biggest concern with the correlated attributes specification is the increase in magnitude and number of extreme outliers, especially on the negative end. The perceived level of support for most attributes decreases as a greater percentage of individuals have negative MWTP. These two issues impact the median values for all attributes, resulting in much more conservative median values. To effectively use a Stage 2 analysis of the MWTP determinants, 10% of observations must be dropped from the correlated attributes model due to the extreme outliers.

Finally I estimate a policy scenario to compare aggregated results against the water utility's stated estimate of upcoming annual drinking water distribution renewal needs and find that they are comparable. There is a distinct difference between the funding amount suggested by the two models because of the more conservative values in the correlated specification. In considering the impact of using correlated RPL models, consistently in the literature and in this study too, they provide a better fit to the data. The information provided by the correlation matrix is useful to policymakers and improves the understanding of preferences. However, these models are more computationally demanding, have greater issues with convergence, and are problematic with regards to extreme negative outliers. Estimating an uncorrelated specification with a second stage analysis of the determinants of the MWTP distribution is a valid alternative to estimating a correlated attributes model. Water utility practitioners should be aware of the challenges and implications of estimating a correlated attributes model. Estimating both correlated and uncorrelated models can complement each other and provide additional information with regards to MWTP.

Table 2.1: Survey Attributes

Attributes	Description	Model specification[a]	Levels[b]
Main effects attributes			
Freq	Frequency of outages the ratepayer experiences at his home over next 5 years	(Freq - 0)/100	**0**, 5, 10
Length	Average length, in hours, of outages for all water utility customers	(Length - 3)/100	**3**, 8, 15
Reuse	Percent of urban greenspace irrigatedby reuse water	(Reuse - 25)/100]	**25**, 45, 65
Green	Percent of energy used by utility from renewable sources	(Green - 20)/100	**20**, 40, 60
Notify	Percent of time ratepayers receive advance notification of outages due to planned maintenance	(Notify - 70)/100	20, **70**, 90
Cost	Additional amount ($) on monthly bill for the next 5 years		**0**, 2, 6, 10, 12, 15
Interaction effect			
$\widehat{Freq * Len}$	Interaction term between Length and Frequency. Attributes centered on their mean mean to minimize collinearity.	(Len-8.6)*(Freq-5.2)	

[a] For model estimation, variables were created to represent the percentage change in the attribute from the status quo level.
[b] Status quo level is in bold. Each respondent was asked for their own individual status quo level of outages experienced. The median level of outages experienced was 0 for 69% of respondents; mean was 0.63. The median value was used.

Table 2.2: Demographic and Attitudinal Characteristics

Characteristic	Description	Survey respondents	Albuquerque metro (owner-occupied)[a]
Income	Pre-tax income, continuous[b]. Divided by $1,000,000 in analysis	$40,000-$59,999	$47,989 ($50,000-$74,999)
NoCollege	Individual a HS Diploma/ GED or less schooling; 1=yes; 0 = some college	15.1%	36.0% (30.9%)
OutExper[c]	Individual had at least one home outage between 2004-09; 1 = one or more; 0 = no outages	30.6%	–
Conserve[d]	Individual has high water conservation index of 11-12; 1 = yes; 0 = else	38.7%	–

[a] Within the Albuquerque metro 63.1% of housing units were owner-occupied (2010 Census & 2006-2010 ACS 5-year estimates), exclusive of multi-family housing.
[b] Income was categorical. For analysis, category mid-point was used. Income for highest and lowest categories are 10% above and below the cutoff points, respectively. Categories: ($\leqslant$ $19,999); ($20,000-$39,999); ($40,000-$59,999); ($60,000-$99,999); ($100,000-$149,999); ($150,000-$199,999); ($\geqslant$ $200,000).
[c] Non-responses (17.4%) were imputed with a value close to the median, 0.001. These observations were not dropped from the analysis.
[d] Strong conservation index was calculated by adding Likert score rating acceptability from [1,3] for each of following conservation methods: (i) higher rates for high use levels; (ii) water education programs; (iii) required conservation/restrictions; (iv) rebates

Table 2.3: Results Model Specification 1

Variable	Parameter description	**MNL1** Coeff. (se)	**RPL-N1u**[a] Coeff. (se)	**RPL-N1c**[a] Coeff. (se)
Freq	Mean coefficient	-8.362***	-24.17***	-20.28***
		(0.666)	(4.21)	(2.78)
Freq_SD	S.d.(coefficient)		30.63***	28.09***
			(6.27)	(5.22)
Length	Mean coefficient	-7.601***	-23.88***	-20.88***
		(0.566)	(4.10)	(3.05)
Length_SD	S.d.(coefficient)		18.14***	19.07***
			(4.59)	(3.46)
Freq*Length	Mean coefficient	-0.004***	-0.009**	-0.007*
		(0.0014)	(0.004)	(0.004)
Green	Mean coefficient	1.427***	4.20***	4.48***
		(0.166)	(0.84)	(0.86)
Green_SD	S.d.(coefficient)		9.16***	7.81***
			(1.73)	(1.34)
Reuse	Mean coefficient	1.766***	4.75***	3.91***
		(0.154)	(0.83)	(0.60)
Reuse_SD	S.d.(coefficient)		6.28***	5.59***
			(1.39)	(1.05)
Notify	Mean coefficient	0.703***	2.09***	2.21***
		(0.086)	(0.39)	(0.35)
Cost	Mean coefficient	-0.107***	-0.32***	-0.27***
		(0.006)	(0.05)	(0.04)
Cost_SD	S.d.(coefficient)		0.34***	0.34***
			(0.06)	(0.05)
LL:		-1618.1579	-1515.7806	-1498.1024
BIC score[b]		3292.4115	3127.725	3172.506
No. parameters		7	12	22
Obs.		3022	3022	3022

[a] Model N1: normal distribution (Grn, Reu, Len, Freq, Cost), 500 Halton draws.
Significance levels: * $\leqslant$0.10,** $\leqslant$0.05,*** $\leqslant$0.01
[b] The BIC information criterion is used to compare model fit as it includes
the number of observations.

Table 2.4: Results Model Specification 2

Variable	Parameter description	**MNL2** Coeff. (se)	**RPL-N2u**[a] Coeff. (se)	**RPL-N2c** Coeff. (se)
Freq	Mean coefficient	-10.096***	-28.27***	-24.81***
		(0.936)	(4.93)	(3.84)
Freq_SD	S.d.(coefficient)		31.49***	26.44***
			(6.83)	(5.00)
Length	Mean coefficient	-8.396***	-24.94***	-21.32***
		(0.616)	(4.07)	(3.01)
Length_SD	S.d.(coefficient)		17.34***	19.79***
			(3.60)	(3.64)
Freq*Length	Mean coefficient	-0.004***	-0.009**	-0.008**
		(0.001)	(0.004)	(0.004)
Green	Mean coefficient	1.101***	3.07***	3.65***
		(0.209)	(0.84)	(0.87)
Green_SD	S.d.(coefficient)		8.54***	7.74***
			(1.53)	(1.30)
Reuse	Mean coefficient	1.442***	3.63***	2.59***
		(0.195)	(0.73)	(0.55)
Reuse_SD	S.d.(coefficient)		5.77***	4.83***
			(1.30)	(0.87)
Notify	Mean coefficient	0.736***	2.08***	2.17***
		(0.088)	(0.36)	(0.33)
Cost	Mean coefficient	-0.157***	-0.46***	-0.40***
		(0.011)	(0.08)	(0.06)
Cost_SD	S.d.(coefficient)		0.32***	0.32***
			(0.06)	(0.05)
Observable heterogeneity about the mean				
Cost*Income[c]		0.646***	2.01***	1.89***
		(0.118)	(0.47)	(0.42)
Freq*OutExper		4.364***	10.49**	9.84**
		(1.349)	(4.29)	(3.80)
Len*NoCollege		4.802***	9.97**	10.58***
		(1.495)	(4.31)	(3.95)
Grn*Conserve		0.907***	2.77**	2.29**
		(0.333)	(1.16)	(1.07)
Reu*Conserve		1.008***	2.84***	3.14***
		(0.323)	(0.97)	(0.89)
LL:		-1580.3461	-1484.7887	-1465.1624
BIC score		3256.84	3105.81	3146.694
No. parameters		12	17	27
Obs.[a]		3018	3018	3018

Significance levels: * $\leqslant$0.10,** $\leqslant$0.05,*** $\leqslant$0.01

[a] There are 3022 observations for MNL1, N1u, N1c; difference is from one education non-response. RPL-N1u and RPL-N1c were re-estimated minus the individual. Similar results.

Table 2.5: Covariance matrix: RPL-N1c and RPL-N2c

	Frequency	Length	Green	Reuse	Cost
Model RPL-N1c					
Frequency	788.77***	.	.	.	.
Length	13.99	363.52***	.	.	.
Green	-13.54	-40.63	60.97***	.	.
Reuse	34.89	33.82	25.19**	31.27***	.
Cost	-2.70*	-1.76*	0.46	0.41	0.12***
Model RPL-N2c					
Frequency	699.11***	.	.	.	.
Length	66.68	391.54***	.	.	.
Green	-28.33	-40.68	59.90***	.	.
Reuse	29.67	39.35*	25.06***	23.34***	.
Cost	-1.57	-1.93**	0.49*	0.34	0.10***

The estimated values on the diagonal are variances for each attribute, which are also given in the standard deviation coefficients in Table **??**.
***,** ,* indicate significance at 1%, 5%, and 10% levels.

Table 2.6: Model Specification 1: Mean and Median MWTP per month

	MNL1 (95% CI[a])	RPL-N1u[b]	RPL-N1c[b]
Monthly MWTP to avoid one additional outage at home in next five years			
Median	\$0.78 (0.67, 0.93)	\$0.56	\$0.35
Mean		\$0.34	\$2.78
Monthly MWTP to avoid a 1-hour increase in average outage length			
Median	\$0.71 (0.61, 0.83)	\$0.61	\$0.39
Mean		\$0.74	\$5.12
Monthly MWTP for a 1% increase in energy use by water utility that is from renewable sources			
Median	\$0.13 (0.11, 0.16)	\$0.11	\$0.10
Mean		-\$0.04	\$0.51
Monthly MWTP for a 1% increase in urban greenspace irrigated with reuse water			
Median	\$0.17 (0.14, 0.19)	\$0.13	\$0.07
Mean		\$0.21	\$0.73
Monthly MWTP for a 1% increase percent of time advance notification of a planned maintenance outage is provided by the utility			
Median	\$0.07 (0.05, 0.08)	\$0.06	\$0.06
Mean		\$0.05	\$0.41

[a] Calculated 95% CI with Krinsky-Robb method, 1000 draws.

[b] Distribution of conditional individual estimated MWTP values.

Table 2.7: Model Specification 2: Mean and Median MWTP per month

	MNL2	RPL-N2u[a]	RPL-N2c[a]
Monthly MWTP to avoid one additional outage at home in next five years			
Median	$0.81	$0.60	$0.51
Mean	-$10.69	-$0.09	-$2.06
Monthly MWTP to avoid a 1-hour increase in average outage length			
Median	$0.68	$0.58	$0.36
Mean	-$4.55	-$1.62	-$1.97
Monthly MWTP for a 1% increase in energy use by water utility that is from renewable sources			
Median	$0.15	$0.11	$0.09
Mean	$3.72	$0.21	-$0.24
Monthly MWTP for a 1% increase in urban greenspace irrigated with reuse water			
Median	$0.19	$0.11	$0.08
Mean	$4.16	-$0.49	-$0.09
Monthly MWTP for a 1% increase percent of time advance notification of a planned maintenance outage is provided by the utility			
Median	$0.06	$0.06	$0.06
Mean	$0.09	-$0.15	-$0.07

[a] Distribution of conditional individual estimated MWTP values.

Table 2.8: Monthly MWTP ($) by percentile for Length

Percentile	*MWTP to avoid a 1-hour longer outage for the average customer* RPL-N1u	RPL-N1c	RPL-N2u	RPL-N2c
99th	17.76	18.86	24.42	22.76
98th	9.75	9.37	9.94	14.17
96th	6.24	5.56	5.46	7.65
95th	5.39	5.02	4.48	6.31
93rd	4.15	3.90	3.59	4.91
90th	2.99	2.87	2.85	3.25
85th	1.69	2.11	1.74	2.10
80th	1.33	1.72	1.34	1.57
75th	1.16	1.17	1.09	1.24
50th	0.61	0.39	0.58	0.36
IQR[a]	0.81	1.02	0.78	1.15
25th	0.35	0.15	0.31	0.09
20th	0.32	0.11	0.24	0.00
15th	0.28	-0.11	0.20	-0.40
10th	0.16	-1.91	-0.28	-1.90
7th	-0.90	-2.73	-2.18	-3.30
5th	-3.01	-4.67	-3.33	-4.91
4th	-4.05	-6.07	-4.66	-6.42
2nd	-8.99	-9.49	-11.55	-13.44
1st	-17.32	-28.28	-22.49	-29.60
Mean	0.87	0.56	0.69	0.56

A negative MWTP for is interpreted that the ratepayer is willing to adapt to deteriorating service levels rather than pay for an improvement in service.

[a] The interquartile range represents the difference between MWTP at the 25th and 75th percentiles. It measures the dispersion of the distribution.

Table 2.9: Monthly MWTP ($) by percentile for Frequency

	MWTP to avoid 1 additional outage at home over next 5 years			
Percentile	RPL-N1u	RPL-N1c	RPL-N2u	RPL-N2c
99th	15.23	14.77	18.68	23.40
98th	10.31	8.05	8.25	12.91
96th	5.83	4.75	5.41	6.82
95th	4.82	3.91	4.78	5.44
93rd	3.96	3.18	3.71	4.31
90th	2.67	2.67	2.85	3.06
85th	1.78	2.18	2.11	2.28
80th	1.57	1.90	1.69	1.85
75th	1.46	1.43	1.46	1.49
50th	0.56	0.35	0.60	0.51
IQR[a]	1.22	1.44	1.23	1.37
25th	0.24	-0.01	0.23	0.12
20th	0.15	-0.11	0.10	-0.03
15th	-0.02	-0.45	-0.08	-0.28
10th	-0.23	-2.05	-0.55	-1.68
7th	-0.89	-3.17	-1.76	-2.97
5th	-1.93	-3.87	-3.57	-4.40
4th	-3.14	-5.42	-4.58	-6.35
2nd	-8.41	-10.44	-11.50	-12.92
1st	-13.43	-21.69	-23.52	-24.12
Mean	0.89	0.50	0.70	0.68

A negative MWTP for is interpreted that the ratepayer is willing to adapt to deteriorating service levels rather than pay for an improvement in service.

[a] The interquartile range represents the difference between MWTP at the 25th and 75th percentiles. It measures the dispersion of the distribution.

Table 2.10: Stage 2 analysis: characteristics and determinants of MWTP

	Frequency		Length	
Demographics[a]	N2u	N2c	N2u	N2c
Income	0.07 (0.03)**	-0.08 (0.04)**	0.05 (0.03)*	-0.01 (0.04)
Female	-0.17 (0.08)**	-0.10 (0.10)	0.003 (0.07)	0.04 (0.11)
Hispanic	-0.04 (0.08)	0.12 (0.10)	-0.18 (0.08)**	0.02 (0.12)
NearbyOut	0.31 (0.10)***	0.51 (0.15)***	0.21 (0.09)**	0.63 (0.16)***
West	0.08 (0.09)	0.16 (0.12)	-0.01 (0.09)	0.06 (0.13)
SouthSE	-0.18 (0.10)*	-0.13 (0.14)	-0.03 (0.09)	-0.04 (0.14)
R^2	0.0303	0.0241	0.0368	0.0300
No. obs.	667	666	668	667

Five percent outliers on each end have been dropped.
Significance levels: $* \leqslant 0.10, ** \leqslant 0.05, *** \leqslant 0.01$
[a] Demographics defined: Income = total household income, categorical.
Female = individual is female; binary.
Hispanic = individual is hispanic; binary. NearbyOut = a high number (16-64) of pipe breaks were within half-mile radius of house in past 5 years; binary. Reported by ABCWUA. GIS-techniques were used to create a half mile radius zone and count the number of pipe breaks. West = household is west of Rio Grande River (base is northeast Albuquerque); binary. SouthSE = household is in south Albuquerque (base is northeast Albuquerque); binary.

Table 2.11: Aggregated WTP ($mil) for all residential ratepayers over 5 years

MNL1[a]	**RPL-N1u**	**RPL-N1c**	N1u:N1c	**RPL-N2u**	**RPL-N2c**	N2u:N2c
Aggregate WTP to avoid one more outage at home over next five years						
$8.38	$6.01	$3.77	-37%	$6.44	$5.470	-15%
Aggregate WTP to avoid a 1-hour increase in average outage length						
$7.62	$6.57	$4.20	-36%	$6.27	$3.87	-38%
Aggregate WTP for a 1% increase in amount of energy used by ABCWUA from renewable sources						
$1.40	$1.20	$1.08	-11%	$1.19	$0.97	-19%
Aggregate WTP for a 1% increase in Albuquerque urban greenspace irrigated with reuse water						
$1.83	$1.35	$0.78	-42%	$1.20	$0.90	-25%
Aggregate WTP for a 1% increase in advance notification of a planned maintenance outage is provided by the utility						
$0.75	$0.61	$0.65	6%	$0.59	$0.65	9%

Median figures from each model used. Total amounts rounded.
There were 178,968 single-family residential ABCWUA customers as of Dec 2013.
(per Katherine Yuhas, March 7, 2014).
[a] These figures represent the amount paid over five years for a one percent or one-unit increase in the attribute level.

Table 2.12: Policy scenario for drinking water distribution infrastructure renewal

Infrastructure Investment	RPL-N2c	RPL-N2u
Avoid 5 hour longer average outage length across all water utility customers	$19,328,544	$31,140,432
Avoid 5 additional outages at home over next five years	$27,382,104	$32,214,240
Increase by 10%, the share of time ratepayer receives advance notification of a planned maintenance outage	$6,442,848	$6,442,848
Total	**$53,153,496**	**$69,797,520**
Annual amount	***$10,630,699***	***$13,959,504***
Annual amount per residential account[a]	***$59.40***	***$78.00***
Monthly amount per residential account[a]	***$4.95***	***$6.50***

Median results from each model used to calculate totals.

In this scenario, the status quo levels for the Reuse and Green attributes do not change.

[a] Total amount divided by 178,968 residential accounts to get per account figures

Figure 2.1: Sample CE Question

8. **Choice 1:** If these were the only two investment packages available, which would you choose: Investment Package A or Investment Package B? *Check one.*

	Investment Package A	**Investment Package B**
Percent of Albuquerque greenspace irrigated with reuse water	25% of greenspace	65% of greenspace
Percent of energy used by the water utility that is renewable	40% of renewable energy	20% of renewable energy
Number of outages you experience at your home	10 outages over 5 years	0 outages over 5 years
Average length of outages for water utility customers	3 hour outage	3 hour outage
Percent of time water utility customers receive advance notification of outages	Advance notification 70% of the time	Advance notification 20% of the time
Additional amount on your monthly water utility bill for the next 5 years	\$0 per month	\$2 per month

I would choose Package ⟶ ☐ A ☐ B

Figure 2.2: ABCWUA pipe breaks in the five years prior to the study (2010 Census Tracts)

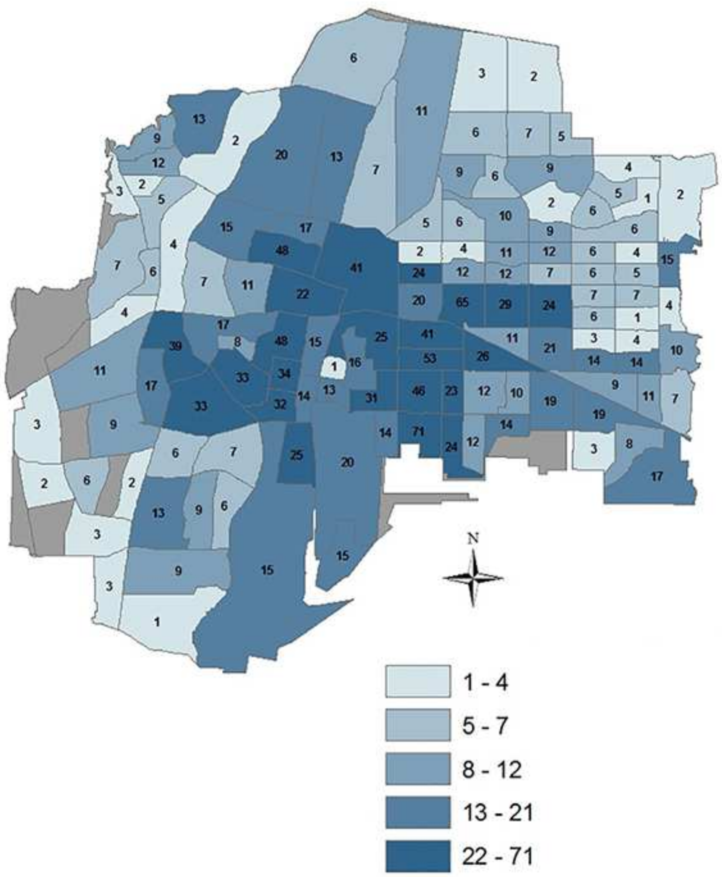


Figure 2.3: MWTP to avoid 1 additional outage at home over the next five years (RPL-N2u), Median MWTP per month by tract

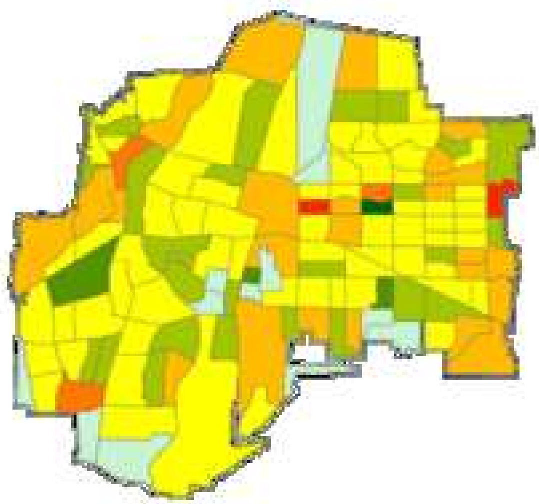
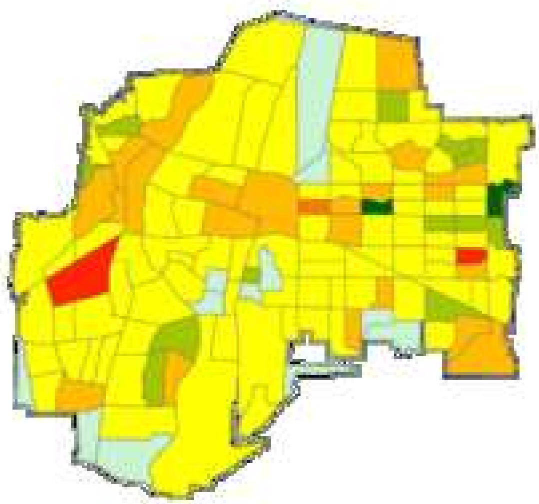


Figure 2.4: MWTP to avoid 1 additional outage at home over the next five years (RPL-N2c), Median MWTP per month by tract



Chapter 3

The estimation of marginal utility of income in preference-space and WTP-space models

3.1 Introduction

Two categories of mixed logit models are used to analyze choice experiment data and estimate marginal willingness-to-pay (MWTP) for environmental goods and services: *preference-space* models and *WTP-space* models. Non-cost attribute coefficients are interpreted as marginal utilities in preference-space models, but as MWTP in WTP-space models. Studies comparing the two methods note that the benefits to a WTP-space model result from directly estimating heterogeneous MWTP separately from the heterogeneous cost scale parameter, while in the preference-space model MWTP is calculated post-estimation as the ratio of two marginal utility coefficients. In the WTP-space model, estimated MWTP has the specified distribution of each random parameter so all distributional moments are defined (Scarpa et al., 2008; Hensher & Greene, 2011; Scarpa et al., 2012). When the marginal utility of income (MUI) is specified random in a mixed logit preference-space model, the both the numerator and denominator in the calculated MWTP ratio are random. The resulting distribution of the MWTP ratio often will not have a defined distribution.

The objective of this paper is to compare the MWTP distributions from the WTP-space model and several specifications of the preference-space model using different assumptions for the MUI. The two models are described as being formally equivalent, but the research question asks under which preference-space distributional assumption for MUI are they equivalent? A comparison with preference-space mixed logit models under different distributional assumptions for cost establishes a baseline to characterize the MWTP distribution in WTP-space.

The issues of the MWTP distribution in preference-space models result from the random MUI.[1] A random MUI parameter typically provides a better fit and is considered more realistic than a fixed cost parameter (Hole, 2008). Theoretically a random MUI is negatively correlated to income. The MUI for a low income individual is usually greater than the MUI for a high income individual, a percentage of whom may have a near-zero or positive MUI depending on the specified distribution. Individuals with a near-zero or positive MUI are considered price insensitive. When MWTP ratios are calculated, near-zero MUI values result in extreme outlier MWTPs. WTP-space models do not allow price insensitive individuals, because the MWTP is directly estimated; a zero MUI is not possible in the denominator, so the WTP-space model has fewer or no ex-

[1]This is the coefficient of the random cost parameter (Lanz & Provins, 2013).

treme outliers. The implicit assumption is that each individual has a non-zero MWTP for an attribute (Lanz & Provins, 2013). A negative MWTP is possible.

WTP-space and preference-space models are often referred to as being 'formally equivalent' (Train & Weeks, 2005; Scarpa et al., 2008). Mathematically they are. But there has been little discussion if they are equivalent in behavior as a result of the different method of including the MUI or under which distributional assumptions are they equivalent. Past research using preference-space mixed logit models conclude that a random cost parameter improves model fit and is more realistic (Balcombe et al., 2009; Hole & Kolstad, 2012). The WTP-space model is described as having a heterogeneous cost scale parameter, implying a random MUI. If so, the resulting MWTP distribution should follow theoretical validity tests of income in a similar manner as the preference-space models with random MUI.[2] Various studies have shown estimated MWTP values to be positively related to income in preference-space mixed logit models (Jacobsen & Hanley, 2009; Giergiczny et al., 2012). I refer to the positive relationship between MWTP and income as the income effect. This paper contributes to the growing WTP-space literature by examining the income effect in the WTP-space estimates and comparing it to preference-space models under different distributional assumptions for the MUI parameter.

Research comparing WTP-space models with preference-space models to-date has been primarily concerned with model fit and the impact on central statistical moments such as the mean, median, and standard deviation since these are the most commonly used results for policy makers. Results have been mixed as to preferred model fit, however several studies have found that the WTP-space models result in more conservative median estimates with tighter

[2]In their paper describing best practices for using stated preference techniques to value the environment, Arrow et al. (1993) suggest using a cross tab of income with WTP as a validity test of contingent valuation results. This is an easy test for the MWTP values estimated from choice experiment studies as well.

confidence intervals (Train & Weeks, 2005; Sonnier et al., 2007; Scarpa et al., 2008). Some researchers advocate for the use of WTP-space models to avoid instability associated with calculating MWTP as the ratio of two random marginal utilities (Balcombe et al., 2010).

This study adds a water utility infrastructure application to the WTP-space literature. Currently, I am aware of only one article using a WTP-space model from the water utility sector; they examined preferences describing tap water delivery (Scarpa et al., 2012). Other papers using WTP-space models have focused on food/agriculture (Balcombe et al., 2009, 2010), transportation (Train & Weeks, 2005; Hensher & Greene, 2011), health (Hole & Kolstad, 2012), recreation (Scarpa et al., 2008), energy (Scarpa & Willis, 2010), retail goods (Sonnier et al., 2007), and environmental economics (Lanz & Provins, 2013).

The empirical application has three purposes. First, the impact of different assumptions about the MUI is compared using the results and model fit of WTP-space and preference-space models. Second, I use validity testing of the MWTP by income from each model to compare the behavior of the WTP-space estimates against the behavior of preference-space models under different cost assumptions. Third, the MWTP estimates are weighted to examine benefits received relative to income and local infrastructure conditions. Data are from a choice experiment survey that valued investment in water utility infrastructure in a southwestern U.S. metropolitan area. Three preference-space mixed logit models are estimated: one model using a fixed cost attribute and two models using random cost attributes that assume a normal and lognormal distributions. These are compared with a WTP-space mixed logit model. Results are consistent with the literature comparing the two models: the preference space model fits the data better, but exhibits extreme outliers in MWTP for the random cost models, most notably when cost is normally distributed. Given that some researchers prefer the WTP-space model because of the tighter distribution, removing between 2% and 10% of outlying values is one solution to obtaining a comparable MWTP distribution in a preference-space model, especially if negative outliers are considered theoretically incorrect.

Estimated MWTPs are often used to assess the social benefits of a policy and are assumed to reflect individuals' value for a good along with the trade-offs they are willing to make (Loomis, 2011). For this dataset, results from the validity test of the WTP-space distribution indicate that MWTP is not related to income. This implies a similar level of social benefits across income classes. By weighting MWTP values with the ratio of household income to Census tract median household income for owner-occupied housing units, I attempt to provide a more precise assessment of social benefits [3]

An important conclusion of this study is that while the WTP-space model provides a more realistic distribution of MWTP, it lacks the income effect that is visible in the preference-space models with random cost. In fact, the distribution and the estimated MWTP values are very similar to the preference-space model with the fixed cost parameter. As a result, I conclude that the preference-space models might be preferable, in spite of the distributional problems, given that a random cost parameter is considered an improvement over a fixed cost parameter. However, more research is needed into the implications of the estimation of MUI in the WTP-space model.

[3] Median household income for owner-occupied housing units was used as this more accurately reflects the survey respondents.

3.2 Theory

The underlying utility equation is the same for both preference-space and WTP-space models. The primary differences between the two is in the estimation of the individual-specific β_n coefficients and the MUI coefficient, λ_n.

3.2.1 Utility equation

Preference-space **models**

Preference-space mixed logit models focus on estimating individuals' preferences or marginal utilities for attributes. The utility equation for individual n who selects an alternative j from choice opportunity t is:

$$U^*_{njt} = \beta^*_n X_{njt} - \lambda^*_n p_{njt} + e^*_{njt} \tag{3.1}$$

Notation is similar to other papers estimating WTP-space and preference-space models for comparison (Scarpa et al., 2008; Scarpa & Willis, 2010; Hensher & Greene, 2011). Utility is assumed to be separable for the vector of non-cost attributes, X_{njt}, and cost, p_{njt}. β^*_n is the vector of associated marginal utilities, p_{njt} represents the cost attribute, and λ^*_n represents the heterogeneous marginal utility of income. The * indicates these are the individual's true underlying preferences, unobservable to the analyst. The error term is distributed iid, extreme value Gumbel, $e^*_{njt} \sim (0, \frac{\sigma_n^2 \pi^2}{6})$ where σ_n is inversely related to the error term's variance and unique to each individual.[4] To obtain a constant error

[4]Typically a homogeneous scale term has been assumed, σ, indicating that each individual has the same randomness inherent in their decision-making. Louviere et al. (2002) argue that this assumption can bias utility estimates and is unrealistic from a decision-making perspective. They propose that each individual's has a unique scale that should be considered in estimation. The WTP-space model allows for this so I use a σ_n term throughout.

term, scale the utility equation by σ_n.

$$\frac{U^*_{njt}}{\sigma_n} = \frac{\beta^*_n}{\sigma_n} X_{njt} - \frac{\lambda^*_n}{\sigma_n} p_{njt} + \frac{e^*_{njt}}{\sigma_n} \tag{3.2}$$

Let $U_{njt} = \frac{U^*_{njt}}{\sigma_n}$, $\beta_n = \frac{\beta^*_n}{\sigma_n}$, $\lambda_n = \frac{\lambda^*_n}{\sigma_n}$, and $\varepsilon_{njt} = \frac{e^*_{njt}}{\sigma_n}$.[5] Because the β_n and σ_n are confounded, preference-space models normalize the scale term at 1. This scaled utility equation is the preference-space model because the estimated coefficients represent preferences:

$$U_{njt} = \beta_n X_{njt} - \lambda_n p_{njt} + \varepsilon_{njt} \tag{3.3}$$

The β_ns are interpreted as the heterogeneous marginal utilities for non-cost attributes and the λ_n is the heterogeneous marginal utility of income. MWTP is estimated as the ratio of the two coefficients, $MWTP = \frac{\beta_k}{\lambda_n}$.

WTP-space **models**

The utility equation for a WTP-space mixed logit model is a reformulation of Equation 3.2. In WTP-space, coefficients for the non-cost attributes are interpreted as MWTP for each attribute (Train & Weeks, 2005; Scarpa et al., 2008). This allows for separate WTP heterogeneity from scale heterogeneity.

Rearrange and simplify Equation 3.2:

$$\frac{U^*_{njt}}{\sigma_n} = \frac{1}{\sigma_n}\left[\frac{\lambda_n}{\lambda_n}\beta^*_n X_{njt} - \lambda^*_n p_{njt}\right] + \frac{e^*_{njt}}{\sigma_n} \tag{3.4}$$

$$U_{njt} = \frac{1}{\sigma_n}\left[\frac{\lambda^*_n}{\sigma_n}\frac{\sigma_n}{\lambda^*_n}\beta^*_n X_{njt} - \lambda^*_n p_{njt}\right] + \varepsilon_{njt} \tag{3.5}$$

$$U_{njt} = \frac{\lambda^*_n}{\sigma_n}\left[\frac{\sigma_n}{\lambda^*_n}\frac{\beta^*_n}{\sigma_n} X_{njt} - p_{njt}\right] + \varepsilon_{njt} \tag{3.6}$$

[5]The scale term is confounded with each attribute in the denominator. Several researchers have pointed out that a heterogeneous scale term leads to some degree of correlation among attribute coefficients. Perfect correlation results if preferences are fixed and scale is random or partial correlation if both are random (Louviere et al., 2002; Scarpa et al., 2008).

$$U_{njt} = \frac{\lambda_n^*}{\sigma_n}\left[\frac{\beta_n}{\lambda_n}X_{njt} - p_{njt}\right] + \varepsilon_{njt} \tag{3.7}$$

$$U_{njt} = \lambda_n\left[w_n X_{njt} - p_{njt}\right] + \varepsilon_{njt} \tag{3.8}$$

Equation 3.8 is the estimated WTP-space model; the vector w_n is directly interpreted as the MWTP for attributes, $MWTP_n = w_n = \frac{\beta_n}{\lambda_n} = \frac{\beta_n^*/\sigma_n}{\lambda_n^*/\sigma_n} = \frac{\beta_n^*}{\lambda_n^*}$. Both w_n and preference-space MWTP are scale-free, leading to the argument that they are directly comparable. In the estimated model, λ_n represents the MUI. It is estimated and reported as the coefficient for the cost parameter, implying that it is not directly a part of the MWTP or w_n coefficient. This results in a reduced income effect between estimated MWTP and income categories.

3.2.2 Individual-specific βs

The estimation of the βs provides some distinction between the two models.

Preference-space β_n

In the preference-space mixed logit model, an individual's unique preferences from Equation 3.3 are expressed as:

$$\beta_n = b + \upsilon_n \tag{3.9}$$

where $\beta_n \sim (b, \Upsilon)$; similar notation would denote the parameters of the random MUI, λ_n. Here b and Υ are the estimated parameters representing the population mean and variance.[6]

[6]Often, independent attributes are assumed, which results in the off-diagonal elements of Υ being zero.

3.2.3 *WTP-space* β_n

Individual β_n coefficients in a WTP-space model should be presented in the context in which they will be estimated, although the underlying theory is the same. Studies using WTP-space models have followed two conventions: (i) estimate in Stata or NLogit using a modified generalized multinomial logit (GMNL) model under certain restrictions (Hensher & Greene, 2011; Hole & Kolstad, 2012); or (ii) directly program, usually in Biogeme and often using Bayesian methods (Scarpa et al., 2008; Balcombe et al., 2009; Thiene & Scarpa, 2009; Balcombe et al., 2010; Scarpa & Willis, 2010; Scarpa et al., 2012).[7] Greene & Hensher (2010) showed that the generalized multinomial logit model resulted in a WTP-space model under specific restrictions.[8] I estimate the WTP-space model using the modified GMNL method because, given the nature of the attributes, it is likely that over the distribution of survey respondents there will be both positive and negative WTP values so the unbounded normal distribution is appropriate.

The utility equation for the GMNL model, as described in Fiebig et al. (2010), starts from Equation 3.3:

$$U_{njt} = \beta_n X_{njt} - \lambda_n p_{njt} + \varepsilon_{njt} \tag{3.10}$$

Introduce the GMNL formulation of the β_n and λ_n coefficients:

$$U_{njt} = \left[\frac{\beta^*}{\sigma_n} + \left[\gamma + \frac{(1-\gamma)}{\sigma_n}\right]\theta_n^*\right] X_{njt} - \left[\frac{\lambda^*}{\sigma_n} + \left[\gamma + \frac{(1-\gamma)}{\sigma_n}\right]\eta_n^*\right] p_{njt} + \varepsilon_{njt} \tag{3.11}$$

[7]Using a GMNL frame work allows for partial scale and price heterogeneity but restricts the distribution of the MWTP values to the normal distribution, while the WTP-space program allows various distributions for the MWTP coefficients but assumes either the scale or price coefficient is fixed, resulting in perfect correlation between the two (Scarpa et al., 2012).

[8]The generalized multinomial logit (GMNL) model nests various models and allows for the testing of scale heterogeneity with preference heterogeneity. Mixed logit, scaled multinomial logit and multinomial logit models are all nested within the GMNL model Fiebig et al. (2010).

In the GMNL model, the γ parameter takes a value between $[0, 1]$; it impacts the influence of the heterogeneous scale on the preference heterogeneity terms, represented by the individual standard deviation terms θ_n or η_n. For the WTP-space formulation, γ is restricted to zero:

$$U_{njt} = \left[\frac{\beta^*}{\sigma_n} + \frac{\theta_n^*}{\sigma_n}\right] X_{njt} - \left[\frac{\lambda^*}{\sigma_n} + \frac{\eta_n^*}{\sigma_n}\right] p_{njt} + \varepsilon_{njt} \tag{3.12}$$

$$U_{njt} = \frac{1}{\sigma_n}\left[\beta^* + \theta_n^*\right] X_{njt} - \frac{1}{\sigma_n}\left[\lambda^* + \eta_n^*\right] p_{njt} + \varepsilon_{njt} \tag{3.13}$$

Let $\beta_n^* = \beta^* + \theta_n^*$ and $\lambda_n^* = \lambda^* + \eta_n^*$, which is the standard manner of writing out individual-specific coefficients in a mixed logit model. β_n^* represents heterogeneous preferences for non-cost attributes and λ_n^* represents heterogeneous MUI:

$$U_{njt} = \frac{1}{\sigma_n}\left[\beta_n^* X_{njt} - \lambda_n^* p_{njt}\right] + \varepsilon_{njt} \tag{3.14}$$

$$U_{njt} = \frac{\lambda_n^*}{\sigma_n}\left[\frac{\beta_n^*}{\lambda_n^*} X_{njt} - p_{njt}\right] + \varepsilon_{njt} \tag{3.15}$$

$$U_{njt} = \lambda_n\left[w_n X_{njt} - p_{njt}\right] + \varepsilon_{njt} \tag{3.16}$$

Equation 3.16 shows how the estimation is done under the GMNL specification to arrive at Equation 3.8. In studies that use WTP-space models, the results tables report w_n as the non-cost attribute coefficients, while λ_n is reported in some manner as the cost parameter. The estimation of λ_n requires explanation. Regardless of whether the WTP-space is estimated as a modified GMNL or directly programmed, λ_n combines the heterogeneous marginal utility of income, λ_n^*, with the heterogeneous scale, σ_n. Hensher & Greene (2011) refer to λ_n as a normalizing constant, in the sense that the coefficient w_n is normalized by λ_n. Lanz & Provins (2013) also describe the WTP-space model as using the MUI to scale the utility equation. When estimating the WTP-space model as a modified GMNL model, λ_n is estimated using the constraints on the scale term σ_n described by Fiebig et al. (2010). The description of estimating

λ_n will use the term scale, but the scale and cost coefficients are confounded so are functionally the same for this discussion.

3.2.4 Random versus fixed cost

An issue with the mixed logit model is that the cost parameter is often fixed for convenience, while non-cost attributes are specified random (Colombo et al., 2009). A fixed cost parameter simplifies the issue of estimating the WTP distribution, which takes on the distribution of the numerator's random attribute. A large number of initial mixed logit studies modeled cost heterogeneity in the classical heterogeneity manner through interactions between the cost attribute and socioeconomic characteristics for issues of convenience and tractability (Revelt & Train, 1998; Hensher & Greene, 2003; Colombo et al., 2007). However, this ignores a current debate about the appropriateness of assuming a constant MUI for all respondents. Hensher et al. (2005) argue that a fixed cost only indicates that the ratio of the scale term to the price is constant, not that all individuals have the same marginal utility of income. A fixed cost parameter simplifies the issue of estimating the WTP distribution, which takes on the distribution of the numerator's random attribute. However, research indicates that this is a restrictive assumption (Hole & Kolstad, 2012). Balcombe et al. (2009) find that models with a fixed cost coefficient underperform the models allowing for cost heterogeneity. Scarpa et al. (2008) considers fixing the cost coefficient to imply an identical MUI across individuals and a constraint on the scale parameter to be fixed.

More recent research modeling cost heterogeneity concludes that modeling cost heterogeneity improves model fit, compared to the case of a fixed cost parameter (Meijer & Rouwendal, 2006; Hole, 2008; Hole & Kolstad, 2012). Some researchers specify cost to be random (Train, 1998; Hole, 2008; Regier et al., 2009); in this case the most commonly chosen distribution is the lognormal, which forces the sign to be positive.[9] The assumption of a random parameter specification for cost, and the log-normal specification in particular, has a number of consequences for the resulting MWTP. First, making cost random means that some individual cost parameters will be quite small, potentially inflating MWTP estimates for these individuals. Second, a log-normal specification means a fat right-hand tail, which will also inflate MWTP when the non-cost attribute is also specified log-normal. The end consequence is that the MWTP can be inflated and will have a very large range (Hensher & Greene, 2003).

Research into the effects of the distribution chosen for a random cost parameter finds that the median is not as sensitive as the mean WTP to different distributions (Meijer & Rouwendal, 2006). A few studies outside the water utility literature have combined unobserved heterogeneity in a random cost parameter with observed heterogeneity due to income, environmental and other demographic characteristics (Greene & Hensher, 2007; Baskaran et al., 2009; Tait et al., 2012). Issues of specifying a distribution for the cost parameter led to the development of the WTP-space models whose estimated coefficients are the ratio of the attribute to the cost parameter, allowing the researcher to specify a distribution for the WTP and avoid the issue of taking the ratio of two different distributions (Train & Weeks, 2005; Scarpa et al., 2008; Hensher & Greene, 2011; Hole & Kolstad, 2012).

[9]For attributes assumed to cause disutility as they increase across the population, the attribute is multiplied by -1 in the model to force the behaviorally-appropriate negative sign.

3.2.5 Validity testing of distributional benefits

Estimated MWTP should be interpreted in the context of an individual's income and MUI (Broberg, 2010). Microeconomic theory suggests that MUI and income have an inverse relationship; as income increases, each extra dollar adds less to overall utility and marginal utility of income decreases. As a result, MWTP and income should be positively related. Giergiczny et al. (2012) find that increasing income leads to lower marginal utility of income and higher WTP values. Examining the relationship between MWTP and income is one method of validity testing.

This relationship typically holds in preference-space models when the cost parameter is random. MWTP is a function of both the marginal utility or preference for the non-cost attribute and the marginal utility of income, $MWTP = \frac{\beta_k}{\lambda_n}$. The improvement in WTP-space models, described via smaller standard deviations and reduced incidence of extreme MWTP, is in part due to the separate estimation of WTP coefficients, w_n, from the heterogeneous cost/scale parameter, λ_n. However this may reduce the income effect on MWTP.

There has been little discussion about validity tests on MWTP distributions as an additional sign of behavioral reliability. Arrow et al. (1993) initially describe various validity checks on resulting MWTP estimates in their paper describing best practices for using stated preference surveys to value the benefit of the environment. They suggest income levels. Construct validity is one type of validity testing using respondent characteristics as predictor variables for WTP values; income is one example cited because theory would say that MWTP values should increase with income. Construct validity can be tested using between-subjects comparisons with mean WTP estimates from sample groups within the respondent group (Freeman III, 2003).[10] Using regression techniques, various studies have shown income to be positively related to MWTP (Campbell, 2007; Jacobsen & Hanley, 2009; Cooper, Burton, & Crase, 2011). Studies argue that theoretically the underlying utility functions are equivalent and the MWTP should be interpreted in the same manner (Train & Weeks, 2005; Scarpa et al., 2008). This implies that the MUI, λ_n, in a WTP-space model is accurately reflected in the MWTP, w_n, coefficients even though it is estimated separately. If true, then the median MWTP coefficients from WTP-space models should also be increasing in income.

3.3 Empirical Application

3.3.1 Survey

The data for this study were collected as part of a choice experiment survey conducted with a sample of residential customers of the water utility in the Albuquerque, NM metropolitan area to understand their preferences for infrastructure investments. Serious infrastructure deterioration is not system-wide in Albuquerque but occurs more often in Census tracts with lower median household incomes. This relationship is depicted in Figure **??** where darker color Census tracts indicate higher numbers of pipe breaks over the five years preceding the survey and the dot size increases to indicate higher median household income. ABCWUA has had a lower annual break rate than six peer cities with similar miles of pipe (ABCWUA, 2006).[11] However, in 2011, the water utility wrote a long-term asset renewal plan and projected increasingly deteri-

[10] Regression techniques and within-subject comparisons are also mentioned.

[11] The six cities were Oakland (CA), Denver (CO), Kenosha (WI), New York (NY), Louisville (KY), and Philadelphia (PA).

orating infrastructure over the next forty years (ABCWUA, 2011).

The CE survey was developed in accordance with the survey protocol detailed in Dillman (2007). Attributes were chosen based on an extensive literature search; Hatton MacDonald et al. (2003); Hensher et al. (2005); Willis et al. (2005) were excellent guides. Eight focus groups conducted throughout the water utility's service area helped refine the survey. The survey was tested iteratively through debriefing interviews and a final pretest survey that was mailed to a sample of 200 customers. The final survey was sent to residential customers using the standard five contacts, where subsequent contacts after the first survey packet were only made with non-respondents.

Infrastructure investments were characterized by six attributes, which are described in Table 2.1. *Cost* was described as a monthly amount added on to the water bill dedicated only for infrastructure investment. The drinking pipe infrastructure investment was described as more frequent outages at home, *Frequency*, longer average outages across all utility customers, *Length*, and the percentage of time ABCWUA can provide advance notification of an outage due to planned maintenance, *Notify*. Reuse pipe infrastructure, *Reuse*, was described as the percentage of urban greenspace irrigated with reuse water. Renewable energy investment, *Green*, was described as the percentage of energy generated from renewable sources. Each non-cost attribute had three levels, while cost had six levels.

The Choiceff macro was used to generate an efficient design under the model assumption of a linear-in-parameters utility function with interactions (Kuhfeld, 2010). The design generated 32 choice sets, each with two investment alternatives.[12] Choice questions were examined to make sure there were no

[12]Similar to Hensher et al. (2005), there was no status quo alternative in each CE question. I chose not to include a status quo option because water pipe infrastructure is not a static good. The status quo service levels will worsen under the current status quo of no additional

dominated alternatives, but rather that trade-offs were being made. Four CE questions were grouped together for eight survey versions. An example of the choice question is seen in Figure 2.1.

The survey sample was 1,900 residential customers randomly selected by the water utility from their address database. These customers were primarily homeowners or renters who received and paid the monthly water bill. Under the assumption that individuals within a household shared the same basic preferences for infrastructure investment, it did not matter who opened the survey packet.[13] A conservative RR1 response rate was calculated of 45.8%, according to guidelines set out by the American Association of Public Opinion Research (AAPOR, 2009).[14] There were 3,317 initial observations.

3.3.2 Sample statistics

Table 3.1 provides mean statistics for all survey respondents and by income category. The median survey respondent is 55 years old, female, non-Hispanic, with a Bachelor's degree, and a household income between $40,000 and $59,999. Her water demand includes light outdoor watering in summer and she has moderate attitudes towards water conservation with no atypical household needs that affected water use.[15] She has no children living at home, is a long-term resident of New Mexico but has only lived at her current home

investment dollars.

[13]In fact, Scarpa et al. (2012) found no significant difference in WTP for tap water attributes between couples in the same house.

[14]An RR1 response rate assumes all survey addresses are eligible respondents even if the post office returns a survey marked undeliverable or unclaimed. $RR1 = E_R/(E_R + E_{NR} + UE_{NR}+NE_{NR})$. The denominator is the sum of eligible surveys returned (E_R) and not returned (E_{NR}), unreturned surveys of unknown eligibility (UE_{NR}), and those who are not eligible at all (NE_{NR}).

[15]Atypical water demand can result from being a stay-at-home parent, running a home business, or having a member of a sensitive sub-population at home.

for 10 years. She has not experienced an outage at home over the past five years and her Census tract has experienced fewer than average pipe breaks. I also compared mean statistics of the survey respondents to two Census survey populations: owner-occupied housing in Bernalillo County and the general population of Albuquerque/Bernalillo County metropolitan region.[16] Survey households were representative by age, geography, and income level, but a greater percentage were female, non-Hispanic, and had a higher education level than the average Albuquerque/ Bernalillo County homeowner.[17]

Descriptive statistics by income are presented in Appendix B since this study focuses on the marginal utility of income. The median low income individual has different characteristics than middle and high income individuals.[18] She is more likely to be Hispanic than the average survey respondent, is slightly older and has attended college a few years but does not have a degree. She has lived in New Mexico longer and lives in a Census tract that has experienced a higher-than-average number of pipe breaks.

3.3.3 Empirical model specification

I estimate four models.[19] A linear-in-parameters utility function is used for the preference-space models:

[16]We use two Census products because ABCWUA's service area does not encompass the entire city and yet includes part of unincorporated Bernalillo County. The owner-occupied housing comparison more accurate reflects the survey population.

[17]In comparison to the metropolitan population, survey respondents were only representative geographically. Survey respondents were wealthier, older, with a higher educational level, and more likely to be female and non-Hispanic than the average Albuquerque resident.

[18]Low income is defined as having an annual household income of less than $39,999, middle income is defined as $40,000 to $99,999 and high income is defined as over $100,000.

[19]Models are estimated in Stata 13.0 using commands written by Hole (2007) and Gu & Hole (2013).

$$U_{njt} = \beta_1 Freq_j + \beta_2 Len_j + \beta_3 Not_j + \beta_4 Reu_j + \beta_5 Grn_j + \beta_6 \widehat{FreqLen} - \lambda_n Cost \quad (3.17)$$

In Equation 3.17 *Notify* and $\widehat{Freq * Len}$ are fixed; the other attributes are random.[20] The non-cost random attributes are specified as normally distributed.[21] Uncorrelated models are estimated since the focus is on the validity of the resulting MWTP distributions.[22]

For the three mixed logit preference-space models, Equation 3.17 is estimated. The distribution of the *Cost* parameter is altered to compare the resulting distributions against the distribution from the WTP-space model. In Model F1, *Cost* is fixed so the marginal utility of income coefficient is constant, $\lambda_n = \lambda$. The subsequent distribution of MWTP has finite moments and follows the distribution of the numerator attribute (Hole & Kolstad, 2012). Researchers have argued against a constant MUI as unrealistic (Scarpa et al., 2008). Many studies now allow for a random cost attribute, which results in better model fit (Balcombe et al., 2009; Hole & Kolstad, 2012; Lanz & Provins, 2013).

Two additional preference-space models are estimated that allow for a random cost using normal (Model N1) and lognormal (Model L1) distributions. Under the assumption of a normally distributed cost attribute m, the estimated marginal utility of income is $\lambda_m = b_m + s_m \omega_m$. Here s represents the individual's standard deviation and ω is a draw from the standard normal distribution that places the individual somewhere on the distribution. Under the assumption

[20]The interaction term $\widehat{Freq * Len}$ has a hat to indicate that the terms were centered on their means prior to being multiplied to reduce collinearity.

[21]Scarpa et al. (2012) argue that while normal distributions may be mis-specified for some attributes, this can be minimized if the estimated standard deviation coefficients are sufficiently small so that only a small percentage of individuals end up with the wrong sign.

[22]Several papers find no significant difference in estimated MWTP values between correlated and uncorrelated mixed logit preference-space models (Colombo et al., 2007; Scarpa et al., 2012). Hole & Kolstad (2012) find similar results between correlated and uncorrelated WTP-space models.

of lognormally distributed cost attribute k, the logarithm of the coefficient is distributed normally, $\lambda_k = exp(b_k + s_k\omega_k)$.

Much research has gone into considering what distribution is appropriate for the cost attribute because it exerts such influence on the MWTP distribution (Hensher & Greene, 2003; Meijer & Rouwendal, 2006; Balcombe et al., 2009; Hensher & Greene, 2011).[23] Individual MUI coefficients very near zero result in unrealistic extreme values of MWTP (Scarpa et al., 2008), while others argue that this is informative of price insensitivity (Giergiczny et al., 2012; Lanz & Provins, 2013).

For the WTP-space model (W1), I follow papers by Hensher & Greene (2011); Hole & Kolstad (2012); Scarpa et al. (2012) and estimate a WTP-space model using a generalized multinomial logit framework under certain restrictions. The utility specification in Equation 3.17 is the basis for the empirical WTP-space model:

$$U_{njt} = \lambda_n[w_1 Freq_j + w_2 Len_j + w_3 Not_j + w_4 Reu_j + w_5 Grn_j + w_6 \widehat{FreqLen} - Cost] \tag{3.18}$$

Equation 3.18 is the empirical specification for the WTP-space model. Non-price MWTP coefficients follow a normal distribution, while the confounded price scale λ_n coefficient is estimated lognormally. Specifying a normal distribution for attributes allows for the possibility of negative MWTP values.

In the WTP-space specification, λ_n term is confounded with the heterogeneous scale, which must be positive. As a result, λ_n is specified lognormal.

$$\lambda_n = exp(\overline{\lambda} + \tau\omega) \tag{3.19}$$

[23] Hess et al. (2005) favor using unconstrained distributions such as the normal and removing some percentage of outliers or wrong sign estimates. Balcombe et al. (2009) found that specifying cost as lognormally distributed outperformed unconstrained and constrained alternative distributions.

where $\overline{\lambda}$ is the mean scale value, τ is the standard deviation with a standard normal distribution, $\omega \sim N(0,1)$. To ensure that λ_n normalizes at 1, take the expectation of Equation 3.19 and set it equal to 1.

$$E[\lambda_n] = E[exp(\overline{\lambda} + \tau\omega)] \tag{3.20}$$

$$E[\lambda_n] = exp(\overline{\lambda} + \frac{\tau^2}{2}) = 1 \tag{3.21}$$

The derivation from Equation 3.20 to Equation 3.21 can be found in Chapter 2, Appendix A. From Equation 3.21, only τ can be estimated. Setting $\overline{\lambda} = -\frac{\tau^2}{2}$ achieves $E[\lambda_n] = 1$. The parameters reported in the results tables of studies using WTP-space models vary in terminology. Some report $ln(\lambda_n)$ and the standard deviation, while others report a *Parameter for cost (WTP-space)* and *Variance parameter in scale* (τ); I report results using the latter terminology. They are reporting the same thing because the random cost and scale coefficients are confounded within λ_n. The standard deviation of λ_n is the estimated τ.

3.4 Results

Table 3.2 provides the estimated means and standard deviation coefficients for all four estimated models. The first three columns are the preference-space models where the marginal utility of income is fixed (F1), normally distributed (N1) and lognormally distributed (L1). The final column reports the WTP-space model (W1) results. Other studies use these model combinations of mixed logit preference-space and WTP-space models for comparison of results.

In general, our results are consistent with the literature comparing model fit between WTP-space and preference-space models. Goodness-of-fit to the data is measured by comparing log-likelihood and information criteria scores.[24] Similar to Train & Weeks (2005); Sonnier et al. (2007); Hensher & Greene (2011); Lanz & Provins (2013), the WTP-space model has a poorer fit with the data than the preference-space mixed logit models that allow for a random cost attribute.[25] Log-likelihood scores, as well as AIC and BIC criteria, indicate that Models W1 and F1 have almost the same model fit in contrast to Balcombe et al. (2009); Scarpa et al. (2012) who find the WTP-space models outperforms the mixed logit with a fixed cost. Overall, Model L1 has the best fit; this model specifies a lognormal cost attribute.

The signs on the coefficients are as expected and consistent across models as are the significance levels. This contrasts from Hole & Kolstad (2012); Lanz & Provins (2013), who find the significance of estimated coefficients can change between model types. All mean and standard deviation coefficients are highly significant at the 1% level.[26] The ratio of mean to standard deviation coefficients are less than one for all attributes except Length, indicating a great deal of variation in preferences for infrastructure investment. All preference variation is due to latent influences as no observable characteristics or attitudes were included.

The comparison of MWTP distributions is of key interest in this paper because it provides a baseline for comparing the behavioral equivalence of the WTP-space and preference-space models. Statistical moments of the distribu-

[24] Likelihood ratio tests could not be used because the models use different distributions but are not nested.

[25] Scarpa et al. (2008); Balcombe et al. (2009); Scarpa et al. (2012) find the WTP-space model to be an improvement.

[26] A more in-depth discussion regarding the interpretation of ratepayer preferences can be found in Chapter 2 of my dissertation. In general, the representative water utility customer prefers less frequent outages at home, shorter average outage lengths, and a lower monthly cost paid to the dedicated Water Infrastructure Investment Fund. Higher rates of investment in renewable energy use by the utility and reuse water pipe infrastructure as well as greater notification of planned outages positively impact the same customer.

tion of MWTP for all are given in Table 3.3 (models L1 and N1) and Table 3.4 (models (F1 and W1). The median, mean, standard deviation, minimum and maximum MWTP are reported for each model. The first column for each model includes the entire MWTP distribution; the second and third columns drop two and ten percent of observations, respectively.[27] Estimated MWTP values are calculated for all four models using conditional individual coefficients estimated using the procedure described by Train (2009). These coefficients are considered a closer approximation of the individual's true, underlying preferences by Greene et al. (2005) and are conditional on their observed choices.[28] The individual-specific coefficient w_n is reported as the MWTP for the W1 model, consistent with the theoretical model.

If estimated MWTP from all four models are considered to provide a realistic range of the underlying MWTP, then the median MWTP per month to avoid an additional outage at home over the next five years ranges from \$0.54 to \$0.92. The median MWTP per month to avoid an increase in the average outage length of one hour ranges from \$0.75 to \$1.01; the median MWTP per month for a one-percent increase the amount of urban greenspace irrigated with reuse water ranges from \$0.12 to \$0.17. The median MWTP per month for a one-percent increase in the amount of renewable energy used by the utility ranges from \$0.11 to \$0.15. Consistently across models, the largest standard deviation is for the frequency of outages experienced at home, which is the primary attribute describing individual experience with deteriorating pipes.

Comparing the central moments and minimum/maximum MWTP estimates between models in Table 3.4, the similarity between the distributions of the WTP-space (W1) model and preference-space fixed cost (F1) model is quite no-

[27]There is no standard for dropping a percentage of extreme outliers although some researchers advocate this practice instead of using a bounded distribution (Hess et al., 2005).

[28]The coefficients represent the mean and standard deviation for customers who would make the same choices with the same set of choices.

table. Hole & Kolstad (2012) also find that the mean WTP estimates from the WTP-space models are much more similar to the WTP estimates from the basic MNL model and the mixed logit with a fixed cost parameter.[29]

As seen in Table 3.4, the WTP-space model, W1, and preference-space model F1 with fixed cost have the smallest, and very similar, standard deviations for all attributes. The tighter distribution interval for the MWTP in WTP-space is consistent with recent papers (Train & Weeks, 2005; Sonnier et al., 2007; Scarpa et al., 2008; Balcombe et al., 2009; Hensher & Greene, 2011; Hole & Kolstad, 2012; Scarpa et al., 2012; Lanz & Provins, 2013).[30] Note that the standard deviation for the Reuse attribute is much smaller than for the Frequency and Length attributes. If WTP-space results are interpreted as the MWTP with a scalar cost, this might imply that individuals have more homogeneous preferences towards investing in reuse pipe infrastructure as compared to investing in drinking pipe infrastructure. This may reflect that urban greenspace is more of a public good enjoyed by all, while drinking pipe infrastructure is related to service experienced by the individual and service levels vary according to the local infrastructure conditions.

As expected, given distributional properties, Models N1 and L1 exhibit extreme outliers (see Table 3.3). When it comes to extreme MWTP values in the distribution, the cause is primarily traced back to marginal utility of income coefficients very close to zero (Scarpa et al., 2008). Unsurprisingly then, the normal distribution, which spans zero and can allow for draws close to zero in both the positive and negative quadrants, displays the most extreme values

[29]Hole & Kolstad (2012) conclude that estimating a random cost and correlated attributes has more impact on model fit than the difference between preference-space and WTP-space estimation.

[30]Kernel density graphs visually demonstrate tighter MWTP distributions in Scarpa et al. (2008) and Hole & Kolstad (2012), while ordered observation graphs are used to compare the magnitude of extreme outliers (Hensher & Greene, 2011).

at both the positive and negative ends of the MWTP distribution. I compare the spread under conditions of dropping two and ten percent of extreme outliers for all models as Hess et al. (2005) recommends.[31] With L1, removing ten percent of the distribution eliminates most of the theoretically incorrect signs on the Length and Frequency attributes and the MWTP distribution is constrained to a reasonable level. Two percent is actually sufficient to correct the negative sign for the Length attribute. With N1, removing ten percent is not enough to truly correct the issue.[32] The mean MWTP for the fixed cost and WTP-space models do not change even as MWTP values at the distribution ends are dropped, confirming a lack of influence due to outliers.

Ordered observation scatter plots allow visual comparison of the positive and negative ends of the MWTP distribution. Figure 2 and Figure 3 focus on the lowest and highest 60 MWTP estimated observations from the W1 and F1 models, using the Frequency attribute. These two models display no presence of extreme outliers and, most notably, have remarkably similar estimated MWTPs at each end.[33]

3.4.1 Income validity

Various studies using preference-space and contingent valuation models have shown income and MWTP to have a positive relationship (Jacobsen & Hanley,

[31] They do not recommend a certain percentage of outliers, just that they be dropped.

[32] Often theoretically incorrect signs are assumed to reflect mis-specification of preferences. I suggest that, for this data, theoretically incorrect signs reflect adaptive behaviors. Individuals prefer to adapt to worsening service levels and not face higher water bills, rather than they actually prefer more outages.

[33] Ordered observation scatter plots were also generated for all four models together. As expected, models L1 and N1 had extreme values. The three most extreme MWTP values for N1, both positive and negative, were not included because their magnitude obscured the information provided by the rest of the observations. The values were $417, $200, and $135 (positive end) and -$118, -$135, and -$367 (negative end). These graphs are available upon request.

2009; Broberg, 2010). Using second-stage regression techniques, income has been found to be significantly related to MWTP (Campbell, 2007; Abildtrup et al., 2013).[34] While many studies have noted that the tighter intervals seen in the WTP-space models are a positive development, there has been a lack of validity testing against theoretical predictions of behavior such as the income effect on MWTP.[35] The MWTP distribution is examined using different income levels as a measure of construct validity recommended by (Arrow et al., 1993; Freeman III, 2003).

MWTP is influenced by the variation in MUI resulting from a random cost parameter, which implies that individuals are affected by an extra dollar differently. Donaldson et al. (2002) argues that the MUI is responsible for most of the variation in MWTP for health care interventions and that MWTP more reflects individuals' ability-to-pay for a health care intervention. Economic theory predicts the MUI should be decreasing with income so higher income individuals should have a smaller λ_n than lower income individuals. Findings show this with both cost estimated using lognormal and normal distributions, although the effect is greater for the lognormal distribution.[36]

Median MWTP by income categories is provided in Table 3.5. Quantiles and median MWTP are reported as they are less affected by outliers caused due to the distribution (Scarpa et al., 2012); it has already been shown that Models N1 and to a lesser extent, L1, have extreme outliers. Three income categories were

[34]Abildtrup et al. (2013) found income to be significant both positively and negatively depending on what type of forest recreation was being valued; it was never insignificant.

[35]Sonnier et al. (2007) find the WTP-space models more closely approximate the true WTP in their research using simulated data, which could be considered a form of convergent validity testing.

[36]I test this by looking at the mean MUI for the seven income categories for model L1 (lognormal) / N1 (normal), respectively. Mean λ = -1.12 -0.38 ($18,000), -1.04 -0.37 ($30,000), -0.76 -0.32 ($50,000), -0.74 -0.32 ($80,000), -0.48 -0.24 ($125,000), -0.69 -0.28 ($175,000), and -0.39 -0.25 ($220,000).

used.[37] Low income is defined as an annual income less than $40,000; twenty-nine percent of households fell in this category. Forty-six percent of respondent households are defined as mid-income, between $40,000 to $99,999. Twenty-four percent of households are considered high-income with an annual income greater than $100,000.[38]

What is immediately noticeable is that the estimated median MWTP for all attributes in Models N1 and L1 are increasing in income and the variation between the 25th and 75th quantiles is increasing. This result is attributable to the random cost parameter. Model F1 shows small positive income effect in estimated median MWTP. The variation between the quantiles doesn't increase but each quantile is increasing in income. But for Model W1, the effect is almost imperceptible for the Reuse and Green attributes and only slightly increasing for the Length and Frequency attributes, even less than Model F1 where the cost is fixed. The variation between quantiles doesn't change, nor does the MWTP at each quantile increase much with income. The distribution appears practically the same for the low income group as for the high income group. Across all attributes the increase in MWTP for Model W1 between low- to high-income ranges from one to thirteen cents while average estimated income increases from $27,000 (low-income) to $146,000 (high-income). For example, the median MWTP to avoid one additional outage at home increases from $0.48 to $0.76 to $1.46 for Model L1 and from $0.79 to $0.92 to $1.08 for Model F1. For Model W1, the increase with income is $0.86 to $0.90 to $1.03. There is a two-cent increase in median MWTP across income categories for

[37] Of the 850 respondent households, 70 did not indicate an income level and are not included in this table.

[38] These income classifications were chosen in part due to the number of survey respondents in each income category. Eight percent of survey respondents had an annual household income of less than $19,999 and eight percent had annual income of $150,000 or more. The low, middle, and high income categories used correspond roughly to income descriptions of working class, middle-class, and upper-middle-class income levels.

the attributes describing increased infrastructure investment in reuse water irrigation.

Scenarios were created and monthly Infrastructure Investment Fund amounts were calculated using the median figures for each income category (see Table 3.6). Every water utility customer faces the same investment fund amount on their monthly bill; using the median MWTP values for low-, mid-, and high-income groups allows water utility managers to understand the bill impact by income groups. Four scenarios were created simulating investment scenarios that focused on deteriorating pipe infrastructure locally (Scenario 1), deteriorating pipe infrastructure in other parts of Albuquerque (Scenario 2), failing infrastructure and water scarcity (Scenario 3), and a focus on water reuse infrastructure and renewable energy (Scenario 4). The goals of each scenario vary and are reflected in the different levels changes to each attribute. Monthly amounts are reported for each income group. The first thing to note, is that with the exception of two high-income WTP values, the monthly amounts for all income groups and all models are less than \$15, the highest cost level presented in the survey. Two high-income WTP values are outside that range due to the log-normal distribution for the cost attribute in Model L1.

Second, Models N1 and L1 with the heterogeneous MUI reflect the greatest spread between the low-income and high-income groups for all scenarios. Models F1 and W1 show relatively small increases between the monthly amounts for each scenario as income increases. Again, notably the scenario amounts are almost identical for F1 and W1, reflecting the similarity of the MWTP distribution. For example, the range of monthly investment amounts calculated using W1(F1) median MWTP values ranges from \$6.49 (\$6.41) for low income individuals to \$7.42 (\$7.46) for high income individuals (Scenario 1) or \$6.50 (\$6.55) for low-income and \$7.65 (\$7.58) for high-income (Scenario 2). In comparison, the range for the same scenarios using L1 model results shows an income effect, where WTP is increasing in income from \$5.08 to \$11.31 for Scenario 1 and \$4.82 to \$11.64 for Scenario 2.

The calculated scenario amounts appear contradictory when compared against respondents' self-reported level of hardship with higher water bills (see Table 3.7). Individuals reported the amount of hardship they would face from water bill increases of \$5, \$10, and \$15 due to infrastructure investment. More low income individuals report hardship at every level than do high income individuals which supports the theory that MUI decreases in income. For instance, 25% of low-income individuals reported that an extra \$5 per month would cause 'no hardship', while 50% and 68% of mid- and high-income individuals reported the same; for an increase of \$15 per month, one percent of low income individuals reported 'no hardship' as compared to 29% of high-income individuals.

Approximately 70% of high-income individuals report that an extra \$10 on their monthly water bill would cause a little or no hardship, while only 21% of low-income individuals report the same. Yet their calculated monthly WTP for Scenarios 1 through 4 are very similar, thus appearing to be lower than what high-income individuals state that they can pay with little hardship or higher than low-income individuals stated hardship level. For instance, high-income individuals would face an additional amount of \$7.42, \$7.65, \$11.62, and \$13.49 under Scenarios 1 through 4, respectively. Low-income individuals would face an additional amount that is only \$1.00 to \$1.50 less in each scenario.

Interestingly, low income individuals would face a higher monthly bill impact in all 4 scenarios if median MWTP values from Model F1 or W1 with the fixed cost are used as compared to the monthly bill impact using the median results from Models N1 or L1 where MUI is allowed to vary. The assumption of a constant MUI adversely impacts these households.[39]

3.4.2 Measuring distributional impact across income category

Many cost-benefit analyses use MWTP to analyze how benefits are distributed. Typically MWTP is used as an indication of how much an individual values an improvement in an environmental good, but that would lead to the assumption that high-income individuals receive a much greater benefit from pipe infrastructure investments than low income individuals do. Map 3.1 shows that the median household income is lower in the Census tracts with the greatest level of deteriorating infrastructure. A lower MWTP in those Census tracts may reflect a willingness to adapt to worsening conditions as a reflection of their ability-to-pay, but the benefits of improving infrastructure would actually be greater than in tracts with good infrastructure.

Deteriorating infrastructure typically is a bigger issue in older and centrally-located neighborhoods in cities where median household incomes are often lower. This is certainly the case in Albuquerque as seen in Map 3.1 which depicts the median household income of each Census tract with the incidence of pipe breaks reported by the water utility. Census tracts with darker colors have higher incidences of reported pipe breaks over the five years preceding the survey. The dots represent the size of the median household income in each Census tract and increase with income. The map shows that, in general, median household income tends to be smaller in the Census tracts with the highest incidence of pipe breaks. Map 3.2 shows the distribution of survey respondent household income levels, which resembles the average Census tract

[39]Conversely, assuming a constant MUI likely positively impacts high-income households by understating their marginal rate of substitution.

income patterns seen in the accompanying map.

In order to measure social benefits of investing in water utility infrastructure, one approach discussed in Loomis (2011) is to weight MWTP values by the ratio of the median income of each income group to the population median income. By overweighting the benefits to low income groups and underweighting the benefits to high income groups, the minimizes the impact of ability-to-pay on MWTP estimates. I extend this to a more localized approach for each household by weighting each household's MWTP for an investment attribute by the ratio of their household income to the median household income for owner-occupied units within their Census tract ('the income ratio').[40] Thus the weighted benefits to each individual are relative to the Census tract in which they live.

Table 3.8 compares the unweighted and weighted mean MWTP estimates from Model W1 for all infrastructure investment attributes. The unweighted mean MWTP estimates show little to no increase as income increases, reflecting the absence of the income effect. For instance, the estimated mean MWTP by income category of avoiding an extra outage at home is $0.78, $0.86, and $0.92 as income categories increase from $20,000 to $70,000 to $175,000 respectively. If the unweighted MWTP is considered the social benefit of the investment, then the benefit of avoiding one more outage to a high-income individual would be more than the benefit to a low-income individual. However, the household income of the wealthier person could be six to seven time larger than for the low-income household. So, I'd argue that the $0.92 MWTP is less valuable to that high-income individual than $0.78 is to the low-income household, which would suggest that MWTP should be weighted by income in some

[40]Using the median household income for owner-occupied units is a more conservative weighting scheme since that median income of home owners is typically greater than the median household income when renters are included.

manner. Weighted MWTP estimates indicate that the net benefits received by income category are \$1.81, \$0.94, and \$0.54 to avoid an extra outage at home. The estimated mean MWTP for an additional 1% of urban greenspace irrigated with reuse water changes by one cent across income categories using the unweighted MWTP. However, the mean weighted MWTP indicate social benefits of \$0.34, \$0.17, and \$0.09 as income increases.

Table 3.9 shows the impact of weighting estimates for the WTP-space W1 model and the preference-space lognormal cost L1 models for all observations within one Census tract in the south-central part of Albuquerque experiencing above average deteriorating infrastructure and with a range of income levels. The water utility recorded 46 pipe breaks in the five years preceding the survey and the median household income for owner-occupied housing units is \$62,054. There were five survey households in this Census tract, whose characteristics are fairly similar with household income showing the greatest variation. The income ratio for these households ranges from 0.48 to 3.55. Two individuals have very similar MWTP to avoid an extra outage at home, but different incomes. Individual A has a MWTP of \$0.79 and a household income of approximately \$75,000; 1.29 is their income ratio. Individual B has a MWTP of \$0.65 and a household income of approximately \$220,000; 3.55 is their income ratio. Weighting the estimated MWTP provides a clearer picture of the benefit of one less outage at home in relation to their income level: \$0.62 and \$0.18, respectively.

The weights are one way of relating estimated MWTP and social benefits, as similar infrastructure benefits are received by multiple households in a Census tract when a failing pipe is repaired. However, the ability-to-pay varies and thus the MUI surely varies as well. One interpretation is that based on their observed choices and estimated preferences, the weighted MWTP values are a more accurate reflection of the value of the infrastructure investment.

3.5 Conclusion

This paper estimated four mixed logit models, three preference-space models with normal (N1) and lognormal (L1) distributions of the cost attribute, plus a fixed (F1) cost attribute and one WTP-space model (W1). There were three purposes to the paper. The first is that while comparisons between mixed logit preference-space and WTP-space models have been studied, the literature is still growing and has not demonstrated overwhelmingly that one method is better than the other (Train & Weeks, 2005; Sonnier et al., 2007; Scarpa et al., 2008; Balcombe et al., 2009; Hensher & Greene, 2011; Scarpa et al., 2012; Lanz & Provins, 2013).

Not all researchers conclude that WTP-space models are an improvement over the preference-space model. Hensher & Greene (2011) note that trade-offs exist between models that fit the data better and those that result in more realistic estimates of the MWTP distribution. Hole & Kolstad (2012) conclude that the difference between the two models matters less than specifying the cost attribute random with a non-zero covariance matrix. Scarpa et al. (2008) note the WTP-space model allows a heterogeneous scale term over individuals that is separate from heterogeneous WTP estimates.[41] This study contributes to the general body of research comparing these models using a dataset on preferences for water utility infrastructure. The second purpose is to use validity testing of the MWTP median measures from each model by income category to establish a baseline for behavioral equivalence between the WTP-space dis-

[41]Hensher & Greene (2011) find that including scale in a preference-space model results in more similar distributions between preference-space and WTP-space distributions of WTP.

tribution and the preference-space distributions under different assumptions about the MUI. The final purpose weights the MWTP estimates to get a clearer picture of social benefits.

One of the more interesting results is how similar the estimated MWTP and distributions are between Models W1 and F1, while the two models that allow for a heterogeneous MUI (L1 and N1) fit this data better than either Model W1 or F1. The mixed logit model with a lognormal cost (L1) provided the best fit overall but has a dispersed MWTP distribution. Consistent with several other studies the calculated MWTP distributions are much tighter and the median MWTP values are more conservative in the WTP-space model (W1), similar to the fixed cost model. Scarpa et al. (2008) argue that either a fixed cost coefficient or estimating in WTP-space will ensure a bounded distribution, although a tight distribution can lessen heterogeneity in MWTP that exists in the population; this is a good description of my results.

I interpret the results from the WTP-space model as an indication that estimating the heterogeneous scale cost parameter separately from MWTP heterogeneity acts to fix the cost in the resulting MWTP estimates. As a result, there Model W1 shows little relationship between increasing income and MWTP estimates. Economic theory and empirical research indicate that MWTP values should increase with income for a normal good, as occurs with the preference-space models that have a random cost. The WTP-space median MWTP increase with income category but only slightly and are more comparable to the increases under fixed cost assumptions. Hypothetical infrastructure investment scenarios are calculated using median MWTP for each attribute by income categories. The monthly amounts calculated using the WTP-space model estimates contradict individuals' self-reported hardship levels when faced with increased water bills.

GIS-mapping techniques show a relationship by Census tract between lower median household income level and more deteriorating pipe infrastructure. Use of a weighting ratio reduces the influence of ability-to-pay and improves understanding of the social benefits of infrastructure renewal projects across Census tracts. The weighted benefits indicate a greater value to lower income individuals, as expected considering the relationship between deteriorating infrastructure and median income.

The WTP-space model may be a promising method, however it does not appear to be significantly different from just estimating a preference-space model with a fixed cost parameter. The MWTP distribution from the WTP-space fails an income validity test, which is problematic from a theoretical standpoint if, indeed, the cost scale coefficient is heterogeneous. The preference-space model with a lognormal cost parameter is found to be the best fitting with a MWTP distribution that increases in income. Between two to ten percent of the distributional outliers must be dropped if negative MWTP are considered theroetically incorrect, which is also problematic since the majority of the dropped observations are from high-income individuals. Using a weighting scheme that attempts to relate the social benefits received to income and local infrastructure conditions is one suggestion to alleviate the problematic issues with both models.

Table 3.1: Descriptive statistics

Attribute	Description	Mean or %	S.d.
Age	Age of respondent, in years; continuous	54	16
Female	Respondent is female; 1=yes, 0=no	0.54	0.50
Hispanic	Respondent is Hispanic; 1=yes, 0=no	0.33	0.47
HSDiploma	Highest level of education is high school diploma or GED; 1=yes, 0=no	0.15	0.36
AA	Highest level of education is some years of college or an AA degree; 1=yes, 0=no	0.30	0.46
BA	Highest level of education is a Bachelor's degree or higher; 1=yes, 0=no	0.55	0.50
HomeOut	Respondent experienced an outage at home in previous 5 years; 1=yes, 0=no	0.31	0.46
TractOut[a]	Number of pipe breaks in Census tract in previous 5 years; continuous	13.4	14.2
Water0	0% pct of property is watered in typical summer month; 1=yes, 0=no	0.03	0.18
Water50	1-50% pct of property is watered in typical summer month; 1=yes, 0=no	0.83	0.38
Water100	51-100% pct of property is watered in typical summer month; 1=yes, 0=no	0.14	0.35
Children	Children live in the household; 1=yes, 0=no	0.30	0.46
HH[b]	Household has aytpical water use; 1=yes, 0=no	0.38	0.48
NM	Years lived in NM; continuous	33	19
Address	Years lived in current home; continuous	15	14
Westside	Lives west of Rio Grande River; 1=yes, 0=no	0.27	0.44
South	Lives in south Albuquerque; 1=yes, 0=no	0.24	0.43
North	Lives in northeast Albuquerque; 1=yes, 0=no	0.49	0.50

Table 3.1: Descriptive statistics

Attribute	Description	Mean or %	S.d.

[a] Pipe breaks reported by ABCWUA for five years prior to the survey, aggregated by Census Tract

[b] Water outages at home may affect certain sub-populations differently, i.e. a stay-at-home parent, a home business, or someone with a sensitive health issue.

Table 3.2: Results Preference- and WTP-space models

Attribute	F1	N1	L1	W1
		Preference-space		WTP-space[a]
	Coefficient (se)	Coefficient (se)	Coefficient (se)	Coefficient (se)
Frequency	-15.47(1.76)***	-23.87(4.07)***	-22.48(3.12)***	-0.83(0.08)***
Freq_sd	20.80(2.87)***	29.41(5.79)***	27.94(5.34)***	1.14(0.12)***
Length	-13.98(1.44)***	-23.66(3.78)***	-21.91(2.90)***	-0.76(0.05)***
Length_sd	11.30(2.00)***	17.90(3.89)***	15.96(3.32)***	0.65(0.10)***
Reuse	2.95(0.33)***	4.70(0.78)***	4.28(0.63)***	0.16(0.02)***
Reuse_sd	3.10(0.58)***	6.00(1.21)***	5.19(0.99)***	0.16(0.03)***
Green	2.58(0.40)***	4.11(0.76)***	4.10(0.70)***	0.14(0.02)***
Green_sd	5.97(0.75)***	9.32(1.69)***	8.36(1.23)***	0.33(0.03)***
Notify	1.14(0.15)***	1.97(0.34)***	1.64(0.26)***	0.06(0.01)***
FreqLen	-0.006***	-0.007*	-0.003	-0.0004***
FreqLen(se)	(0.002)	(0.004)	(0.004)	(0.0001)
Cost	-0.18(0.02)***	-0.32(0.05)***		
ln(Cost)[b]			-1.93(0.20)***	
Cost_sd		0.34(0.06)***	1.86(0.35)***	
Cost (λ_n)				-1.51(0.20)***
Variance in scale (τ)				0.74(0.35)**
Parameters	11	12	12	12
Observations	3317	3317	3317	3317
LL score	-1709.2031	-1665.157	-1651.295	-1708.0547
AIC	3440.4062	3354.314	3326.59	3440.1094
BIC	3506.5566	3426.4781	3398.7541	3512.2735

Significance levels *** $\leqslant$ 0.01, ** $\leqslant$ 0.05, * $\leqslant$ 0.10

[a] Coefficients on non-cost attributes are interpretable as the mean MWTP.

[c] Using Revelt & Train (1998), Cost (Model L1) is calculated mean=0.825, median=0.145, sd=1.925

Table 3.3: Models N1 & L1: MWTP ($) distribution with 0%, 2%, and 10% of outliers trimmed

	N1 (Cost normal)			L1 (Cost lognormal)		
	100%	98%	90%	100%	98%	90%
Monthly MWTP to avoid one additional outage at home over next five years						
Median	0.54	0.54	0.54	0.77	0.77	0.77
Mean	0.97	0.86	0.83	1.30	1.26	1.15
St. dev.	21.99	2.18	0.85	1.95	1.44	1.12
Max.	417.20	16.38	4.04	25.69	7.46	4.17
Min.	-367.37	-11.87	-1.57	-12.86	-1.24	-0.08
Monthly MWTP to avoid a 1-hour increase in average outage length						
Median	0.60	0.60	0.60	1.01	1.01	1.01
Mean	1.07	0.92	0.84	1.39	1.32	1.24
St. dev.	14.02	2.35	1.02	1.66	1.28	1.09
Max.	315.67	13.52	5.34	26.83	5.98	4.03
Min.	-117.91	-11.50	-2.28	-0.66	0.01	0.05
Monthly MWTP for a 1% increase in urban greenspace irrigated with reuse water						
Median	0.12	0.12	0.12	0.16	0.16	0.16
Mean	0.13	0.16	0.16	0.24	0.25	0.22
St. dev.	1.60	0.44	0.20	0.61	0.28	0.21
Max.	22.28	2.94	0.92	3.28	1.50	0.87
Min.	-18.86	-2.69	-0.37	-14.39	-0.34	0.003
Monthly MWTP for a 1% increase in energy use by water utility that is from renewable sources						
Median	0.11	0.11	0.11	0.11	0.11	0.11
Mean	-0.14	0.08	0.12	0.24	0.24	0.21
St. dev.	5.10	0.59	0.21	0.53	0.41	0.27
Max.	58.80	2.90	0.64	2.55	1.83	1.25
Min.	-86.55	-5.13	-0.71	-6.16	-0.98	-0.32
Obs.	850	834	765	850	834	765

Table 3.4: Model F1 and W1: MWTP ($) distribution with 0%, 2%, and 10% of outliers trimmed

	F1 (Cost fixed)			W1 (WTP-space)		
	100%	98%	90%	100%	98%	90%
Monthly MWTP to avoid one additional outage at home over next five years						
Median	0.90	0.90	0.91	0.92	0.92	0.92
Mean	0.86	0.86	0.87	0.85	0.85	0.87
St. dev.	0.64	0.61	0.53	0.64	0.61	0.53
Max.	2.62	2.18	1.70	2.76	1.97	1.70
Min.	-1.26	-0.63	-0.25	-1.19	-0.78	-0.30
Monthly MWTP to avoid a 1-hour increase in average outage length						
Median	0.76	0.76	0.76	0.75	0.75	0.75
Mean	0.77	0.77	0.77	0.76	0.76	0.76
St. dev.	0.28	0.27	0.23	0.32	0.29	0.25
Max.	1.62	1.43	1.26	1.80	1.50	1.30
Min.	-0.40	0.10	0.34	-0.73	0.08	0.29
Monthly MWTP for a 1% increase in urban greenspace irrigated with reuse water						
Median	0.17	0.17	0.17	0.16	0.16	0.16
Mean	0.16	0.16	0.16	0.15	0.15	0.16
St. dev.	0.08	0.07	0.06	0.07	0.06	0.05
Max.	0.38	0.31	0.28	0.43	0.30	0.26
Min.	-0.21	-0.06	0.04	-0.11	-0.02	0.04
Monthly MWTP for a 1% increase in energy use by water utility that is from renewable sources						
Median	0.15	0.15 ‘	0.15	0.15	0.15	0.15
Mean	0.14	0.14	0.15	0.14	0.14	0.15
St. dev.	0.21	0.20	0.17	0.20	0.20	0.17
Max.	0.61	0.52	0.45	0.65	0.55	0.45
Min.	-0.44	-0.38	-0.21	-0.44	-0.35	-0.22
Obs.	850	834	765	850	834	765

Table 3.5: MWTP ($) per month, distribution by income category

	Income: Less than $39,999				Income: $40,000 to $99,999			
Percentile	F1	N1	L1	W1	F1	N1	L1	W1
To avoid one more home outage over next 5 years								
25th	0.38	0.22	0.08	0.40	0.43	0.27	0.12	0.40
50th	0.79	0.47	0.48	0.86	0.92	0.57	0.76	0.90
75th	1.32	1.26	1.83	1.32	1.39	1.40	2.11	1.37
S.d.	0.66	8.02	1.69	0.65	0.62	22.38	1.55	0.63
To avoid a 1-hour increase in longer average outage								
25th	0.56	0.35	0.12	0.51	0.57	0.34	0.22	0.55
50th	0.71	0.48	0.54	0.69	0.76	0.63	1.03	0.77
75th	0.94	0.95	1.56	0.96	0.97	1.10	1.94	0.99
S.d.	0.28	4.93	1.28	0.30	0.29	9.82	1.35	0.33
1% more urban greenspace irrigated with reuse water								
25th	0.11	0.04	0.02	0.11	0.12	0.05	0.03	0.12
50th	0.15	0.10	0.11	0.15	0.18	0.11	0.17	0.16
75th	0.20	0.21	0.31	0.19	0.21	0.24	0.37	0.20
S.d.	0.08	0.36	0.37	0.06	0.08	1.93	0.33	0.07
1% increase in renewable energy use								
25th	0.00	0.02	0.01	0.03	-0.03	-0.03	0.01	-0.02
50th	0.15	0.10	0.07	0.16	0.15	0.11	0.13	0.15
75th	0.31	0.24	0.34	0.31	0.29	0.27	0.41	0.30
S.d.	0.21	1.90	0.45	0.20	0.21	6.96	0.57	0.20

	Income: $100,000 or more			
	F1	N1	L1	W1
To avoid one more home outage over next 5 years				
25th	0.46	0.25	0.25	0.43
50th	1.08	0.90	1.46	1.03

Table 3.5: MWTP ($) per month, distribution by income category

75th	1.43	1.58	2.45	1.44
S.d.	0.64	34.03	2.19	0.66
To avoid a 1-hour longer average outage				
25th	0.62	0.38	0.47	0.57
50th	0.80	0.74	1.33	0.82
75th	1.03	1.54	2.78	1.03
S.d.	0.28	25.98	1.56	0.32
1% more urban greenspace irrigated with reuse water				
25th	0.11	0.05	0.07	0.10
50th	0.17	0.14	0.22	0.17
75th	0.22	0.31	0.46	0.21
S.d.	0.08	2.10	0.36	0.07
1% increase in renewable energy use				
25th	-0.01	-0.07	0.01	-0.03
50th	0.17	0.12	0.22	0.16
75th	0.33	0.33	0.51	0.34
S.d.	0.21	4.58	0.53	0.22

Reported quantiles characterize the MWTP distribution per income category. There are 227 low-income, 356 mid-income, and 187 high-income individuals.

Table 3.6: Infrastructure Investment Scenarios Estimated WTP/month per Ratepayer, by Income Category

Scenario by Income Level[a]	F1	N1	L1	W1
Scenario 1: -20% notification of planned outages, avoid $+3$ hours average outage length, avoid $+2$ home outages, $+10\%$ in urban greenspace irrigated with reuse water				
Low Income	\$6.41	\$4.38	\$5.08	\$6.49
Mid Income	\$7.12	\$5.13	\$7.91	\$6.91
High Income	\$7.46	\$6.62	\$11.31	\$7.42
Scenario 2: Repairs in other parts of Albuquerque... Avoid $+6$ hours avg outage length, avoid $+1$ home outage, $+10\%$ urban greenspace irrigated with reuse water				
Low Income	\$6.55	\$4.35	\$4.82	\$6.50
Mid Income	\$7.28	\$5.45	\$8.64	\$7.12
High Income	\$7.58	\$6.74	\$11.64	\$7.65
Scenario 3: Failing infrastructure locally + water scarcity...avoid $+1$ hour avg outage length, $+10\%$ notification of planned outages, avoid $+5$ home outages, $+25\%$ greenspace irrigated with reuse water, $+5\%$ renewable energy use				
Low Income	\$9.76	\$6.33	\$6.74	\$10.14
Mid Income	\$11.21	\$7.28	\$10.53	\$10.62
High Income	\$11.90	\$9.94	\$16.33	\$11.62
Scenario 4: Renewable Portfolio Standards policies... avoid $+3$ hours average outage length, avoid $+1$ outage at home, $+40\%$ greenspace irrigated with reuse water, $+20\%$ renewable energy use				
Low Income	\$11.92	\$7.91	\$7.90	\$12.13
Mid Income	\$13.40	\$9.06	\$13.25	\$12.61
High Income	\$13.68	\$11.12	\$18.65	\$13.49

Low income: Less than \$39,999; Mid income: \$40,000 to \$99,999;
High income: \$100,000 or more

Table 3.7: Financial Burden of Infrastructure Investment

	Level of Hardship											
	None			Small			Some			Mod./ Great		
	(L)[b]	**(M)**[c]	**(H)**[d]	**(L)**	**(M)**	**(H)**	**(L)**	**(M)**	**(H)**	**(L)**	**(M)**	**(H)**
\$5/ month	26	50	68	27	28	20	20	12	5	28	11	7
\$10/ month	6	14	42	15	32	27	24	27	17	55	27	15
\$15/ month	1	9	29	5	14	22	14	21	18	79	56	31

[a] Low income (**L**): Less than \$39,999; Mid income (**M**): \$40,000 to \$99,999;
High income (**H**): \$100,000 or more
The survey question asked respondents to indicate the level of hardship that would result should the water utility increase the monthly bill by the stated amount. Levels are None, Small, Some, Moderate, Great Hardship.

Table 3.8: Unweighted and Weighted Mean MWTP estimates (Model W1)

	Low Income		Mid Income		High Income	
	W1 Mean(sd)	W1norm[a] Mean(sd)	W1 Mean(sd)	W1norm Mean(sd)	W1 Mean(sd)	W1norm Mean(sd)
Freq.	0.78(0.65)	1.81(1.79)	0.86(0.63)	0.94(0.82)	0.92(0.66)	0.54(0.44)
Length	0.72(0.30)	1.63(0.90)	0.76(0.33)	0.80(0.45)	0.82(0.32)	0.48(0.25)
Reuse	0.15(0.06)	0.34(0.20)	0.16(0.07)	0.17(0.10)	0.16(0.07)	0.09(0.05)
Green	0.15(0.20)	0.34(0.55)	0.13(0.21)	0.14(0.23)	0.15(0.22)	0.09(0.14)
Notify	0.06(0)	0.14(0.05)	0.06(0)	0.06(0.02)	0.06(0)	0.03(0.01)

[a] The column W1norm reports WTP-space estimates weighted by the ratio of respondent's household income to the median Census tract owner-occupied household income ('income ratio').

Table 3.9: Social benefits (weighted MWTP $), Census Tract 5.02 in South Central Albuquerque

	Id: No. MH3C9FUA				Id: No. BM4XPE9A			
	W1	W1n[a]	L1	L1n[a]	W1	W1n	L1	L1n
Frequency	0.74	0.57	2.83	2.19	-0.36	-0.73	0.05	0.11
Length	0.44	0.34	1.45	1.12	0.26	0.53	0.08	0.16
Reuse	0.32	0.25	0.78	0.60	0.10	0.20	0.02	0.04
Green	0.09	0.07	-0.03	-0.02	0.22	0.45	0.01	0.03
Gender/Ethnicity	Male, Non-Hispanic				Female, Non-Hispanic			
Age	40 yrs				60 yrs			
Education	B.A.				M.A.			
Water	1 - 25% of property				26-50% of property			
Income	$60,000 to $99,999				$20,000 to $39,999			
IncRatio[c]	1.29				0.48			
	Id: No. MK3ET96A				Id: No. KJMY8GHA			
	W1	W1n	L1	L1n	W1	W1n	L1	L1n
Frequency	0.99	0.49	5.21	2.59	0.65	0.18	0.09	0.03
Length	1.25	0.62	6.57	3.26	0.74	0.21	0.09	0.03
Reuse	-0.02	-0.01	-0.53	-0.26	0.11	0.03	0.01	0.00
Green	0.00	0.00	0.39	0.19	0.12	0.03	0.02	0.01
Gender/Ethnicity	Male, Non-Hispanic				Female, Non-Hispanic			
Age	34 yrs				45 yrs			
Education	M.A.				B.A.			
Water	1 - 25% of property				26-50% of property			
Income	$100,000 to $149,999				$200,000 or more			
IncRatio[c]	2.01				3.55			
	Id: No. UHBPMEBA							
	W1	W1n	L1	L1n				
Frequency	0.79	0.62	0.34	0.26				
Length	1.10	0.85	0.41	0.32				
Reuse	0.16	0.11	0.03	0.03				
Green	0.14	0.13	0.08	0.06				
Gender/Ethnicity	Female, Non-Hispanic							
Age	48 yrs							
Education	M.A.							
Water	1 - 25% of property							
Income	$60,000 to $99,999							
IncRatio[c]	1.29							

ABCWUA reported 46 pipe breaks in Census tract 5.02 between 2004-2009.
[a] Models W1n and L1n were normalized using the income ratio.
[c] Income ratio = Individual HH income / Tract median HH (owner-occupies) income
Median HH income for owner-occupied housing in tract 5.02 was $62,054.

Figure 3.1: Median HH income (Census) and ABCWUA-reported outages, 2004-2009

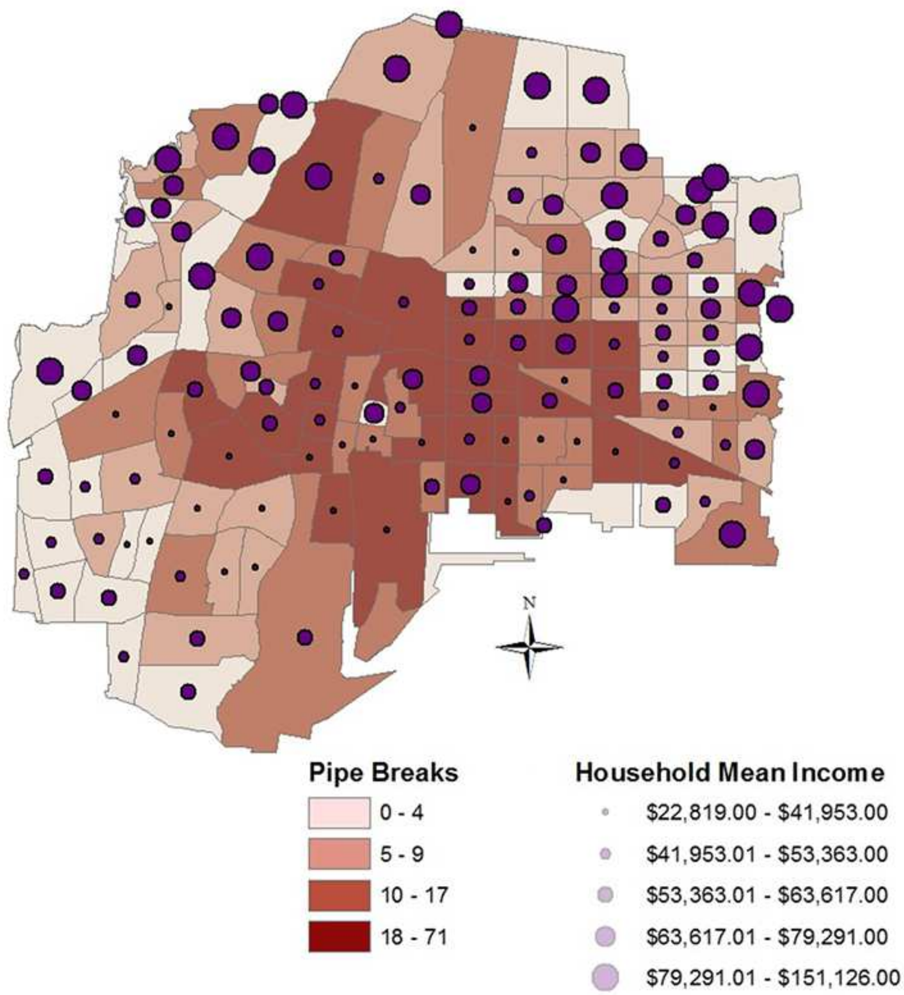


Figure 3.2: Respondent income (interpolated across service area by Kriging)

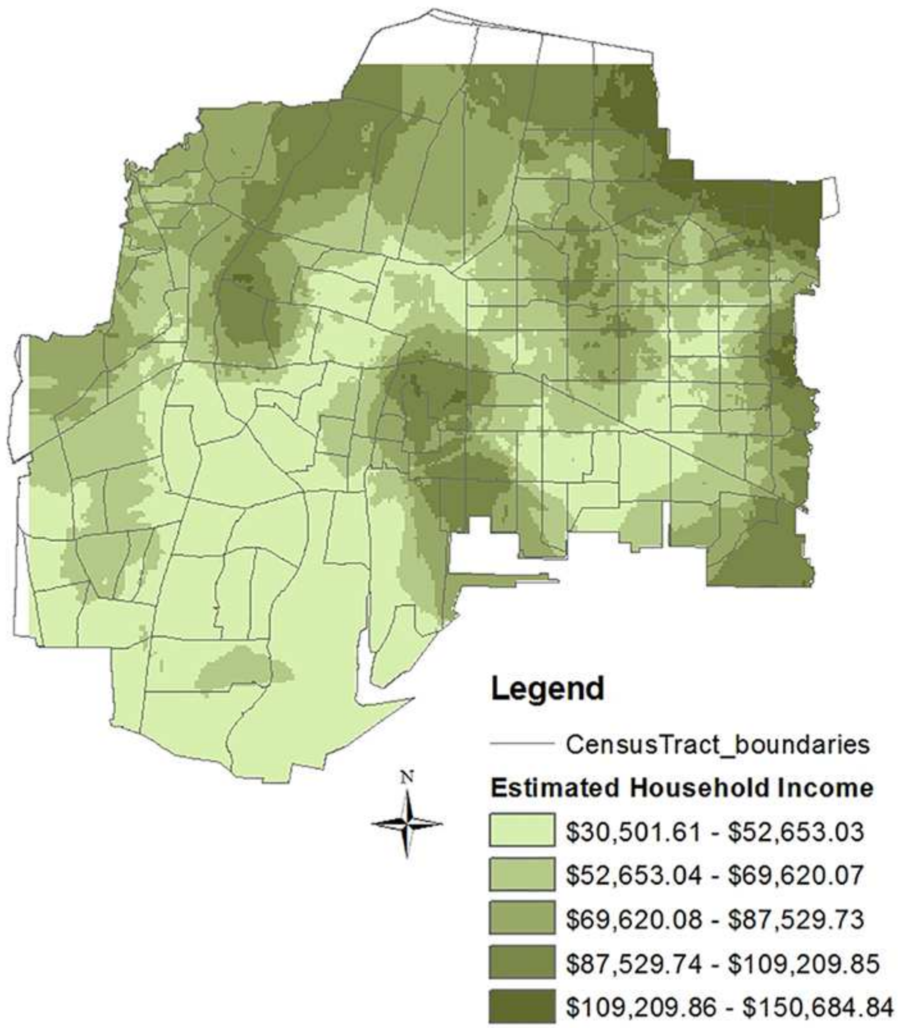


Figure 3.3: Negative end of MWTP distribution for WTP-space and F1 fixed cost preference-space models, Frequency attribute

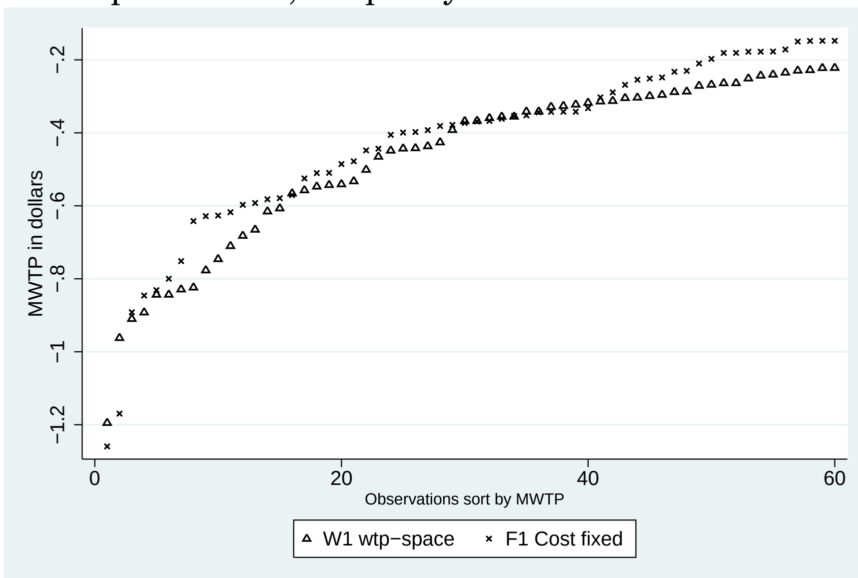
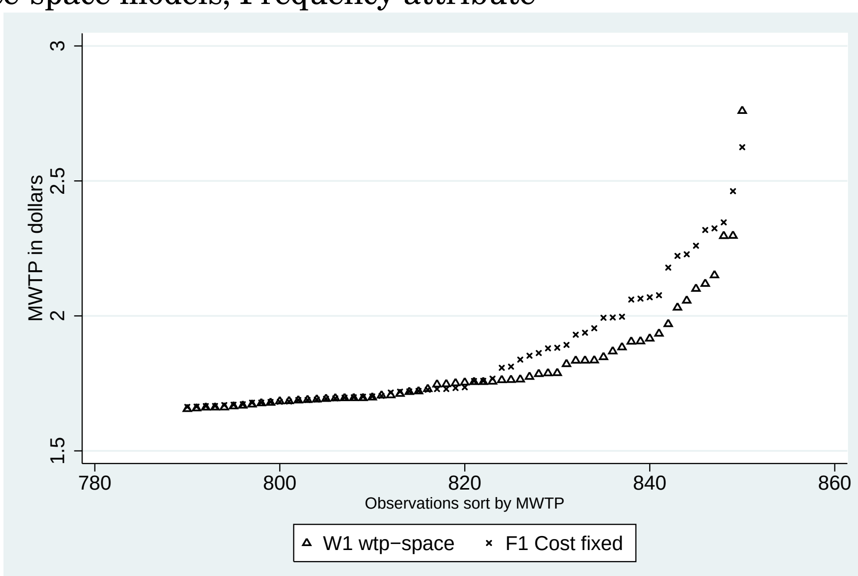


Figure 3.4: Positive end of MWTP distribution for WTP-space and F1 fixed cost preference-space models, Frequency attribute



Chapter 4

Water consumption by irrigation-only customers under an irrigation budget program in a southwestern U.S. water utility

4.1 Introduction

As water utilities transition from using unsustainable withdrawals from underground aquifers as a primary water supply to more sustainable surface water, they must account for the water they use.[1] An initial quantity of acre-feet of water is diverted, treated, and distributed throughout the system for consumption. At the end of the utility's service cycle, a prescribed number of acre feet of water must be cleaned to environmental standards and returned to the river under return flow requirements for use downstream or to meet interstate water compacts. Consumptive water demand is

[1]Examples include the water utilities that service Albuquerque (NM), Fresno (CA), Chicago (IL)

the percentage of water used that is not returned to the river. Landscape irrigation is an example of consumptive use of water resources. The research questions in this chapter focus on estimating the price elasticity of demand and the characteristics that influence demand under a irrigation water budget program whose goal is to optimally manage consumptive water use.

Albuquerque Bernalillo County Water Utility Authority (ABCWUA) provides water service to ratepayers in Albuquerque,NM. It is a representative utility for a metropolitan city in the southwestern U.S. facing the need the maximize water use efficiency due to recurring drought conditions, population growth, and a switch to a surface water supply. The San Juan Chama (SJC) project was finished in 2008 to provide a more sustainable water supply using surface water from the Rio Grande River to reduce the reliance on an overused underground aquifer. The SJC project involves a series of tunnels, pipelines, and intakes that transfer water from southern Colorado's San Juan River (part of the Colorado River Basin system) to New Mexico's Chama River, a tributary of the Rio Grande. The SJC water permit requires approximately fifty percent of the surface water taken from the Rio Grande to be returned to the river downstream from the city as return flow credits, leaving fifty percent for consumptive use.

Population growth and severe drought periods also increase the pressure to make every drop of water count. Between 1990 and 2010, the population of metropolitan Albuquerque increased by 41%.[2] During the summer of 2002, between 70 and 83% of the state was classified as experiencing extreme to exceptional drought. These drought patterns repeated in 2011 and 2013 as well.[3] Many urban water utilities in the southern U.S. and California face some combination of these challenges.

In order to maximize optimal water use while facing the challenges mentioned, water utilities implement conservation programs targeted at different types of water demand. Outdoor water use is often the focus, because it is considered nonessential

[2]According to the U.S. Census Bureau, the population increased from 387,486 to 546,364 in those 20 years.

[3]Data from U.S. Drought Monitor maintained by the National Drought Mitigation Center at the University of Nebraska-Lincoln. Available at http:droughtmonitor.unl.edu

use yet can have a larger effect on demand than indoor water use (Ramachandran & Johnston, 2011). In addition, even though general water demand is price inelastic, outdoor water use tends to be more price elastic than indoor water use.

Water budgets are an effective tool for water utilities with a high need for conserving water and are useful for managing consumptive water use, including irrigation. Approximately 25 utilities use water budgets for irrigation or residential customer classes, primarily in California and the western U.S. (Mayer et al., 2008).

As a long term demand-side conservation tool, water budgets are relatively new. They combine non-price quantity restrictions with an increasing block rate price structure to achieve demand-reduction conservation programs.[4] Unique customer characteristics determine an efficient allotment of water for each account and surcharge penalties increase for excess water use over the allotted amount (Mayer et al., 2008). Baerenklau et al. (2014) find that they significantly reduce demand, although it is most effective as a long term conservation tool.

There is mixed evidence as to the effectiveness and impact of quantity restrictions on demand (Kenney et al., 2008; S. Olmstead, 2014) and (Wichman et al., 2014). Wichman et al. (2014) find that mandatory quantity restriction policies have the greatest impact as compared to other non-price conservation policies. Kenney et al. (2008) argues that overall restrictions are more useful for high volume consumers but price is more effective for low volume households; this is even more true during drought. They find that an additional effect of quantity restrictions is to reduce price elasticity for all households. Others argue that restrictions are a more effective demand management tool than increasing water prices; Duke et al. (2002) finds that water prices in summer months would have to increase 591 percent in order to realize the same 25 percent reduction that can be mandated under quantity use restrictions.

[4]Non-price conservation policies include educational programs, rebates, incentives, outdoor use restrictions on watering technologies or specific days, and quantity restrictions mandating a percentage reduction in demand. Price policies include increasing block rates, penalties for water waste, and scarcity pricing.

However, pricing conservation policies have been advocated by economists who argue that the welfare loss to households is less and households have the most flexibility to optimally allocate their water demand to their highest priority uses, although equity issues due to income are acknowledged (Renwick & Archibald, 1998; Grafton & Ward, 2008; S. Olmstead & Stavins, 2008; Mansur & Olmstead, 2012). Under pricing policies, high income households can avoid conserving water because they can afford the high marginal rates; low income households cannot so the conservation burden falls more heavily on them (Duke & Ehemann, 2004). This trade-off between conservation burden efficiency and equity due to income is reduced under a water budget program. Mayer et al. (2008) note that water budgets allocate the burden of conservation and promote efficient water use in a more equitable manner than the use of restrictions or pricing policies alone.[5] To my knowledge, only Baerenklau et al. (2014) has studied water budgets; they focused on the residential context.

The analysis uses a unique dataset comprised of water use and surcharge data for 1,107 irrigation-only accounts of ABCWUA. They initiated the irrigation water budget (IWB) program for large-scale public sector and commercial customers in 2004 to encourage more water-saving xeriscape landscapes as those accounts were consistently among the biggest water users and water wasters.[6] Water conservations savings for indoor use had approached the maximum amount possible according to their calculations; they began to examine the impact of outdoor irrigation practices.

This study uses a 2SLS model to estimate the elasticity of demand for all IWB accounts as well as site categories, public versus private sector, and low versus high water users while controlling for standard weather variables and site characteristics. A random effects model examines the impact of the past season's irrigating behavior on this year's irrigating behavior. An ordered logit model examines the characteristics

[5]Mayer et al. (2008) notes that each water utility must define 'efficient' for themselves and their ratepayers; there is no single accepted definition of what constitutes efficient water use.

[6]ABCWUA defines large water wasters as accounts who are frequently fined for irrigating excessively so that water runs into the street or during restricted daytime hours of 11a.m. to 7p.m.. Many irrigation-only accounts fell into this category prior to the implementation of the IWB program *Email exchange with Katherine Yuhas, May 6, 2015.*

that affect the probability of an account's irrigation decision reflecting efficient, excess, or extreme water consumption. This study contributes to the literature on water demand by showing that within the irrigation-only customer class, commercial and HOA accounts, landscaped lots under 100,000 feet^2, and low water users are more price sensitive.

In addition, this paper contributes to a limited water literature examining water budgets. Baerenklau et al. (2014) has studied water budgets in a residential customer context, but as far as I am aware, nobody has examined the irrigation-only customer class. Residential customers under a water budget conservation program often have other non-price and price policies operating simultaneously so it is difficult to completely separate out the effect of the water budget alone (Kenney et al., 2008). Corral et al. (1999) also argue that the effect of using price policies to encourage conservation is reduced when water utilities have non-price conservation policies as well. IWB customers in this dataset have no competing conservation programs, so changes in water demand with respect to the water budget program can be studied easier. Results from this study can be compared to residential water budget programs that combine indoor and outdoor use. By focusing on irrigation water budgets separate from other conservation policies, a water utility can fine tune the approach for residential outdoor use. Findings suggest that accounts with water consumption of 100-150% of their IWB have a greater probability of irrigating behavior changes than either efficient or extreme water budget consumers. ABCWUA might want to target this group first.

4.2 Literature Review

In the water economics literature, residential consumers have been the focus of a large quantity of research into water demand. Residential consumers are a large percentage of any water utility's customer base, so looking at residential water demand for single-family households helps utilities target policies to this group (Kenney et al., 2008).[7] Less attention has been given to non-residential or irrigation-only customers since they are a much smaller percentage of the customer base. Thus to consider conservation policies and elasticity of demand for irrigation-only ratepayers, I examine the literature on conservation for residential customers. There is an extensive literature that has looked at the elasticity of demand for indoor and outdoor water use at the household level (Arbues et al., 2003; Dalhuisen et al., 2003).

4.2.1 Elasticity of demand

Researchers consistently find that water demand is price inelastic. Arbues et al. (2003) cite 63 studies in their discussion of issues involved in estimating water demand with price elasticity ranging from -1.12 to $+0.332$. Meta-analyses by Espey et al. (1997) and Dalhuisen et al. (2003) report mean and median estimates of price elasticities at $-0.51, -0.38$ (short run),-0.64 (long run) and $-0.41, -0.35$, respectively.

Studies have compared price elasticity and water demand functions by income quintile (Ruijs et al., 2008), income and lot size (Renwick & Archibald, 1998; Mansur & Olmstead, 2012), the water utility's pricing structure (S. M. Olmstead et al., 2003; S. Olmstead et al., 2007), summer/winter seasons (Klaiber et al., 2012), geographical region or cities (Nieswiadomy, 1992; Renwick & Archibald, 1998), household size (Arbues et al., 2010), level of water consumption (Kenney et al., 2008; Klaiber et al., 2012), modeling approach (Dalhuisen et al., 2003), and droughtnormal years (Corral et al., 1999; Kenney et al., 2008). In addition, Gaudin (2006) argue that while microeconomic theory indicates a relationship between price and quantity demanded for consumers, in the water industry, utilities don't have to post prices and consumers may not realize the price until after they consume a given quantity. They look at the effect of increasing the amount of water price information to consumers and find that price elasticity increases with price information, although it is still inelastic.

[7] Kenney et al. (2008) note that between 70% and 80% of Aurora (CO) Water's customer base are residential customers.

Price responsiveness is usually greater for non-essential, outdoor water use although the elasticity can vary by season, drought years, or income level (Mansur & Olmstead, 2012). Ramachandran & Johnston (2011) shows that water use for outdoors activities such as lawns and pools has a larger effect on demand than water use for indoor needs. Mansur & Olmstead (2012) find that outdoor water use is elastic, -1.20, in wetter months and inelastic, -0.67, in dry months, while also the households who are wealthy with big housing lots have the most inelastic outdoor demand, -0.41, while lower income/small lot households are the most price responsive for outdoor use, -0.791. However, Martin & Kulakowski (1991) conclude that formal studies on price elasticities are not a good guide for setting water prices based on their case study of Tucson Water.

4.2.2 Conservation

Research into the effect of conservation policies is a subset of the literature on water demand. Conservation policies can be grouped by price and non-price policies. Price policies affect demand through price structure of water rates (increasing block rates, uniform) and through penalties for water waste, and scarcity pricing. Non-price policies include educational programs, new technologies rebates, incentives, outdoor use restrictions, and quantity restrictions. Ramachandran & Johnston (2011) note that educational and technological policies work to reduce demand in the long-run, while use restriction policies are a short-run demand reduction tool.

There is considerable debate as to whether price or non-price conservation policies are more effective. Renwick & Archibald (1998) note that non-price conservation policies encourage reduced demand in a way that price policies cannot because water demand tends to be price inelastic. Pint (1999) argues that an increasing block rate (IBR) price structure is effective as a drought management strategy. S. Olmstead & Stavins (2008) also argue for price-based conservation policies, saying that those provide households with the most flexibility in their individual water demand yet collectively, the demand reduction goal is achieved. They also point out that non-price policies are more costly to enforce and monitor.

Most water utilities do not have strictly price or non-price conservation policies, but rather a mixture of both. They may have a block rate tariff system with a rebate program for low flow appliances, an individual water budget with scarcity pricing, and restrictions under drought conditions. Corral et al. (1999) argue that the effect of using price to encourage conservation is reduced when water utilities have non-price conservation policies as well.

Initial research into the effect of conservation programs indicated that they had little effect but they only included a dummy variable to indicate the presence of a conservation program. Nieswiadomy (1992) find that conservation programs do not significantly influence on household demand in any region of the United States. Corral et al. (1999) created three dummy variables for each of five types of conservation policies to indicate level of enforcement/severity of the restriction. Halich & Stephenson (2009) created a conservation policy implementation index that incorporated the intensity with which non-price conservation programs were used in a water district; this means what type of non-price policy is used, how the policy is advertised to consumers, and whether it is voluntary or mandatory. Mandatory restrictions resulted in a 4 to 22% decrease in water demand as compared to 0 to 7% for voluntary restrictions. Martin & Kulakowski (1991) argues that water conservation policies must be combined with real price increases to be effective; in the case of Tucson Water, a real price increase meant raising prices by 10 percent minimum. An increasing block rate structure does not count as a real price increase.

Renwick & Archibald (1998) look at the effect of increasingly severe price and non-price conservation policies mandated in two California water districts during a drought period and find that they were the most effective for households with larger outdoor water needs due to more landscaped areas. However, when they looked at the effect of the policies by income level, the evidence was mixed. In one community, the wealthier households responded the most, while in the other community, the poorest households were more responsive. The effect of rebates varies across the focus of the rebate. Indoor rebates were effective for all customers but the outdoor rebates were only significant for high volume users, so likely the other household types were using less water than the restrictions allowed anyways (Kenney et al., 2008).

Several studies look at the effect of price and non-price conservation policies on water demand under drought or scarce water conditions (Renwick & Archibald, 1998; Corral et al., 1999; Hensher et al., 2006; Kenney et al., 2008; S. Olmstead & Stavins, 2008; Cooper, Burton, & Crase, 2011; Mansur & Olmstead, 2012). Using stated preference surveys, Hensher et al. (2006); Cooper, Burton, & Crase (2011) look at consumers' WTP to avoid drought restrictions. Fines for water waste are a method of penalizing non-compliance with water use restrictions and during times of drought, the penalties often increase. Renwick & Archibald (1998) include penalties for violating the water allocation scheme in their marginal price variable. Pint (1999) considers how households respond to price increases in Alameda County Water District during the California drought of the late 1980's and concludes that an IBR price structure is an effective conservation tool in drought periods.

Quantity restrictions can be moderate or severe. Moderate quantity restrictions might include time of day watering or certain days of the week. Stricter quantity restrictions involve limiting or banning certain outdoor uses or restricting watering to hand held hoses for a few hours. Some research argues that restrictions are more effective than increasing water prices; Duke et al. (2002) finds that water prices in summer months would have to increase 591 percent in order to realize the same 25 percent reduction that can be mandated under quantity use restrictions.

Restrictions appear to be effective under certain conditions and are more effective on certain classes of customers. Corral et al. (1999) find that use restrictions are effective in reducing water demand but only if they are mandatory; landscaping audits also have a significant effect although not as large as mandatory use restrictions. The effect of use restrictions is even larger when the regression is run using just dry months' data. Kenney et al. (2008) argues that overall, but especially during drought times, restrictions are more useful for high volume consumers but price is more effective for low volume households. They find that an additional effect of quantity restrictions is to reduce price elasticity for all households. They also find that both restrictions and price are not effective at the same time, households appear to respond to one or the other. On the other hand, Ramachandran & Johnston (2011) find that non-price water use restrictions have a very small effect on water demand, and in fact, all else equal, water demand increases during periods of use restrictions. Neighborhood effects also play a role; using a GIS cluster analysis for lot size, they find that very large parcels tend to have relatively higher water demand, even under use restrictions. Cooper, Rose, & Crase (2011) find that individuals have preferences for how use restrictions are implemented and that they prefer having some method of reporting noncompliance. Use restrictions are only effective if individuals comply and that occurs if the net cost of complying is less than the net benefit, including fines avoided.

Further research has studied the loss in welfare from stringent outdoor use restrictions (Dandy, 1992; Grafton & Ward, 2008; S. Olmstead & Stavins, 2008; Mansur & Olmstead, 2012). In particular, Mansur & Olmstead (2012) estimate welfare gains of $96 per household from using price-based conservation policies over outdoor use restrictions although they acknowledge the implications that while overall consumption would be reduced, the less price sensitive larger income, big lot size households would reduce water consumption less than low income, small lot households. In allocative terms, the former group would consume 47% of total water demand, up from 34%, while the latter group would consume only 17%, a decrease of 6%. Grafton & Ward (2008) find an average welfare loss of about $150 per household from using restrictions, concluding that price would be a better mechanism to achieve conservation goals with less welfare loss. Dandy (1992) finds that the loss in welfare resulting from stringent outdoor water use restrictions is greater than using a price mechanism to encourage the same conservation.

Several authors discuss the allocation issue of different conservation policies. (Duke et al., 2002) looks at the three conservation policies: scarcity pricing, water rationing, and mandatory restrictions. Under scarcity pricing and mandatory restrictions, households living on large lots bear the majority or all of the conservation burden, while with a water rationing policy everyone bears the burden as the conservation target is set for each household, however the conservation target goal may hit harder on lower income/smaller lot sizes who do not have as much nonessential water use. Renwick & Archibald (1998); S. Olmstead & Stavins (2008) note that under price conservation policies, the burden falls more on low income households, who are typically more price sensitive and for whom the water bill represents a greater percentage of their income. Duke & Ehemann (2004) discuss the equity issues with scarcity pricing because high-income households can pay the high marginal rates above the scarcity price threshold, while low-income households cannot, so they are forced to conserve.

However, S. Olmstead & Stavins (2008) note that while price conservation policies can be regressive in water allocation, these type of policies cause utilities to earn large profits in the short run when they use drought pricing, due to the price inelasticity of water demand. However, utilities are usually restricted by their regulatory boards to earn no profit or very low profits as a natural monopoly. To address allocative equity issues, these excess profits could be returned to consumers based on some income formula as rebates or subsidies.

Water budgets combine quantity restrictions with increasing block rates, while assigning each customer an allotment of water sufficient for efficient consumption based on their unique characteristics. Mayer et al. (2008) note that more than 20 water utilities have implemented some form of water budget; the most common kind of water budget is for landscape irrigation use. . However, they work best for water utilities that face the need to encourage efficient consumption and are a more proactive approach to addressing drought conditions. Communities must define what efficient means in their own context, but overall customers and water utility staff tend to consider water budgets a fairer and more equitable way of reaching a community's conservation goals.

Because water budgets are a relatively new conservation tool, very few studies have been conducted. Baerenklau et al. (2014) study the impact on reducing water demand of a residential water budget for the Eastern Municipal Water District (EMWD) over a ten-year period. Between 2003 and 2008, the EMWD had a uniform price structure. Demand elasticity for those years is estimated using a fixed effects model and then used to predict demand during the four years of the water budget, 2009-2012, in order to compare demand savings. Demand under the water budget is estimated with a discrete continuous choice (DCC) modeling strategy. They estimate price elasticity of demand as being more inelastic under the water budget structure (-0.58) than under the uniform rate structure (-0.76). Under the water budget, demand reduction of approximately 17% was achieved, gradually over four years. Their results also suggest that households retain the more water conservation behaviors that are learned in order to avoid higher marginal prices, even in the face of future price declines.

4.2.3 Theoretical issues

Endogeneity is often assumed to exist due to modeling quantity demanded as a function of price, given that the price charged depends on the quantity used. This leads to biased and inconsistent estimated parameters if OLS is used because of possible correlation between the error term and independent variables. Two-stage least squares regression that employs instrumental variables techniques is commonly used to overcome this issue (Renwick & Archibald, 1998; Kenney et al., 2008; Ruijs et al., 2008; Arbues et al., 2010; Wichman et al., 2014). However, using a Hausman test Nieswiadomy (1992) fails to reject the hypothesis of endogeneity and uses an OLS model in their study. Effects of being in a pricing structure with increasing block rates were dealt with by including a dummy variable (Kenney et al., 2008).

4.3 ABCWUA irrigation water budget program and data

Irrigation-only accounts comprise approximately 2% of ABCWUA's customer base but use 9% of the total water consumption (see Table 4.1).[8] In contrast, single-family residential accounts comprise 87% of the total accounts but only 53% of the total water demand.[9] Water consumed by irrigation-only accounts is 100% consumptive, irrigation demand, while less than 40% of residential water use is lost to outdoor use.

ABCWUA does not offer other conservation programs to irrigation-only accounts; any estimated changes in demand as a result of the water budget program can be isolated. So while this customer class is small in relation to the entire customer base, outdoor water demand by all customer classes still accounted for approximately 40% of ABCWUA's total water demand in 2013 (see Table 4.1). Controlling consumptive water demand helps manage water supplies in arid regions, where outdoor water use by all customer classes can be a large percentage of the water system loss.[10]

Prior to 2004, large irrigation-only accounts were consistently among the group of customers fined for water waste prompting ABCWUA to initiate the IWB program to encourage better irrigation practices and water conservation for these customers. Each customer was budgeted an efficient quantity of water for irrigation purposes.[11]

IWB allotments are determined by the annual amount of water necessary to efficiently irrigate the square area and customer type.[12] Aerial photography and a map-

[8]Fire hydrants and fire lines also fall into this category.

[9]Data provided by Katherine Yuhas, Conservation Office at ABCWUA. Account statistics indicate numbers in December 2013.

[10]For instance, the Southern Nevada Water Authority reports 60% of water use is considered consumptive, primarily for landscape irrigation (Bennett, 2012).

[11]Calculating an irrigation water budget differs from a residential water budget which include historical winter use to allow for essential indoor water needs by household (Mayer et al., 2008). Irrigation water budgets rely on landscaped area and use type because irrigation typically does not occur in winter months.

[12]Most customer accounts have a water budget of 35 inches of irrigation water per square foot of landscaping annually. Golf courses receive 37-40"/square foot depending on the construction

ping software were used to calculate the amount of irrigated square feet for each property. The water budget reflects the amount of water needed for efficient watering.[13] For instance, if the customer's property is 100% turf area, fully efficient watering would still use approximately 140% of their irrigation budget.[14] Accounts that irrigate with reuse water from ABCWUA receive an additional 10% water use over their budget.

Water consumption within an account's IWB is charged the commodity rate of $1.531 per unit of water.[15] Surcharges are assessed for every unit of water consumed above the IWB allotment. Efficient water consumption up to 100% of the IWB receives no surcharge. For excess water consumption between $100 - 150\%$, the surcharge is 50% of the commodity charge; each unit of water costs 1.5 times the commodity charge. The surcharge for extreme water consumption above 150% of the IWB allotment equals the commodity charge; each unit of water costs double the commodity rate. Accounts are billed monthly for water consumption using only the commodity charge during the irrigating season, March through November. Then total water consumption is calculated and the surcharge determined. The surcharge appears on the following March's irrigation water bill.[16] Table 4.2 provides descriptive statistics on annual water consumption, percentage of IWB used and assessed surcharges. Figure 4.1 displays water consumption levels overall between 2008-2013 and Figure 4.2 shows consumption lev-

date, and athletic fields receive 45"/square foot because of greater wear and tear on the turf (ABCWUA, 2014)

[13]An efficient level of watering is considered 0.5" of water soaking into the ground after a watering session. Fully efficient watering, where the water that leaves the sprinklers all soaks into the ground is impossible due to wind, evapotranspiration, and the slope of the land. Irrigating efficiency of 70% is considered good. *Conversation with Richard Chapman, SmartUse, on June 1, 2015.*

[14]Distribution uniformity is another issue. After an irrigating session, approximately the same amount of water should soak in at all spots across the landscape, as measured using catch cans to capture irrigation water. Most properties are approximately 50% in their irrigation practices, meaning that the lowest quartile of catch cans has approximately half the water as the overall average across all catch cans. *Conversation with Richard Chapman, SmartUse, on June 1, 2015.*

[15]Prior to July 1, 2011 the commodity rate was $1.385 per unit of water. A unit of water is 748 gallons.

[16]Accounts may request an ABCWUA high consumption use water audit of their property to improve their irrigation practices. Approximately 52% of IWB accounts have received a landscape audit.

els for each individual year.[17]

The mean and median percentage of water budget use are shown in Figure 4.3, while 4.4 shows the water consumption for all observations plus the median consumption level, including outliers, for each year. Most notably, the mean and median percentages of the IWB used are declining between 2011-2013, however the outliers indicating mega-water consumption are more extreme and more numerous. During those years a large percentage of Bernalillo County was classified as experiencing moderate and severe-to-exceptional drought levels and new accounts were added from the smaller utility acquired by ABCWUA.[18] [19]

The statistics given on efficient, excess, and extreme water consumption levels do not mean that the same accounts are in each water use category every year. I consider irrigating patterns as how many years an account exceeded their water budget and categorize them as never, occasional, half, most, and consistent. The items of specific interest are the extremes in behavior, i.e. how many accounts always are within their IWB or always exceed it. ABCWUA's policy aims to reduce the latter category. Table 4.3 describes the irrigation pattern variables. These are not used in the models, merely to classify behavior.

Historically, the biggest water wasters were the public sector accounts and the parks.[21] Histograms are used to examine irrigating patterns by ownership/landscape size, (see Figure 4.5), and by site type (see Figure 4.6). The x-axis reflects the scale of irrigating patterns, from 0 (never exceeds the IWB) to 4 (always exceeds the IWB). A greater percentage of private sector accounts never exceed their water budget as

[17]In their study of residential water budgets, Baerenklau et al. (2014) note that 82% of their sample consume a water quantity within the two price blocks considered efficient use.

[18]The years of 2011 through 2013 experienced recurring drought, however water utility customers were within the annual consumption goals and so mandatory drought restrictions were not needed.*Conversation with Katherine Yuhas, ABCWUA Water Conservation Officer, on March 19, 2015*.

[19]In 2012 25% of Bernalillo County was classified as experiencing moderate drought conditions, while 61% of the county was classified under severe to exceptional drought.[20] For 2013, the percentages are 22% and 79%, respectively.

[21]It could also be said these accounts were the most non-compliant.

compared to public sector accounts with the same size landscape area. Private sector accounts with less than 100,000 feet^2 of landscaping have lower rates of consistently exceeding their IWB as compared to the other three groups. These statistics are in line with prior behavior. The final panel in each figure show the irrigating pattern percentages for all accounts for comparison. Almost 40% never exceeded their IWB, while another 12% occasionally exceeded it. Nine percent exceeded their IWB half the time. Forty percent consistently or most years exceeded their IWB.

Public and private sector accounts with a landscape size of greater than or less than 100,000 feet^2 have different water consumption. The mega-water consumption above 1000% of IWB occurs in the smaller landscaped accounts both public and private sector (see Figure 4.7 and Figure 4.8). This level of water consumption is not seen in the large landscaped accounts. The median accounts across the years are signified with a red diamond and connected with a line. The median private sector account is typically within the irrigation budget as compared to the median public sector account, regardless of landscape size.

Data are in a micropanel format with a small number of years, ($T = 6$), and a large number of accounts, ($N = 1,107$). It is an unbalanced panel; there is not annual data for each account between 2008-2013. ABCWUA purchased a smaller water utility in northwest Bernalillo County in 2010, so those accounts only have two years of data for 2012-2013.[22] Other customers are missing a year's data due to faulty meter readings, broken water pipes with misleading water consumption, or zero water use due to landscape renovation. I started with 5,461 observations of irrigation data on 1,107 customers. We decided to omit observations with less than 10 percent of their irrigation budget used in year t because less than ten percent was not seen as a realistic amount of irrigating to keep even xeriscape alive; a faulty meter was assumed.[23] The final dataset has 4,748 valid observations.

[22]There are 245 accounts from this small water utility.
[23]Conversation with Richard Chapman, SmartUse, on February 27, 2015.

4.4 Theory and Empirical models

This paper addresses two research questions that focus on estimating the price elasticity of demand and the characteristics that influence demand. Random effects, ordered logit, and 2SLS instrumental variables models are used for analysis. The first research question examines what influences an account's irrigating behavior in two ways: (1a) the influence of the previous year's water consumption level on this year's demand; and (1b) the characteristics that affect an account's current water consumption decision. The second research question looks at the price elasticity of demand resulting from the increasing block surcharge rate structure.

4.4.1 Question 1a: Does consumption last year affect the current year water consumption level?

A random effects model is used to initially examine how past water consumption affects the current percentage of the water budget used. Random effects allow for unobserved heterogeneity both between groups and within groups. This analysis wants to specifically examine the differences in irrigating behavior due to organizational characteristics that are time invariant such as public and private accounts with different landscape sizes as well as different business categories. I assume between group variation is more relevant in this case than within group variation. This motivates using a random effects model rather than the more standard fixed effects model (Moulton, 1986).

$$\text{Model I: } PctIWB_{jt} = \gamma Lag1.Pctbud_{jt} + \beta_1 P_j + \beta_2 W_t + \beta_3 O_j + (\phi_j + \varepsilon_j) \tag{4.1}$$

Account j's irrigating behavior in year t is modeled through the percentage of the budget used, *PctIWB*$_{jt}$. It is a function of last year's irrigating behavior, denoted by the $Lag1$ indicator and variables describing physical characteristics of the site, $\mathbf{P}_j$, weather, $\mathbf{W}_t$, and organizational characteristics $\mathbf{O}_j$. The error term has two components: ϕ_j, which represents the 'between accounts' latent heterogeneity of account j, while ε is the remaining, random error term 'within accounts'.

First I consider the issue of serial autocorrelation, which is usually present in cross-sectional time series data, and if using a lagged dependent variable is an appropriate solution. Serial autocorrelation violates the OLS assumption of independent error terms and instead, $E(\varepsilon_j \varepsilon_i) \neq 0$ occurs. I test for autocorrelation using a standard Lagrange Multiplier test under a random effects specification using accounts with at least four years of data.[24] Honoré & Kyriazidou (2000) show that at least four observations is an identification restriction for binary discrete choice models with panel data. The percentage of the IWB used is also the basis for the dependent variable in the second part of the research question, so any autocorrelation present in Model I should be present in Models II and III.

I estimate the model given in Equation 4.1 without the lagged variable and predict the residuals, which are then regressed on the explanatory variables including the lagged residual. The coefficient on the lagged residual is positive and significant at the 5% level, indicating serial correlation is present.[25]

Including a lagged dependent variable (LDV) is one solution for eliminating autocorrelation.[26] A LDV allows the dynamic process of changing behavior to be included in the model; past behavior influences present behavior. This is a reasonable assumption with irrigation water demand since the basic water requirements of the landscape remain the same. I re-estimate Equation 4.1, including a one-period lagged term,

[24] Often independent variables are lagged as well in an AR(p,q) model, where p and q represent the number of lags for dependent and independent variables. I choose not to do this because the effect of last year's weather variables is likely incorporated in last year's water consumption decision.

[25] I also test against the lagged residuals for two time periods, but the coefficient on the residual with two lags is not significant.

[26] Including LDVs is not without controversy. An unpublished paper in political science by Achen (2000) has been cited frequently to argue that in the absence of a causal relationship between the dependent variable and the LDV, including a LDV appears to improve model fit but at the cost of possibly altering the signs and significance of other explanatory variables. LDVs should only be included to avoid omitted variable bias.

$Lag1.Pctbud_{jt}$. A Durbin's alternative statistic is calculated to test for serial autocorrelation once a lagged dependent variable is included; the more standard Durbin-Watson statistic is unreliable in the presence of lagged dependent variables (Durbin, 1970; Greene, 2003). The calculated h statistic has a value of -0.291.

Equation 4.1 is the empirical specification for this research question. The coefficient on *Lag1.PctIWB*$_{jt}$ variable is a proxy indicator of the influence of last year's behavior.

4.4.2 Question 1b: What characteristics affect an account's water consumption level decision?

Every year an IWB account makes one of three observable water consumption choices based on the percentage of the budget used: an efficient level of water use within their irrigation budget quantity, excess water use, or extreme water use. An ordered logit model is appropriate when the annual water consumption level is observed but factors influencing the choice are latent; the breakpoint between ordered choices is also unseen.

The discrete choice variable, Y, represents observed irrigating behavior $w_{js}, s \in [0, 2]$ for irrigation account j; s is the numerical representation of water consumption levels. Underlying the irrigating behavior is a continuous latent variable, y^*, and an unobservable random component ε:

$$y^* = \beta X + \varepsilon \tag{4.2}$$

The probability of falling into a specific category, s, depends on whether the dependent variable, Y, has crossed the threshold of latent variable, y^*, where κ represent the breakpoints between thresholds (Greene, 2003). If irrigation account j does not exceed its IWB, then $Y = 0$; if excess water consumption, $Y = 1$; if extreme water consumption, $Y = 2$. More generally, it is written:

$$Pr(Y_j = s) = Pr(\kappa_{s-1} < Y_j \leqslant \kappa_s), \forall s = 0, 1, 2 \tag{4.3}$$

$$Pr(Y_j = s) = Pr(\kappa_{s-1} < \beta X + \varepsilon_j \leqslant \kappa_s), \forall s = 0, 1, 2 \tag{4.4}$$

The probability of the observed decision, Y_j being in a category s is related to the error term being between the two breakpoints minus the deterministic portion of the equation.[27] Each probability is the difference between two CDF functions.

$$Pr(Y_j = s) = Pr(\varepsilon_j < \kappa_s - \beta X) - Pr(\varepsilon_j \leqslant \kappa_{s-1} - \beta X) \tag{4.5}$$

$$Pr(Y = 0) = F(-\beta X) \tag{4.6}$$

$$Pr(Y = 1) = F(\varepsilon_1 - \beta X) - F(-\beta X) \tag{4.7}$$

$$Pr(Y = 2) = F(\varepsilon_2 - \beta X) - F(\varepsilon_1 - \beta X) \tag{4.8}$$

Under the assumption of a logistic random error term, the probability of observed choice $q \in S$ is written:

$$Pr(Y_n = q|X_n) = \frac{exp(X_n \beta_q)}{1 + \sum_{s=1}^{S} exp(X_n \beta_s)} \tag{4.9}$$

Research question 1b examines the characteristics that influence the water consumption decision. In the empirical model, the dependent variable for the ordered logit model is the observed water consumption category for account j in year t. The decision Y_{jt} is described by the dependent variable *Consumption*$_{jt}$, whose three categories are: ***Efficient***$_{jt}$, ***Excess***$_{jt}$, ***Extreme***$_{jt}$. The ordered categories are based on the water budget surcharge structure, which is similar to the residential water budget described by Baerenklau et al. (2014). ABCWUA allots each account's water budget, w_{j0}, based on its organizational characteristics, $\mathbf{O}_j$, including square footage and landscape use.

$$\text{Efficient water use: } w_{j0} = f(O) \tag{4.10}$$

$$\text{Excess water use: } w_{j1} = 1.5 * w_{j0} \tag{4.11}$$

$$\text{Extreme water use: } w_{j2} = w_{j1} + 1 \tag{4.12}$$

[27]This is obtained by subtracting the deterministic portion: $Pr(Y_j = s) = Pr(\kappa_{s-1} - \beta X < \varepsilon_j \leqslant \kappa_s - \beta X)$

Following the procedure in Model I, a one-period lagged variable (*Lag1.Con*) represents the previous year's observed irrigation consumption level.[28] Two empirical specifications are estimated:

$$\text{Model II: } Consumption_{jt} = \beta_1 Lag1.Con_{jt} + \beta_2 P_j + \beta_3 W_t + \beta_4 PPsize_j + \varepsilon_{jt} \tag{4.13}$$

$$\text{Model III: } Consumption_{jt} = \beta_1 Lag1.Con_{jt} + \beta_2 P_j + \beta_3 W_t + \beta_4 SiteCat_j + \varepsilon_{jt} \tag{4.14}$$

In addition to the previous year's consumption level , other exogenous variables that influence the probability for this year's irrigation behavior are the same as previously discussed for Model I. Models II and III differ only in the vector of organizational site characteristics, $\mathbf{O}_j$, which describe the accounts based on latent factors common to the organizational structure hypothesized to influence irrigation choices. Model II uses a categorical interaction variable between public/private sector and landscape size, *PPsize*. Model III includes organizational characteristics through eight site categories, $SiteCat_j$.

4.4.3 Question 2: What is the elasticity of water demand?

The second research question using a 2-stage least squares (2SLS) regression to examine the elasticity of demand and the price responsiveness. The endogenous issue between water demand and water price has been discussed extensively in the residential water demand literature (Pint, 1999; S. Olmstead et al., 2007; Baerenklau et al., 2014; Wichman et al., 2014). This occurs because with a block rate or tiered surcharge rate design, the price charged for water is a function of the quantity of water consumed so OLS estimates are biased and can result in an upward sloping demand curve. Various researchers have estimated 2SLS models to resolve these two issues.

Given the structure of the data, I estimate a 2SLS-IV random effects model similar to (S. M. Olmstead et al., 2003; Wichman et al., 2014).[29]

[28] In the residential literature, variables from the previous period are often used as explanatory variables given the delayed reaction to price and weather signals (Kenney et al., 2008).

[29] The discrete-continuous choice (DCC) model has been used to estimate water demand un-

This data feature a uniform rate structure for monthly consumption and the increasing surcharge block rate structure for the aggregate total.[30] Baerenklau et al. (2014) estimate a fixed effects OLS model for water demand under a uniform rate structure, where the marginal price faced is the uniform price. Under the increasing surcharge block rate structure, endogeneity occurs because the final surcharge, which ultimately influences the marginal price paid by each account, is a function of the quantity consumed. Under these circumstances, the 2SLS model is a more appropriate choice for modeling water demand.

Baseline water demand, Use_{jt}, by account j in year t is modeled as a continuous choice and estimated as a function of a vector of weather, $\mathbf{W}_t$ and physical site characteristics, $\mathbf{P}_j$, and the natural log of the average price faced by each account:

$$ln(Use_{jt}) = \alpha + \beta \widehat{lnAP}_{jt} + \delta W_t + \phi_j + \varepsilon_{jt} \tag{4.15}$$

The price variable is the log of the instrumented variable average price, AP. All other variables ϕ_j and ε_{jt} were explained with Model I.[31]

Similar to Wichman et al. (2014), the first stage instrumental variables were a series of simulated block marginal prices for different consumption quantities, MP_{jkt}, for each account where k represents the simulated water block.[32] An account's water

der increasing block rate structures by estimating a non-linear budget constraint. Several researchers advocate the DCC model over a 2SLS approach because it has the capacity to estimate conditional demand based on the block in which a household chooses for consumption. In addition, it incorporates consumption decisions for consumers located at the budget kink points between the blocks (Pint, 1999; S. M. Olmstead et al., 2003; S. Olmstead & Stavins, 2008; Baerenklau et al., 2014).

[30] The water budget surcharge structure is assessed annually, while water consumption decisions are made daily and billed monthly. As a result, the marginal price per unit each month is not based on their expected total annual consumption. The marginal price of water consumed above their IWB only becomes apparent after all consumption has occurred. While it is possible that an account could track their monthly consumption to see if they are within their budget as the year progresses, I assume that the majority of accounts do not.

[31] Residential water demand models typically estimate income elasticity as well using Census tract income levels or some other estimate. I attempted to obtain data on property taxes or total revenues for each account to use as a proxy for income but were unsuccessful. As a result, the error term, ϕ_j, is assumed to capture the effects of each account's unique budget constraint.

[32] IWB are calculated as a function the square footage of irrigated area and range from 54

consumption rate for each level is based on their specific IWB. Then I calculated each account's marginal price of water faced at that level of consumption. This incorporates the increasing surcharge fees that occur at different consumption levels for each account. The first-stage regression is:

$$\widehat{lnAP}_{jt} = \sum_{k=1}^{K} \beta ln(MP_{jt}^{k}) + \delta L_j + \gamma P_j + \phi_j + \epsilon_{jt} \tag{4.16}$$

In addition to the marginal price instruments, known landscape characteristics and site elevation characteristics are included. These instruments are used because they influence the irrigation water budget for a particular account and thus are correlated with the average price over the range of marginal prices. There is debate in the literature over using lagged versus current prices and average versus marginal rates in estimating water demand (Arbues et al., 2003). With respect to electricity demand, Ito (2014) finds a lack of customer bunching at the kink points of the nonlinear rate schedule, which would be present if consumers responded to marginal pricing. There is strong evidence that electric customers respond to average prices instead. Lagged prices are often used in residential water demand literature because customers receive the bill after the consumption period and become aware of their consumption block by the related price. However, I chose to use current average price because the irrigation-only accounts face the same commodity price per unit for their entire seasonal consumption and I assume they are aware of the surcharge fees for exceeding their IWB.

The model described in Equation 4.15 is the basic water demand equation. Several additional specifications are estimated to further examine the elasticity of price demand for other groups.

$$\text{Model IV: } ln(Use_{jt}) = \alpha + \beta \widehat{lnAP}_{jt} + \delta W_t + \delta_2 PPsize_j + \phi_j + \varepsilon_{jt} \tag{4.17}$$

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square feet to 7.4 million square feet. I simulated a wide range of block rates per 100 units to account for the various tiers faced by both small and large accounts, k = {2, 4, 6, 8, 10, 12.5, 15, 18, 21, 24, 27, 30, 34, 38, 45, 50, 60, 70, 80, 90, 100, 110, 120, 130, 150, 180, 210, 250, 300, 350, 400, 500, 600, 700, 800, 1000, 1200, 1400, 1600, 1800, 2000.

$$\text{Model V: } ln(Use_{jt}) = \alpha + \beta \widehat{lnAP}_{jt} + \gamma(\widehat{lnAP}_{jt} * SiteCat_j) + \delta W_t + \phi_j + \varepsilon_{jt} \tag{4.18}$$

$$\text{Model VI: } ln(Use_{jt}) = \alpha + \beta \widehat{lnAP}_{jt} + \gamma(\widehat{lnAP}_{jt} * D_{jt}) + \delta W_t + \delta_2 PPsize_j + \phi_j + \varepsilon_{jt} \tag{4.19}$$

$$\text{Model VII: } ln(Use_{jt}) = \alpha + \beta \widehat{lnAP}_{jt} + \gamma(\widehat{lnAP}_{jt} * PPsize_j) + \delta W_t + \phi_j + \varepsilon_{jt} \tag{4.20}$$

Model VI includes a vector of interaction variables between the average price and site categories. This allows us to examine the elasticity of price demand by site categories. Model VII includes interaction variables between the average price and accounts that consume only 5 or 10 percent of their IWB and those that consume 90 or 95 percent of their IWB. This captures the effect of elasticity of low water consumers and high water consumers. Finally, Model VIII includes interaction variables between average price and the account ownership size variable, *PPsize*.

4.5 Data

The weather variables, $\mathbf{W}_t$ are annual in nature and describe the seasonal summer intensity and length.[33] I calculated the number of days above the average monthly temperature for each month, April through October. After trying several specifications, we aggregated the months May through August, *DaysAboveAvg*, to measure the intensity of warm season temperatures each year. The length of summer is measured by the number of days between the first and last 90° days, *Days90*.[34]

[33]Temperature and precipitation data were gathered from the National Oceanic & Atmospheric Administration (NOAA) website. Daily temperature data and mean minimum/maximum monthly temperature data were gathered from the weather station at the Albuquerque International Sunport airport. Drought index data for the state of New Mexico and Bernalillo County were gathered from the U.S. Drought Monitor compiled by the University of Nebraska at Lincoln.

[34]Alternate intensity measurements were considered: the number of days with temperatures above 90°F each month and using drought index variables to measure the percentage of Bernalillo County classified as experiencing moderate or severe drought. The drought index variables were significant but inconsistent, likely due to the fact that the first three years of data both variables were equal to zero as the severe drought occurred between 2011-2013. These variables were ultimately not used.

Physical site characteristic variables, $\mathbf{P}_j$, include elevation and soil composition for account j. *SoilWater* is a categorical variable that indicates the degree of water absorption of the soil . The values equal 0, 1, or 2; higher values indicate the soil more readily absorbs water.[35]

Within the ABCWUA service area elevation varies from 4,900 feet in the river valley to 6,700 feet at mountain foothills creating micro-climates with varying temperature and precipitation.[36] Dummy variables indicate accounts located 5,000 feet and lower, *Elevation5000*; between 5,050 and 5,650 feet, *Elevation5300*; and above 5,700 feet, *Elevation5700*.[37] I have no *a priori* expectation on the signs for the elevation or soil variables.

Organizational characteristic variables, $\mathbf{O}_j$, include two categorical variables: (i) *PPsize* indicates public/private sector and if the landscaped area exceeds $100,000$ feet^2; and (ii) *SiteCat* indicates the type of site. With regards to *PPsize*, private sector accounts have a profit incentive to stay within their IWB. In addition, the size of the landscaped area might influence the IWB account's ability to flexibly adjust irrigation habits.[38] Four categories are used for *PPSize*: *PublicSmall*$_j$ (baseline category), *PublicLarge*$_j$, *PrivateSmall*$_j$, and *PrivateLarge*$_j$. I expect private ownership and smaller landscaped areas to have a greater probability of efficient water consumption based on prior experience by ABCWUA. There are eight categories in: *Commercial* (baseline category), *Parks*, *HOA*, *StreetMedians*, *Multi*, *Education*, *Government*, and *Churches*. Accounts within each category are hypothesized to possess similar characteristics such as landscape patterns or business structures that require certain irriga-

[35]Data on soil types for Bernalillo County were gathered from the national Web Soil Survey conducted by the U.S. Department of Agriculture, Natural Resources Conservation Service. The variable was created following conversations with Rick Strait, USDA State Soil Scientist, New Mexico

[36]I gathered 50-foot contour elevation data for Bernalillo County from the RGIS website maintained by the University of New Mexico and then spatially mapped irrigation meter locations with the contour data using version 10.1 of ESRI ArcMap software.

[37]Using a continuous elevation variable was not significant.

[38]Residential water demand studies typically include household parcel size as a proxy for the amount of outdoor landscape needs (Pint, 1999).

tion needs.

Demand characteristics $\mathbf{D}_{jt}$ indicate if an account used relatively less or more of their water budget in year t as compared to other accounts as measured by their water budget consumption percentile. The $PctIWB_{jt}$ was ordered for each year and the water budget percentage amount was calculated for the 5th, 15th, 85th and 95th percentiles. Dummy variables indicate if the annual percentage of the water budget used by each account is within those percentile breakpoints. An account with very low water budget consumption, relative to other accounts, was in the 5th percentile or lower for year t, $Budg5_{jt}$. $Budg15_{jt}$ indicates the account was between the 5-15th percentile and was a low water budget consumer, relatively. High and very high water budget consumers are indicated by $Budg85_{jt}$ and $Budg95_{jt}$, respectively. $Budg85_{jt}$ indicates the account was between the 85th to 95th percentile and $Budg95_{jt}$ indicates the account was at the 95th percentile or greater.

4.6 Results and Discussion

I first consider if there are significant differences in water consumption and irrigating patterns between public/private sector accounts and different types of site categories. Irrigation-only accounts differ from residential accounts because they involve individuals whose incentives differ. If the irrigator is not the same individual who can make budget decisions, the price signal is less informative. My hypothesis is that the private sector will respond to price signals as a profit maximizer. Public sector accounts do not have the same profit maximizing incentive. Results of a t-test between the mean annual percentage of IWB used for public and private sector accounts are reported in Table 4.5. For the first year, 2008, the mean percentages are not significantly different. Every subsequent year the mean percentage of the private sector is significantly less in comparison to the mean percentage of public sector accounts. This implies perhaps a greater responsiveness to the water budget program for private sector accounts.[39]

Figure 4.5 and Figure 4.6 report irrigating patterns by public or private sector and by site types using the index variables described in Table 4.3. X^2 tests of significant differences in overall irrigating patterns between public/private sector and site types were calculated. The X^2 test statistics were 29.78 and 152.25, respectively, as compared to the $X^2_{4,\alpha=.05}$ = 9.488 and $X^2_{28,\alpha=.05}$ = 41.337. The null hypothesis is rejected; there are significant differences in the irrigating patterns across time of public versus private sector and between site types.

4.6.1 Results: Influences on the water consumption decision

Both parts of the first question examine the influence on an account's water consumption decision. Table 4.6 reports results from part (a) that estimated a random effects model to examine the influence of the previous year's consumption.[40] The variable of interest is the one period lagged percentage of the water budget used. It is positive and highly significant with a value of 0.55, indicating that approximately 55% of the current year's consumption use is determined by last year's consumption use. This is positive news for ABCWUA, implying that there is room for behavior change.

All private sector accounts and large area public sector accounts have significantly lower water budget use than small area public sector accounts. *Ceteris paribus*, a small area private sector account will use 17% less than a small area public sector account; a large area private sector account will use about 20% less. More than 70% of these small public sector accounts are parks, schools fields and government accounts; the

[39]For robustness, I also calculate X^2 statistics on the differences in public sector versus private sector account changes in irrigating behavior from year to year that result in movement between surcharge levels. Table D.2 in the Appendix reports statistics across time. The X^2 test supports the earlier finding that there are significant differences in irrigating decisions between public and private sector accounts.

[40]All analysis was conducted using Stata 13.

remainder are low water use street medians. As seen in Figure 4.7, these small public sector accounts have higher rates of mega-water consumption above 1000% of the water budget, which helps to explain why the other three categories all have significantly less use.

Interestingly, none of the control variables describing physical site characteristics or weather are significant, except *DaysAboveAvg* which is positive and significant at the 5% level. If there are 100 days between May and August with above average temperatures, the percentage of the water budget used will increase by 42%.

Subsequently I estimate two specifications of the basic ordered logit model, noted as Models II and III. There are three ordered categories to the dependent variable, *Consumption*, with the categories ordered in increasing severity from efficient water consumption to extreme water consumption. An ordered logit model assumes proportional odds or parallel regressions between each category and the combined other categories. For this data that would mean an exogenous variable has the same impact on the log odds of *P>0* as *P>1*. More simply, a variable has the same impact on an account having either excess or extreme water consumption levels (P=1,2) as on an account having extreme water consumption (P=2). I use a Brant test to test the parallel regression assumption for both models, rejecting the null hypothesis that each set of binary logit regressions has the same coefficients (Brant, 1990).[41]

I estimate and report results from a generalized ordered logit model that relaxes the assumption of parallel regressions (see Tables 4.8 and 4.7).[42] This model estimates $J-1$ binary equations, where J represents the number of ordered categories in the dependent variable. There are three categories, $Y = 0, 1, 2$. The binary regressions estimated are $log\left(\frac{P(Y>0)}{P(Y=0)}\right) = X\beta_k$ and $log\left(\frac{P(Y>1)}{P(Y\leqslant 1)}\right) = X\beta_k$. The first equation estimates the probability of excess or extreme consumption versus efficient water consumption. The second equation estimates the probability of extreme consumption versus efficient

[41]The Brant test statistics were $B = 164.09$ against a $X^2_{0.05,10} = 18.31$ (Model II) and $B = 176.77$ against a $X^2_{0.05,14} = 23.69$ (Model III).

[42]The generalized ordered logit model was estimated in Stata 13 using the $gologit2$ command (Williams, 2006).

or excess water consumption. Using an iterative process, the variables that rejected the hypothesis of equal coefficients were allowed to vary between the two binary regressions. The remaining variables were fixed. In this partial proportional odds model, only the variables *Lag1.Excess*, *Elevation5000*, *Park*, *HOA*, *Govt*, *PublicLarge*, and *PrivateLarge* had a varying impact on the log odds of the two probabilities.

The coefficients in an ordered logit regression model are difficult to interpret alone. A positive coefficient indicates an increase in the log odds of being in a higher category when the exogenous variable changes by one-unit. A negative coefficient is the opposite. Marginal effects are more intuitive. A marginal effect is the partial derivative of the ordered function when the exogenous variable changes by one unit. Marginal effects for each account are calculated based on their characteristics and then average the marginal effects across the lagged consumption variable and the organization characteristics *PPsize*. This is the preferred method for calculating marginal effects (Greene, 2003).

Table 4.9 reports the marginal effects from Model II according to the probability of each water consumption category as a function of last year's water consumption behavior and the *PPsize* variable. Efficient water consumption the previous year has the strongest probability of repeat behavior this year, between 75% and 84% across all public/private sector accounts of all sizes. Small landscape, private sector accounts that had excess water consumption the previous year have a 47% probability of repeating the behavior but a 32% probability of having efficient water consumption in the current year. Large landscape public sector accounts have a 66% probability of having excess water consumption in the current year if they had excess consumption the previous year. Small landscape public sector accounts have the largest probability of repeating extreme water consumption behavior if they were extreme water consumers the previous year.[43]

[43]In the residential literature finds mixed results as to the effect of conservation policies on accounts with large landscaped areas or large water consumption needs. Renwick & Archibald (1998); Kenney et al. (2008) find they are more responsive to conservation policies, while Klaiber et al. (2012) find that these accounts are more price inelastic than low volume wa-

Marginal effects from Model III are reported in Table 4.10 using the site categories. For all accounts, if they engaged in efficient water consumption the previous year, there is a high probability that they will again be efficient water consumers; the probabilities range from 71% to 88%. The same patterns of repeating the previous year's behavior are similarly high for accounts that were extreme water consumers. All accounts, except HOAs and street medians, have more than a 60% probability of extreme water consumption behavior in the current year. The probability that any account that engages in extreme water consumption moves to efficient water consumption in the current year is very small, under 15% probability for most. However, there is between a 10% and 30% probability of reducing water consumption behavior to the excess consumption category. For ABCWUA, focusing on this consumption level might be the most productive as they use proportionally more water (see Table 4.13); i.e. with MultiFamily, 41% of account years are categorized as extreme water consumption with 67% of the total water use. And they have a very high probability of continuing extreme water consumption.

At first glance, excess water consumption seems less problematic because less water is consumed than with extreme water consumption. The probability of changing behavior appears more for this group. For most of the sites, except parks and HOAs, there is less than a 50% probability that they will again have excess water consumption. For commercial, HOA, street medians, and churches, the probability of improving their consumption behavior to the efficient consumption level is greater than the probability of becoming extreme water consumers. Parks, multi-family, education, and govt have a greater probability of worse consumption levels becoming extreme consumers. Preventing these four categories from higher consumption levels might be an area of focus for ABCWUA as they have among the highest probability of repeating extreme water consumption behavior.

ter users.

4.6.2 Results Question 2: What is the elasticity of water demand?

The second issue examined is the price elasticity of water demand. I estimate four model specifications (Models IV through VII) to look at the elasticity of demand. Results are reported in Tables 4.11 and 4.12. Overall results indicate that demand is inelastic, however it varies according to business types, water consumption levels, and ownership/size. Within the site categories, parks and golf courses have the most inelastic demand, while commercial businesses have the most elastic demand. Accounts with smaller landscaped areas have more elastic demand than accounts with larger landscaped areas.

Model IV is the first column in Table 4.11. It is the baseline model. All variables are significant. Both water use and average price are logged variables so the estimated coefficient is interpreted as an elasticity. Estimated coefficients on the linear variables are interpreted as the growth rate for a one-unit or one-percent change in the variable.

The elasticity is the primary coefficient of interest. Results indicate that demand is inelastic, with an elasticity of demand of -0.845. A 10% increase in the average price would result in a reduction of 8.45% in water demand, *ceteris paribus*. While this elasticity falls in the range of the absolute value of residential water demand elasticities, it is at the higher end (Dalhuisen et al., 2003). However, residential demand also includes indoor use which is more price inelastic than outdoor use (Mansur & Olmstead, 2012). Kenney et al. (2008) estimate a year-round elasticity in Aurora, Colorado of -0.60 and suggest that the elasticity would have been greater if they had strictly focused on the season with high irrigation demand. The irrigation water budget program in some ways mimics a uniform pricing rate structure since the irrigation customer pays a uniform commodity charge throughout the irrigating season, facing a possible surcharge if the end consumption total exceeds their IWB. Estimated elasticity of demand is more comparable to elasticities found under uniform water pricing. Baerenklau et al. (2014) estimate an elasticity of of -0.76 for this price structure. In their meta-analysis of residential water demand studies, Dalhuisen et al. (2003) find that the rate structure influences the elasticity of demand.

Also of interest, ownership and size have a significant effect on water demand. Small landscape, private sector accounts use 66% less water in comparison to similar size, public sector accounts. Not surprisingly, both public and private accounts with large landscaped areas of more than 100,000 square feet have a greater water demand. In the residential water demand literature, Mansur & Olmstead (2012) also find that increasing lot sizes have a significant and positive relationship with outdoor water demand. However large public accounts use 182% more water, while large private accounts use 152% more water, all else equal.[44]

Finally, water demand is affected more by differences between irrigation-only customers, σ_u, than strictly random error, σ_e. This is similar to other studies as well (S. Olmstead et al., 2007).

The second column in Table 4.11 reports the price elasticity for Model V, while Table 4.12 reports the price elasticity for Models VI and VII. Model V estimates price elasticity by *SiteCat* groups. Are all highly significant, as expected. The base price elasticity of -1.152 reflects commercial accounts. This group is the only site type with elastic demand as measured with an absolute value of the elasticity of demand greater than one, although both HOA and Govt site types have an elasticity of demand very close to elastic (-0.986). Parks/golf have the most inelastic demand (-0.697). Subsequent t-tests between the coefficients on the site types indicate that HOA, StreetMedian, Govt, and Church site types do not have statistical differences in their elasticity estimates. Also there is not a significant difference between multi-family and education site type elasticities.

Figure 4.11 display the difference between the first and last account years by *Site-*

[44] I tested for significant differences in water demand between the other three categories using a X_1^2 test and found that both public and private sector large landscape accounts are significantly different from private sector small landscape accounts at the 1% level. However, public and private sector large landscape accounts have weak significant differences at the 10% level.

Cat. The y-axis indicates the average underlying consumption decision y^*, described in Equation 4.2. Average water consumption as seen on the y-axis ranges between efficient use (y=0) and excess use (y=1). Largest decrease in water consumption comes in commercial, education, and churches. This suggests they were more responsive to water budget programs. However, parks/golf and multi-family increased water consumption between the average first and last year. This confirms the results from Model V, which shows that they have among the most inelastic demand.

Results from Model VI compare the elasticities of accounts based on the 5th, 15th, 85th, and 95th percentiles of overall budget use. The interaction terms *budg5* and *budg15* indicate accounts that were very efficient water consumers. Those accounts used, on average, 18% and 34% of their water budgets. *Budg85* and *budg95* were the most extreme water consumers, using 182% and 292% of their water budget, respectively.

Budg5 and *budg15* accounts are significantly more price responsive (although still price inelastic) as compared to the middle 70% of accounts of budget use, while *Budg85* and *budg95* are significantly more price inelastic. This could reflect the landscaping decision of accounts. Accounts that use smaller percentages of the IWB might have more of their landscape using xeric plantings while the accounts that are in the highest percentile of budget use could have a greater percentage dedicated to turf or athletic fields. Or it could reflect a different organizational structure where the accounts in the highest use percentiles are indifferent to the surcharge rate and so ignore it when making their water consumption decision.

Finally, Model VII interacts *PPsize* with price. With regards to the price elasticity, the size of the landscaped area appears to have a great impact on the price responsiveness. The baseline for comparison are small, public sector accounts. Compared to the baseline, both private and public large landscape accounts are significantly less price responsive. This contradicts Renwick & Archibald (1998), who find that increasingly severe, mandatory price and nonprice conservation policies were the most effective for households with larger outdoor water needs due to more landscaped areas. However, perhaps the small landscape accounts have a correspondingly small employee size and so can better manage their water consumption or respond quicker to a surcharge. Small private sector accounts have a greater absolute value of price elasticity, but the effect is weak at the 5% level and small (-0.033). T-tests between the coefficients of each dummy variable indicate that there is no significant difference between the price elasticity of private and public large accounts.

4.7 Conclusion

The irrigation water budget program is a long-term conservation policy designed to encourage irrigation-only customers to optimally consume water and reduce wasteful consumptive water practices. Water budgets are seen as more equitable because they avoid many of the allocative issues associated with conservation policies while preserving a greater measure of flexibility for customers to make optimal water consumption decisions for their household. Customers with certain characteristics, such has households on large parcels or different income levels, bear a greater conservation burden under certain policies. Water budgets assign a quantity of water based on customer characteristics, that is sufficient for efficient water consumption. Irrigation water budgets are annual in nature, so the customer receives an allotment of water to use throughout the irrigating season. They can allocate their watering in response to weather patterns and make optimal landscaping decisions.

To analyze the ABCWUA water budget program, I use an unbalanced panel of six years of annual water consumption data for 1,107 irrigation-only accounts. Annually, approximately half of all accounts are within their water budget (efficient water use), while 25% have excess water use and 25% have extreme water use. Overall the account years, 40% of accounts never exceed their water budget, while 27% consistently exceed it.

There are organizational differences in irrigating patterns across the years of the dataset and the percentage of the water budget used. Public and private sector accounts have significantly different water consumption behavior. Almost half of private sector accounts with less than 100,000 square feet of landscaped area never exceed their IWB, while only one-fourth of large landscape public sector accounts do. All private sector accounts use significantly smaller percentage of their water budget than public sector accounts. Findings indicate differences in water consumption behavior between site categories as well. Commercial, HOA, and street median accounts have the highest percentages of never exceeding their water budgets; parks/golf, education and multi-family accounts have the lowest percentages of never exceeding and the highest percentage of accounts that consistently exceed their water budget.

Estimated marginal effects from the ordered logit, partial proportional odds model indicate that the previous year's consumption level affects the probability of this year's consumption level. Accounts that either had efficient or extreme water consumption the previous year, have very high probabilities of being in the same consumption level this year. I find this is less true for accounts who had excess water consumption (defined as between 100-150% of the water budget), who have higher probabilities of behavior changes. Results by site categories indicate that commercial, HOA, street medians, and churches have a greater probability of moving from excess to efficient water consumption in comparison to moving from excess to extreme water consumption. ABCWUA might achieve greater results in terms of encouraging efficient water consumption with these categories.

A 2SLS model is used to estimate price elasticity of demand. For all accounts, the elasticity is -0.845, which is in line with other studies in the literature. When interaction terms are included to analyze the price responsiveness of different groups, interesting policy recommendations emerge. Accounts with large landscaped areas, regardless of whether they are public or private sector, have more inelastic demand than public/private sector accounts with small landscaped areas. Many of the large landscaped areas are golf courses and athletic fields which already have water budgets that incorporate a greater number of irrigation inches per square foot. So the greater inelasticity should not reflect their water budget allotments, but rather latent organizational characteristics. Commercial, HOA, and govt accounts are the most price responsive and parks/golf, multi-family, and educational accounts are the least. A look at their irrigating status across all years of data, these three groups also consistently exceed their water budget at a higher rate than other groups.

From a policy standpoint, the demand elasticity results suggest that the price signal through the rate structure is not steep enough to make a change in behavior. Recently, ABCWUA enacted a third water surcharge tier for consumption above 200% of the irrigation budget with a surcharge of 1.5 times the commodity charge (ABCWUA, 2014). This is a step in the right direction, however higher fines may be necessary. The Las Vegas Valley Water District calculates excess water use surcharges for golf courses at a rate of 200%, 500%, and 900% of the highest non-potable water rate.[45]

[45](Las Vegas Valley Water District website, Service Rules Section 12: Conservation, accessed March 7, 2014 at http://www.lvvwd.com/assets/pdf/serv_rules_fulldoc.pdf)

4.8 Tables

Table 4.1: Characteristics of ABCWUA water customers and water use

ABCWUA Customer Types[a]	Number of accounts, Dec 2013	Percent of total accnts	Percent of total consumption	Gallons consumed, 2013 (million)	Percent of consumption, outdoor use
Residential	178,968	87%	53%	14,900	37%
Multi-family[b]	6,589	3%	15%	4,307	25%
Commercial, Industrial, & Institutional	14,299	7.06%	23%	6,495	44%
Other	3,964	2%	9%	2,403	70%
Total ABCWUA	205,316	99.06%[c]	100%	28,104	

Data on customer classes, 2013 water usage, and outdoor water usage provided by Katherine Yuhas, March 5, 2014.

[a] Residential include single-family detached, condos, townhouse, duplexes and mobile homes all with individual meters. Multi-family indicates an common meter account for one or more units, i.e. 3- and 4-plexes, apartment complexes, and homes with guest houses. Commercial includes retail, offices, hotels/motels, shopping centers that do not use water in production. Industrial means a manufacturing facility using water in production. Institutional are government buildings, hospitals, schools. Other includes irrigation-only accounts, fire hydrants, and fire lines. ABCWUA Water and Sewer Rate Ordinance, accessed 3/7/14 on-line at: http://www.abcwua.org/uploads/files/waterrate.pdf

[b] Accounts represent 96,976 units. An apartment building is one account with multiple units. Email from K. Yuhas, 3/5/14.

[c] Solid waste accounts are excluded.

Table 4.2: Water consumption and surcharge statistics by year

Variable	Description	2008	2009	2010	2011	2012	2013
Use_t	Avg. water use (in units[a])	5,352	5,129	5,795	5,579	4,998	4,468
	Max. water use (in units[a])	308,980	291,339	293,970	306,249	327,374	317,671
$Budget_t$	Avg. water budget (units[a])	5,127	5,008	5,395	5,340	4,372	4,319
	Max. water budget (units[a])	272,620	272,620	272,620	272,620	272,620	272,620
$PctIWB_t$	Avg. % of water budget used	127%	120%	107%	127%	124%	122%
	Max. % of water budget used	1,436%	1,441%	697%	2,875%	2,625%	2,696%
$Surch_t$	Avg. surcharge	\$1,876	\$1,848	\$2,065	\$2,156	\$1,735	\$1,625
	Max. surcharge	\$48,493	\$42,429	\$42,874	\$61,253	\$54,867	\$36,433
Obs.		678	698	660	709	1,002	1,001

[a] 1 unit of water = 748 gallons
[b] This excludes the observations that were dropped for using < 10% of the IWB.

Table 4.3: Statistics describing water consumption patterns related to the water budget

Variable	Description	Freq. (%)
Never	Never exceeded its water budget for valid data years	432 (39%)
Occasional	Stayed within water budget most valid data years	136 (12%)
Half	Equal years within and exceeding water budget	98 (9%)
Most	Exceeded water budget the majority of valid data years	147 (13%)
Consistent	Exceeded water budget every valid data year	294 (27%)
Total Obs.		1,107

Table 4.4: Model Variables

Variables	Description	Mean	S.d.	Min.	Max.
Dependent Variables for Models					
PctIWB_{jt}	Percent of water budget used (Model I); continuous (WaterUse/WaterBudget)	122	143	11	2,875
Consumption_{jt}	Water consumption, f(PctIWB) (Models II-III); categorical 0=efficient, 1=excess, 2=extreme	0.70	0.82	0	2
WaterUse_{jt}	Water use (in units[a]) (Models IV-VII); continuous	5,154	21,094	1	327,374
Weather Characteristics ($\mathbf{W}_t$) in year$_t$					
DaysAboveAvg_t	Days with above average temperatures, May-August	85	13	71	102
Days90_t	Days between the first and last 90°F days	112	10	100	126
Physical Site Characteristics ($\mathbf{P}_j$) at site$_j$					
SoilWater_j	Ease of water infiltration in soil 0=little, 1=somewhat, 2=more	1.12	0.52	0	2
Elevation5000_j	Elevation $\leqslant$ 5000 ft.; 1=yes, 0=no	0.22	0.42	0	1
Elevation5300_j *(base category)*	Elevation is 5050 - 5650 feet; 1=yes, 0=no	0.71	0.45	0	1
Elevation5700_j	Elevation $\geqslant$ 5700 feet; 1=yes, 0=no	0.07	0.25	0	1
Organizational Site Characteristics ($\mathbf{O}_j$) at site$_j$					
Site category (SiteCat_j)					
Commercial_j *(base category)*	Restaurant, Healthcare, Fitness, Other Commercial, Retail,	0.31	0.46	0	1

Table 4.4: Model Variables

Variables	Description	Mean	S.d.	Min.	Max.
	Wholesale, Office, or Shop. center				
HOA_j	Home Owners Association, townhome, or condo association	0.16	0.37	0	1
Park_j	Parks, little league fields, community center, golf course, cemetery	0.22	0.42	0	1
StreetMedian_j	City or county street median	0.09	0.29	0	1
Multi_j	Hotel/Motel; Multi/Apartment; Senior Housing	0.07	0.25	0	1
Education_j	Albuquerque Public Schools, community college, or other school	0.06	0.23	0	1
Govt_j	City Public Works Dept., County, Federal, State buildings	0.08	0.27	0	1
Church_j	Church	0.02	0.15	0	1
Public or private sector and size ($\textbf{PPsize}_j$)					
PublicSmall_j *(base)*	Public sector, $\leqslant$ 100,000 ft^2	0.27	0.45	0	1
PublicLarge_j	Public sector, $\geqslant$ 100,000 ft^2	0.16	0.37	0	1
PrivateSmall_j	Private sector, $\leqslant$ 100,000 ft^2	0.49	0.50	0	1
PrivateLarge_j	Private sector, $\geqslant$ 100,000 ft^2	0.08	0.27	0	1
Demand Characteristics ($\textbf{D}_{jt}$)					
Budg5_{jt}	Mean *PctIWB*, very low budget use accts, $\leqslant$ 5th percentile of budget use[b]	14	2.3	11	18
Budg15_{jt}	Mean *PctIWB*, low budget use accts, 5th - 15th percentile of	26	5	17	36

Table 4.4: Model Variables

Variables	Description	Mean	S.d.	Min.	Max.
	budget use[b]				
Budg85$_{jt}$	Mean *PctIWB*, high budget use accts, 85th - 95th percentile of budget use[b]	219	32	167	322
Budg95$_{jt}$	Mean *PctIWB*, very high budget use accts, $\geqslant$ 95th percentile of budget use[b]	530	398	230	2,875

[a] 1 unit of water = 748 gallons (1 cubic foot of water = 7.48 gallons, so 1 unit = 100feet^3

[b] Statistics indicate the percentage of the budget used by accounts at the 5th, 15th, 85th, and 95th percentiles.

Table 4.5: Tests of significance between average water budget use of public and private sector accounts

Variable	2008 Mean (S.d.)	2009 Mean (S.d.)	2010 Mean (S.d.)	2011 Mean (S.d.)	2012 Mean (S.d.)	2013 Mean (S.d.)
Public	129	130	116	148	134	134
	(138)	(150)	(82)	(222)	(157)	(165)
Private	126	110	98	109	117	113
	(141)	(124)	(74)	(97)	(137)	(155)
t-statistic	-0.3451	-1.9569	-2.9609	-3.0823	-1.8993	-2.0812
t-stat*$_{-}(df, \alpha = 0.05)$	1.645	1.645	1.645	1.645	1.645	1.645
d.f.	676	696	658	707	1000	999
Pr($\|T\| > \|t\|$)	0.7301	0.0508	0.0032	0.0021	0.0578	0.0377
Obs	678	698	660	709	1002	1001

H_0: $\text{Mean}_{Private}$ - Mean_{Public} = 0, H_a= $\text{Mean}_{Private}$ - $\text{Mean}_{Public} \neq 0$
Variable being compared is *PctIWB*

Table 4.6: Results Model I: Does past water consumption influence current irrigating behavior?

Variable	**(Model I)** Coefficient (s.e.)
Dependent variable: $PctIWB_{jt}$	
Lag1.PctIWB	0.55 (0.01)***
Soilwater	0.48 (3.90)
Elevation5000	-6.69 (3.79)
Elevation5700	-0.83 (5.56)
Days90	-0.21 (0.20)
DaysAboveAvg	0.42 (0.17)*
PubLarge[a]	-17.46 (4.59)***
PrivSmall[a]	-16.93 (3.89)***
PrivLarge[a]	-19.66 (6.41)***
Constant	52.69 (34.13)
σ_u	14.95
σ_e	67.07
ρ	0.05

Significance levels: *** $\leqslant$ 0.001, ** $\leqslant$ 0.01, * $\leqslant$ 0.05

[a] The baseline category is: public sector, $\leqslant$ 100,000 ft^2.

Table 4.7: Results Model II: What characteristics increase the probability of an account exceeding its water budget or engaging in extreme water consumption?

	(Model II)	
Logit probability	Prob $Y > 0$	Prob $Y > 1$
	Excess or Extreme Use	Extreme Use
	vs.	vs.
	(Efficient Use)	(Efficient or Excess Use)
Variable Name	Coeff. (s.e.)	Coeff. (s.e.)
Ordered dependent variable: Consumption_{jt}		
Independent variables		
Lag1.Excess	2.44 (0.10)***	1.53 (0.13)***
Lag1.Extreme	3.50 (0.11)***	3.50 (0.11)***
DaysAboveAvg	0.02 (0.005)***	0.02 (0.005)***
Days90	0.01 (0.006)*	0.01 (0.006)*
Elevation5000[b]	-0.27 (0.10)**	-0.27 (0.10)**
Elevation5700	-0.09 (0.14)	-0.09 (0.14)
SoilWater	0.02 (0.10)	0.02 (0.10)
PublicLarge[c]	0.17 (0.13)	-1.00 (0.15)***
PrivateSmall	-0.39 (0.10)***	-0.398 (0.10)***
PrivateLarge	-0.22 (0.18)	-0.98 (0.21)***
Constant	-4.62 (0.98)***	-5.79 (0.98)***
LL score	-2379.1983	
Psuedo R^2	0.2796	
AIC	4788.397	
BIC	4879.413	
Number of obs.	3190	

[a] Significance levels: $*\,*\,* \leqslant 0.001$, ** $\leqslant 0.01$, * $\leqslant 0.05$

[b] The baseline category is Elevation5300.

[c] The baseline category is public sector with landscape size $\leqslant 100,000$ ft^2.

Table 4.8: Results Model III: What characteristics increase the probability of an account exceeding its water budget or engaging in extreme water consumption?

	(Model III)	
Logit probability	Prob $Y > 0$	Prob $Y > 1$
	Excess or Extreme Use	Extreme Use
	vs.	vs.
	(Efficient Use)	(Efficient or Excess Use)
Variable Name	Coeff. (s.e.)	Coeff. (s.e.)
Ordered dependent variable: Consumption_{jt}		
Independent variables		
Lag1.Excess	2.37 (0.10)***	1.50 (0.13)***
Lag1.Extreme	3.49 (0.12)***	3.49 (0.12)***
DaysAboveAvg	0.02 (0.005)***	0.02 (0.005)***
Days90	0.01 (0.006)*	0.01 (0.006)*
Elevation5000[b]	-0.27 (0.11)*	-0.02 (0.12)
Elevation5700	-0.15 (0.14)	-0.15 (0.14)
SoilWater	0.01 (0.10)	0.01 (0.10)
Park[c]	0.82 (0.12)***	-0.16 (0.13)
HOA	-0.07 (0.14)	-0.42 (0.17)*
StreetMedian	-0.22 (0.19)	-0.22 (0.19)
Multi	0.57 (0.17)***	0.57 (0.17)***
Education	0.29 (0.19)	0.29 (0.19)
Govt	0.48 (0.20)*	0.82 (0.21)***
Church	0.11 (0.27)	0.11 (0.27)
Constant	-5.18 (0.99)***	-6.38 (0.99)***
LL score	-2360.0544	
Psuedo R^2	0.2854	
AIC	4762.109	
BIC	4889.532	
Number of obs.	3190	

[a] Significance levels: $*** \leqslant 0.001$, $** \leqslant 0.01$, $* \leqslant 0.05$

[b] The baseline category is Elevation5300.

[c] The baseline category is commercial IWB account.

Table 4.9: Marginal effects Model II: probability of Public/private sector accounts' water consumption given last year's irrigating behavior

	Lag1.Efficient			Lag1.Excess		
	P(0)[a] (CI)[b]	P(1) (CI)	P(2) (CI)	P(0) (CI)	P(1) (CI)	P(2) (CI)
Public, sm[c]	0.809 (0.80,0.82)	0.130 (0.12,0.14)	0.061 (0.06,0.07)	0.234 (0.22,0.24)	0.552 (0.54,0.57)	0.214 (0.21,0.22)
Public, lg[c]	0.741 (0.73,0.75)	0.205 (0.20,0.21)	0.054 (0.05,0.06)	0.203 (0.20,0.21)	0.610 (0.60,0.62)	0.187 (0.18,0.19)
Private, sm	0.844 (0.84,0.85)	0.105 (0.10,0.11)	0.051 (0.05,0.05)	0.336 (0.33,0.35)	0.471 (0.47,0.48)	0.193 (0.19,0.20)
Private , lg	0.825 (0.82,0.83)	0.122 (0.12,0.13)	0.053 (0.05,0.06)	0.312 (0.30,0.33)	0.487 (0.48,0.50)	0.201 (0.19,0.22)

	Lag1.Extreme		
	P(0) (CI)	P(1) (CI)	P(2) (CI)
Public, sm	0.102 (0.10,0.11)	0.235 (0.22,0.25)	0.663 (0.65,0.67)
Public, lg	0.076 (0.07,0.08)	0.293 (0.28,0.31)	0.631 (0.62,0.65)
Private, sm	0.140 (0.14,0.14)	0.210 (0.21,0.22)	0.650 (0.64,0.66)
Private , lg	0.128 (0.12,0.14)	0.216 (0.20,0.23)	0.656 (0.63,0.68)

Marginal effects were estimated at the means of the physical site and weather variables.
[a] P(0) = Pr(efficient consumption); P(1) = Pr(excess consumption);
P(2) = Pr(extreme consumption)
[b] 95% confidence intervals (CI) were calculated from the individual average using:
$\overline{x} \pm 1.96 * \frac{\sigma_x}{\sqrt{n}}$ where $\overline{x}$ is the average individual marginal effect, σ_x is the s.d. and n is the number of observations.
[c] Small (sm) indicates landscaped area $<$ 100,000feet^2, Large (lg) indicates $>$ 100,000feet^2

Table 4.10: Marginal effects Model III: probability of water consumption by site category given last year's consumption

	Lag1.Efficient			Lag1.Excess			Lag1.Extreme		
	P(0)[a] (CI)[b]	P(1) (CI)	P(2) (CI)	P(0) (CI)	P(1) (CI)	P(2) (CI)	P(0) (CI)	P(1) (CI)	P(2) (CI)
Commercial	0.848	0.098	0.054	0.344	0.453	0.204	0.152	0.208	0.640
	(.85,.85)	(.10,.10)	(.05,.06)	(.34,.35)	(.45,.46)	(.20,.21)	(0.15,0.16)	(0.20,0.21)	(0.63,0.65)
Parks	0.714	0.240	0.046	0.188	0.631	0.181	0.072	0.317	0.611
	(.71,.72)	(.24,.24)	(.05,.05)	(.19,.19)	(.63,.63)	(.18,.18)	(0.07,0.07)	(0.31,0.32)	(0.60,0.62)
HOA	0.858	0.105	0.037	0.364	0.492	0.143	0.163	0.296	0.540
	(.86,.86)	(.10,.11)	(.04,.04)	(.36,.37)	(.49,.50)	(.14,.15)	(0.16,0.17)	(0.29,0.30)	(0.53,0.55)
StreetMedian	0.880	0.077	0.043	0.399	0.430	0.171	0.200	0.216	0.584
	(.88,.88)	(.07,.08)	(.04,.04)	(.38,.42)	(.42,.44)	(.16,.18)	(0.19,0.21)	(0.21,0.22)	(0.57,0.60)
MultiFamily	0.760	0.147	0.093	0.228	0.467	0.306	0.089	0.152	0.759
	(.75,.77)	(.14,.15)	(.09,.10)	(.22,.24)	(.46,.47)	(.29,.32)	(0.09,0.09)	(0.15,0.16)	(0.75,0.77)
Education	0.799	0.129	0.072	0.283	0.466	0.251	0.117	0.173	0.710
	(.79, .81)	(.12,.13)	(.07,.08)	(.27,.30)	(.46,.47)	(.24,.26)	(0.11,0.12)	(0.17,0.18)	(0.70,0.72)
Govt	0.790	0.099	0.111	0.248	0.386	0.366	0.097	0.099	0.804
	(.78,.80)	(.09,.11)	(.11,.12)	(.24,.26)	(.38,.40)	(.35,.38)	(0.09,0.10)	(0.10,0.10)	(0.80,0.81)
Church	0.828	0.109	0.063	0.329	0.456	0.214	0.138	0.194	0.669
	(.82,.84)	(.10,.12)	(.06,.07)	(.31,.35)	(.45,.45)	(.20,.23)	(0.13,0.15)	(0.18,0.20)	(0.65,0.69)

Marginal effects were estimated at the means of the physical site and weather variables.
[a] P(0) = Pr(efficient consumption); P(1) = Pr(excess consumption);
P(2) = Pr(extreme consumption)
[b] 95% confidence intervals (CI) were calculated from the individual average using:
$\overline{x} \pm 1.96 * \frac{\sigma_x}{\sqrt{n}}$, where $\overline{x}$ is the average
individual marginal effect, σ_x is the s.d. and n is the number of observations.

Table 4.11: Results Models IV and V: What is the elasticity of water demand?

Variable Name	**(Model IV)** Coefficient (s.e.)	**(Model V)** Coefficient (s.e.)
Dependent variable: Ln(wateruse$_{jt}$)		
AvgPrice	-0.845 (0.227)***	-1.152 (0.221)***
AvgPrice * Park		0.455 (0.029)***
AvgPrice * HOA		0.166 (0.031)***
AvgPrice * StreetMedian		0.206 (0.038)***
AvgPrice * MultiFamily		0.327 (0.043)***
AvgPrice * Education		0.352 (0.047)***
AvgPrice * Govt		0.166 (0.041)***
AvgPrice * Church		0.214 (0.068)**
DaysAboveAvg$_t$	0.002 (0.001)*	0.002 (0.001)*
Days90$_t$	-0.003 (0.001)**	-0.004 (0.001)***
PublicLarge$_t$	1.819 (0.104)***	
PrivateSmall$_t$	-0.662 (0.101)***	
PrivateLarge$_t$	1.517 (0.165)***	
Constant	12.996 (1.723)***	13.858 (1.621)***
σ_u	1.353	2.668
σ_e	0.449	0.536
ρ	0.901	0.961
No. of observations	4578	4578
No. of irrigation accounts	1085	1085

Significance levels: *** $\leqslant 0.001$, ** $\leqslant 0.01$, * $\leqslant 0.05$

Table 4.12: Results Models VI and VII: What is the elasticity of water demand?

Variable Name	**(Model VI)** Coefficient (s.e.)	**(Model VII)** Coefficient (s.e.)
Dependent variable: Ln(wateruse$_{jt}$)		
AvgPrice	-0.605 (0.178)***	-0.782 (0.224)***
AvgPrice * budg5	-0.203 (0.004)***	
AvgPrice * budg15	-0.125 (0.003)***	
AvgPrice * budg85	0.089 (0.006)***	
AvgPrice * budg95	0.166 (0.010)***	
AvgPrice * PubLg		0.272 (0.014)***
AvgPrice * PrivSm		-0.033 (0.014)*
AvgPrice * PrivLg		0.249 (0.023)***
DaysAboveAvg$_t$	0.002 (0.001)**	0.002 (0.001)*
Days90$_t$	-0.003 (0.001)**	-0.003 (0.001)**
PublicLarge$_t$	1.843 (0.072)***	
PrivateSmall$_t$	-0.565 (0.074)***	
PrivateLarge$_t$	1.308 (0.119)***	
Constant	11.241 (1.341)***	12.258 (1.688)***
σ_u	1.026	1.504
σ_e	0.308	0.481
ρ	0.917	0.907
No. of observations	4578	4578
No. of irrigation accounts	1085	1085

Significance levels: *** $\leqslant$ 0.001, ** $\leqslant$ 0.01, * $\leqslant$ 0.05

Table 4.13: Policy issues: Water use by consumption level and category

	Consumption level							
	All obs.		Efficient		Excess		Extreme	
	Obs.	Use (units)	Pct. obs.	Pct. use	Pct. obs.	Pct. use	Pct. obs.	Pct. use
Commercial	1,270	1,824,894	60%	31%	16%	31%	24%	38%
Parks	1,246	16,151,427	36%	26%	41%	62%	23%	12%
HOA	817	2,315,605	66%	37%	21%	46%	14%	16%
StreetMedian	388	635,310	72%	51%	13%	30%	14%	18%
MultiFamily	330	859,938	39%	16%	20%	17%	41%	67%
Education	249	1,753,253	43%	38%	29%	37%	27%	25%
Govt	336	776,543	52%	22%	15%	33%	33%	44%
Church	112	152,096	56%	33%	19%	27%	25%	40%
Total	4,748	24,469,066						

Includes all years of valid observations based on consumption levels.

Figure 4.1: Irrigation consumption level all accounts, 2008-2013

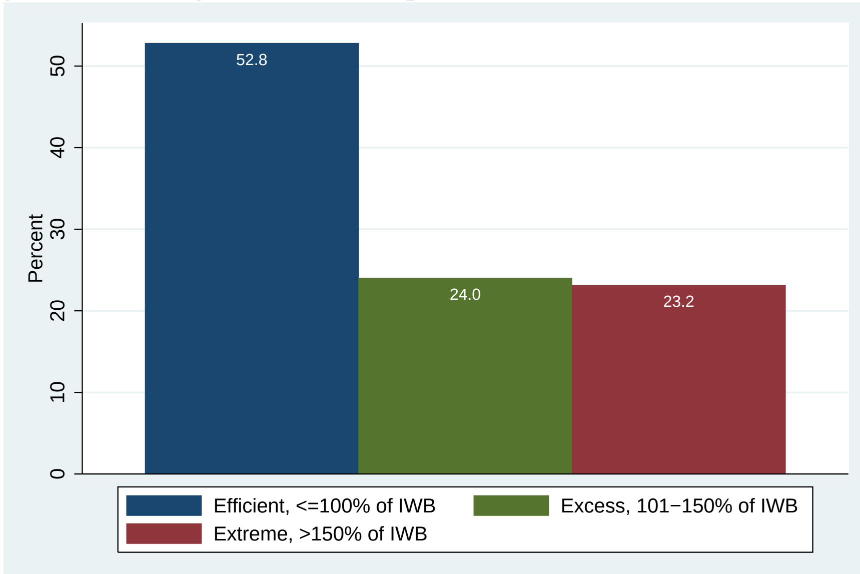


Figure 4.2: Irrigation consumption level all accounts, by year

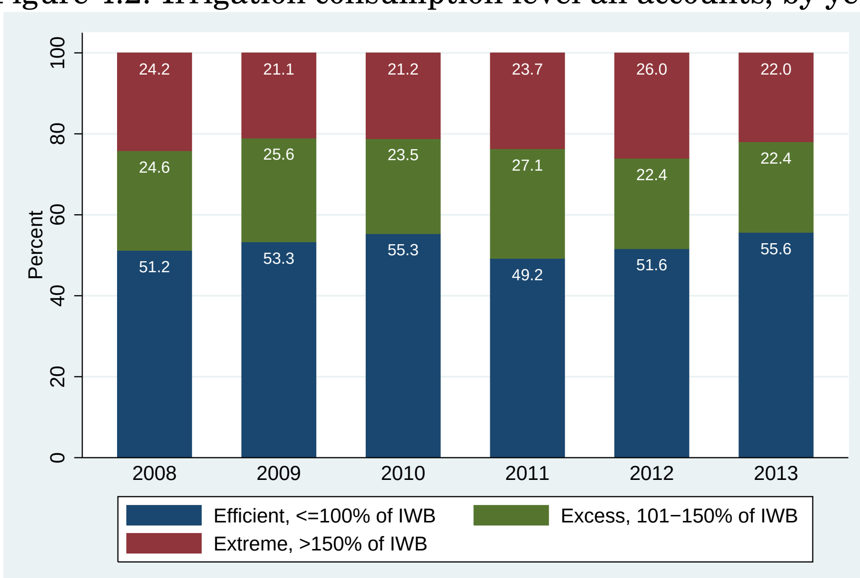


Figure 4.3: Mean and median percent water budget used by year

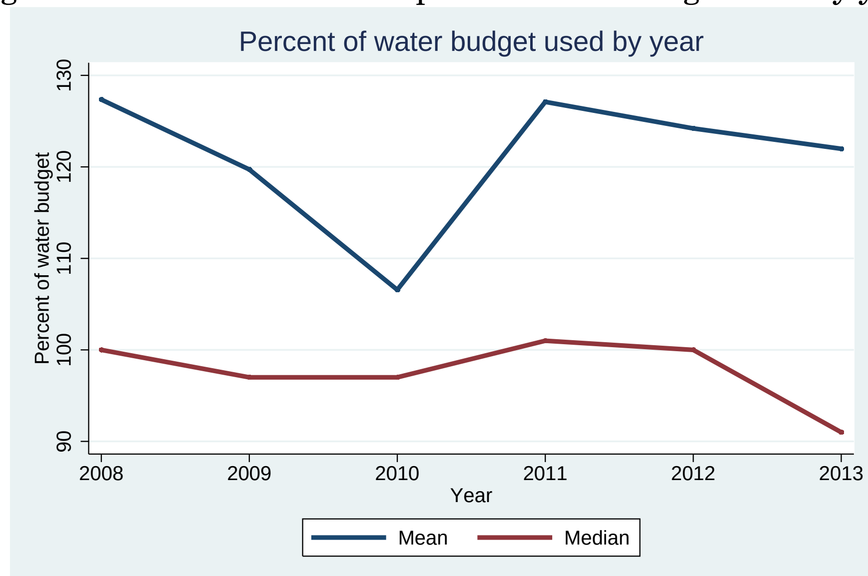


Figure 4.4: Water budget pct used with median all accounts, by year

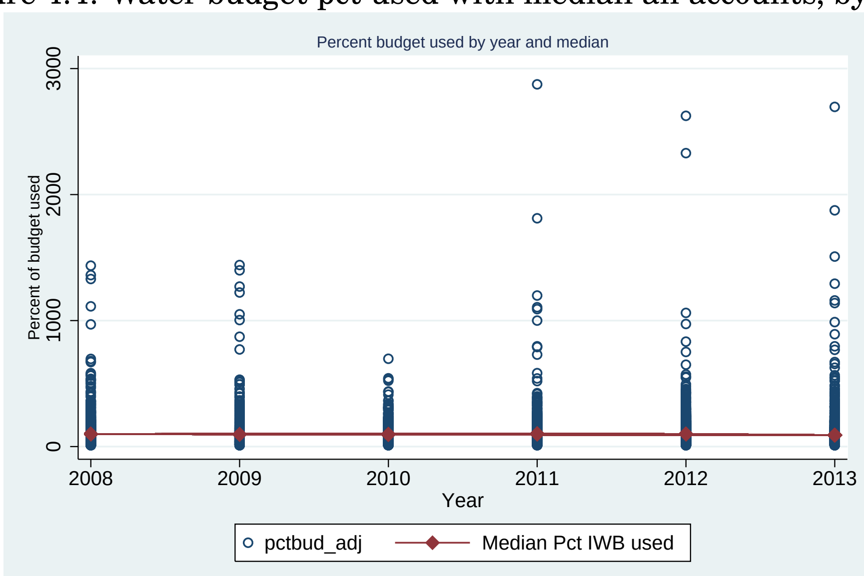


Figure 4.5: Irrigation patterns by public/private sector and landscape

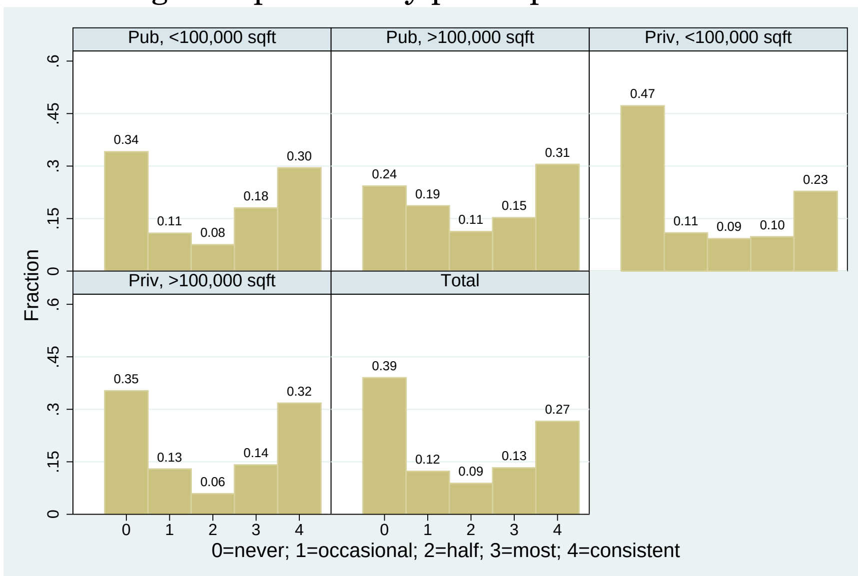


Figure 4.6: Irrigation patterns by site categories

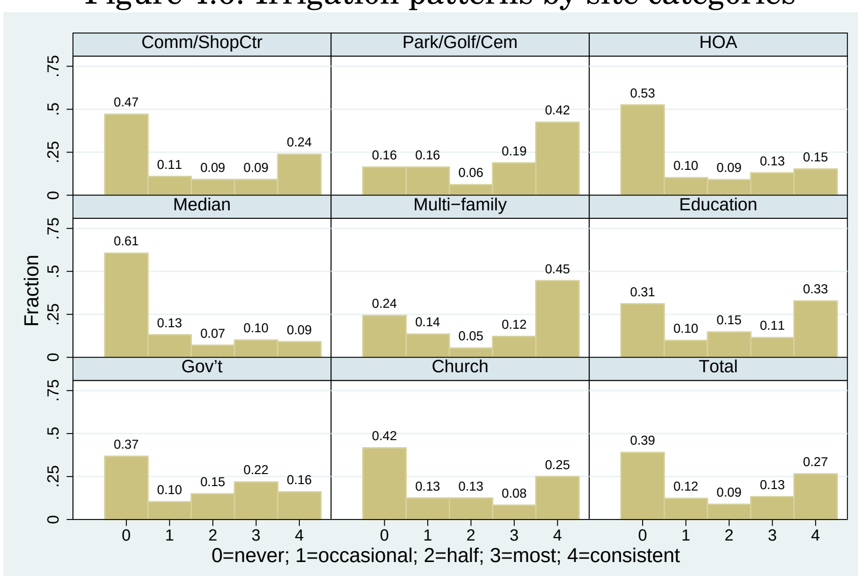


Figure 4.7: Percent budget use, public sector small landscape

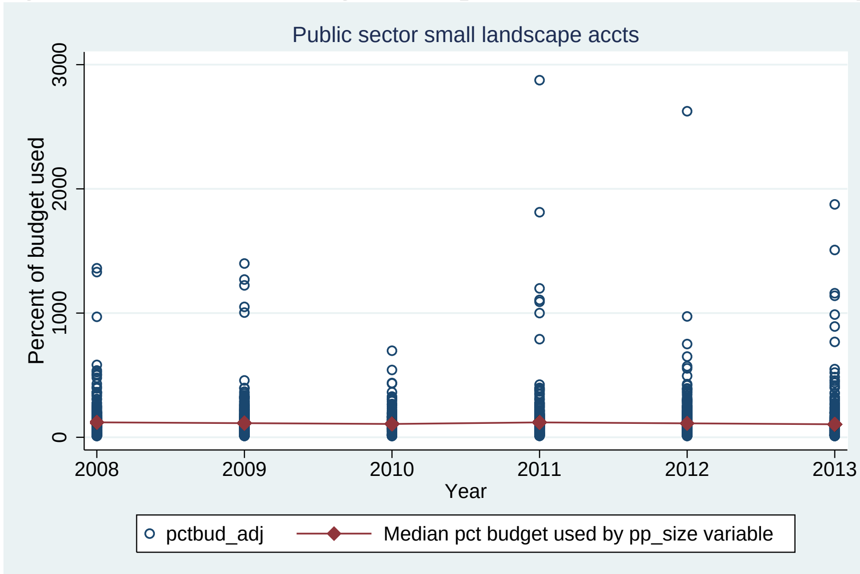


Figure 4.8: Percent budget use, private sector small landscape

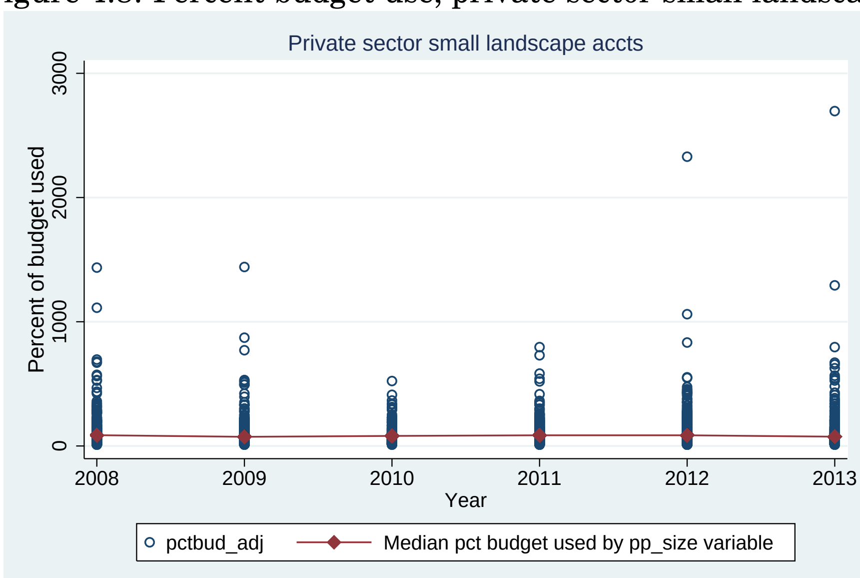


Figure 4.9: Percent budget use, public sector large landscape

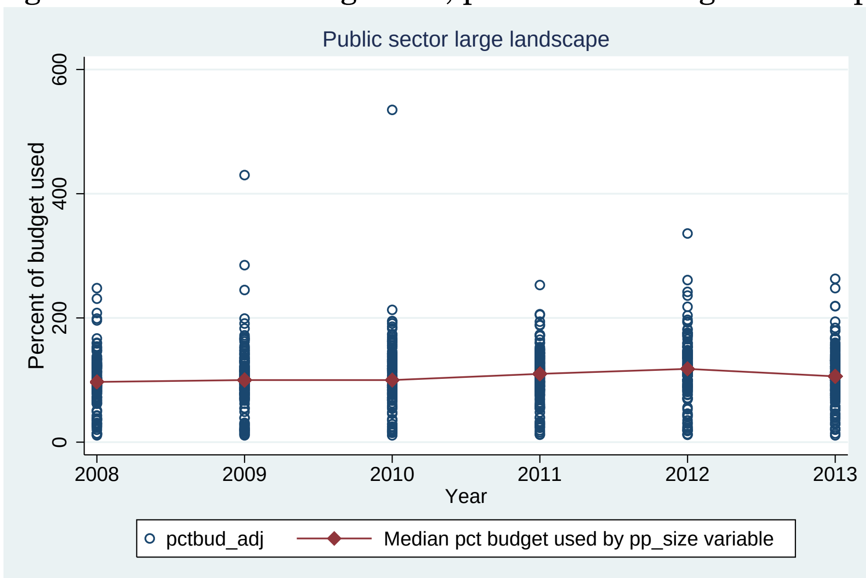


Figure 4.10: Percent budget use, private sector large landscape

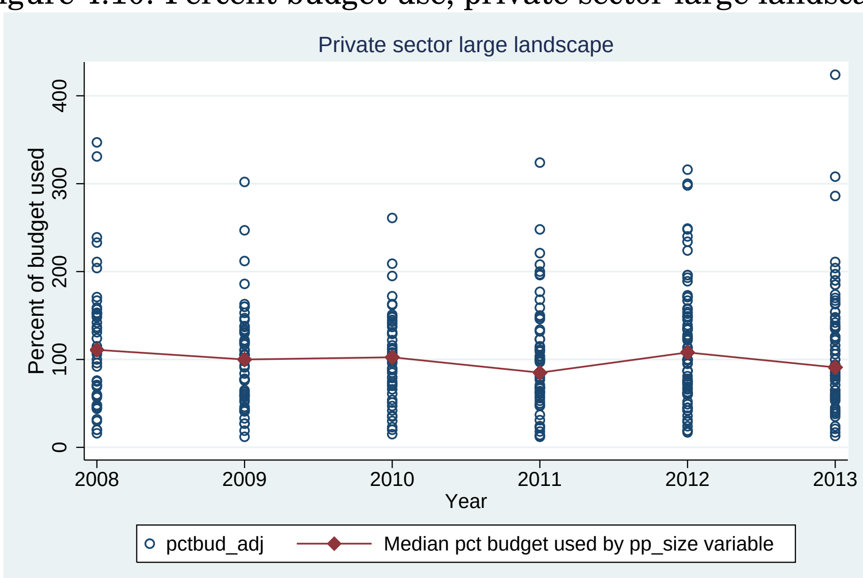
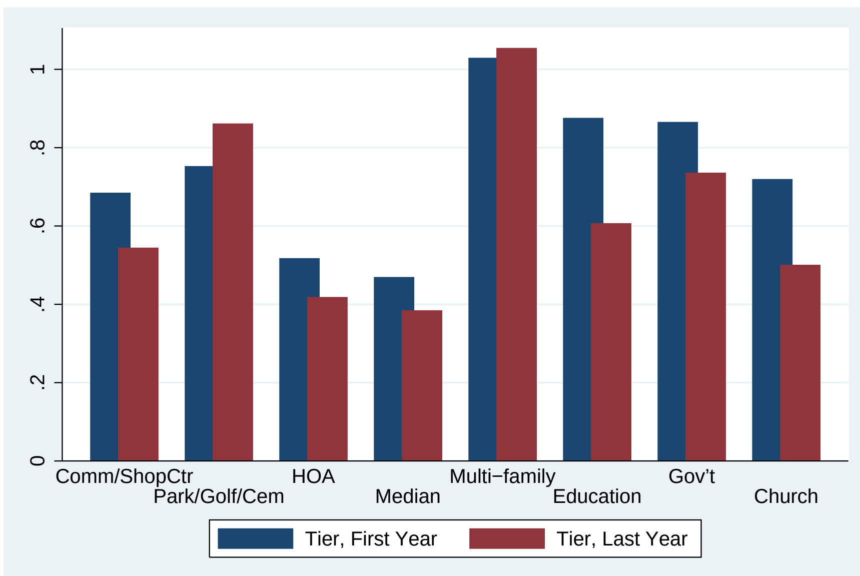


Figure 4.11: Comparison of first and last year consumption levels, by site categories



Chapter 5

Conclusion

5.1 Overview

Water utilities must balance conflicting goals. Federal agencies, industry organizations and utilities themselves are warning ratepayers that infrastructure is deteriorating and will need increased levels of investment to maintain or improve on current service levels. All have warned that ratepayers will likely pay for the majority of needed investments through higher rates or taxes. Investment costs are rising as utilities delay investing.

At the same time, finding additional sources of water supply needed due to population growth and changing climate are forcing utilities to promote water conservation policies that encourage efficient water consumption. These policies have had the unintended effect of reducing revenues to the point that water utilities have had to raise rates just to cover their current fixed costs. Encouraging additional conservation or efficient consumption policies can also have the effect of allowing a water utility to delay investing in additional large capital infrastructure projects, which could help them focus their investment funds on the currently deteriorating infrastructure.

Water utility managers cannot just raise rates to cover their costs. As a regulated natural monopoly, rate increases must be approved by a regulators or a water board. Utility managers should understand their ratepayers' priorities and their willingness-to-pay for improved service levels as one way to substantiate any rate increase request. In the face of increasing rates, water utilities need to promote efficient water consumption so ratepayers feel that their rates are being used efficiently. These are the issues addressed by my dissertation. Specifically, I first examine the issues of ratepayer preferences for infrastructure investments and distribution of benefits using choice experiment data from a water utility serving a metropolitan city in the southwest U.S.. I conclude by analyzing the water budget program developed by the same utility for a category of customers whose water consumption is strictly for outdoor, irrigation purposes.

5.2 Chapter 2

5.2.1 Gaps in the literature

Chapter 2 examines the question of ratepayers' preferences for investing in three types of water utility infrastructure using a random parameters logit model that specifies correlated attributes. In the literature on modeling preferences from discrete choice models, there is a trade-off between econometrically sophisticated methods and information that is useful. Studies have focused on improved econometric specifications or on basic policy-useful models; this chapter attempts to examine them both together.

Allowing preference heterogeneity is seen as more behaviorally realistic and more informative to policymakers who want to understand how preferences and WTP vary across groups with different attitudes or demographics. Random parameters logit models are widely used in the economic valuation literature; both observable and latent heterogeneity can be modeled in RPL models. Specifying a correlated attributes structure within the RPL structure is gaining ground. It has been shown to be an econometric improvement on uncorrelated attribute specifications through improved model fit. Some researchers note that correlated attribute structures provide additional, policy-useful information regarding how individuals view groups of attributes together. However, there have been conflicting results as to whether a correlated attributes structure results in more or less conservative central statistical moments of the MWTP distribution. And there is a lack of consensus as to whether estimated welfare effects from RPL models with correlated and uncorrelated attributes are statistically different.

Specifically, the water utility literature has primarily used studies that incorporated either multinomial logit models with classical heterogeneity or random parameters models that allow heterogeneity about the mean. Only a couple have used more recent econometric methods. I estimate RPL models with and without correlated attributes in order to examine the impact on preference heterogeneity and the distribution of estimated MWTP.

5.2.2 Summary of major findings

The results of this chapter indicate that the majority of ratepayers are WTP for investments in drinking water distribution infrastructure that maintain their current levels of service, in reuse pipe infrastructure that allows for increased irrigation of urban greenspace with reuse water, and in infrastructure that allows the water utility to increase their use of renewable energy to treat and distribute water for consumption. Preference heterogeneity exists for all infrastructure attributes except for the percentage of time the utility notifies ratepayers of a planned outage due to preventive maintenance on pipes. Latent reasons for heterogeneity appear to cause the greatest variation in preferences. However differences in income, education level, previous outage experience and water conservation attitudes are observable influences resulting in heterogeneity about the mean.

The best econometric fit occurs with a correlated attributes structure within an RPL model that allows for both latent heterogeneity and heterogeneity about the mean. The correlation matrices indicate that individuals who prefer high levels of investment in reuse water infrastructure also prefer higher levels of investment in renewable energy infrastructure. Individuals who are willing to tolerate longer average outages prefer lower costs, indicating perhaps that they are more price sensitive and would prefer adaptive behavior to worsening service rather than higher rates.

However, the best fitting model has a more dispersed distribution of estimated MWTP and a greater number of individuals with extreme, negative preferences. This causes the more conservative mean and median MWTP estimates. Due to the wide variance, we do not find that the MWTP estimates from correlated and uncorrelated attribute specifications are not significantly different.

5.2.3 Contribution

This paper demonstrates the importance of looking at the whole distribution of MWTP and not just the central statistical moments to understand the impact of a model. Often, more conservative estimates are considered an improvement without considering what is driving them. Findings indicate that the correlated attributes structure may be an improvement econometrically, but at the cost of a wider variance in MWTP distribution and more extreme MWTP values, especially at the negative end. This results in the more conservative mean and median moments. Yet due to the large variance, there is no statistical difference between the mean values between a correlated and uncorrelated attributes model specification. Estimates from the correlated model are up to 24% less than those from the uncorrelated model.

This paper also contributes WTP values for attributes described in the context of needed infrastructure investments. Given the issues faced by water utilities, it is important to frame the issue not just as maintaining or increasing service levels, but the infrastructure required to achieve desired service levels. The attributes describing the percentage of urban greenspace watered by reuse water and the percentage of energy used by the utility coming from renewable sources have not been used in many prior studies and can be applied in the context of current renewable energy regulations and the discussion about renewable water sources for non-potable water demand.

5.2.4 Policy implications

Water utility managers can use the results to support their rate increase requests to their regulatory boards. My results indicate that individuals are willing-to-pay an additional amount on their monthly bills for additional investments in pipe and renewable energy infrastructure. Several U.S. water agencies are re-examining their water demand and conservation policies to be more responsive to increasing drought conditions; Australia's experience with their decade-long extreme drought provides an example of the changing climate in water utilities. Regulatory boards in Australia and England already require water utilities to provide evidence that they have included their customers' WTP in their cost-benefit analyses of investment projects. Economic valuation surveys are useful in this regard.

ABCWUA acknowledges an investment gap between current investment levels in capital and what is needed over the next century, especially in the next 50-60 years when replacement levels will peak. They have considered various funding scenarios to increase investment levels, however discarded the scenario that would most effectively remove the investment gap as not feasible economically for their ratepayers. In examining a hypothetical infrastructure project, we show that utility customers have a WTP of around $6.50 per month.

5.2.5 Directions for future research

Given the competing priorities currently faced by water utilities, choice experiment surveys are an useful tool for examining ratepayers' preferences across different policies. The climate under which utilities operate has changed drastically in the past decade in the face of climate change and infrastructure that is rapidly deteriorating. Water utilities cannot completely rely on the results of studies done a decade ago under different circumstances. Issues of benefit transfer should be investigated as well to understand how how well point estimates or the MWTP distribution transfers from the original study. If the same choice experiment was done in a different utility then benefit transfer values could be compared. More investigation into the correlated attributes model structure is also called for to improve understanding of the impact of the variance covariance matrix on coefficients and preferences.

5.3 Chapter 3

5.3.1 Gaps in the literature

Chapter 3 uses the same dataset as in the previous chapter. I use another new approach to estimating WTP from discrete choice models and compare it to the standard practice. The WTP-space model has been praised for reducing the extreme variances and outliers present in the MWTP distribution when estimating standard mixed logit models (referred to as estimating 'preference-space' models). The WTP-space model re-parameterizes the coefficients in the standard preference-space mixed logit, separating the heterogeneity in willingness-to-pay values from heterogeneity in scale/price. This is accomplished through mathematically rearranging the preference-space mixed logit model so that estimated coefficients on non-cost attributes can be interpreted as willingness-to-pay values while the coefficient on the cost attribute is interpreted in the standard way as the heterogeneous marginal utility of income, still confounded with a heterogeneous scale term. This allows the researcher to directly specify the MWTP distribution. Studies have shown that this model specification leads to tighter confidence intervals and more realistic MWTP distribution.

The two models are referred to as functionally equivalent, however little attention has been paid to if they are behaviorally equivalent or if the MWTP distribution in the WTP-space conforms to theory. To my knowledge, there has not been any study that looks at the effect on the MWTP distribution of separately estimating a heterogeneous MUI from the WTP coefficients. Early practitioners of environmental valuation methods suggested using various validity tests on the distributional results from contingent valuation studies to assess if the results are theoretically sound. An example is the income validity test; MWTP values should be increasing in income because of the marginal utility of income in the denominator of the WTP ratio. This positive relationship has been shown in studies using choice experiment data and is one method of assessing behavioral reliability of the WTP-space results.

5.3.2 Summary of major findings

My initial findings are consistent with other studies that find the results from the mixed logit preference-space model fit the data better but the MWTP distribution from the WTP-space model does have a tighter variance and fewer extreme outliers. However, the impact of the separate MUI is to reduce the heterogeneity of WTP across income classes. The WTP-space estimates fail an income validity test. There is little difference between median MWTP estimates for low income individuals and high income individuals.

Findings indicate that the WTP-space model and the preference-space model with fixed cost have very similar distributions and MWTP estimates. With the preference-space model, between 2 and 10% of MWTP estimates can be dropped to have a MWTP distribution that does not have theoretically-incorrect negative estimates. These individuals tend to be the higher-income, price insensitive individuals whose MWTP is thus disregarded. However, in this dataset negative MWTP values are interpreted as adaptive behaviors, so there is no need to drop them. In this case, a preference-space model with heterogeneous MUI might be preferable.

5.3.3 Contribution

This paper contributes to the growing WTP-space literature by using a modified GMNL method to estimate the WTP-space model and then examining the distribution of MWTP across income groups. While estimated MWTP from WTP-space models are an attractive alternative to preference-space methods, a clear understanding of the impact of the income effect is needed. This paper is a first step. I briefly discuss a weighting scheme to look at the benefits received by income class.

5.3.4 Policy implications

Aggregate social benefits are often estimated using WTP values and impact on socio-economic groups can be studied. Federal policies often mandate impact studies to better understand how increasing costs affect the welfare of low-income or other affected groups. In order to effectively use the results from WTP-space models, weighting the MWTP estimates provides an income effect context that is otherwise lacking. Without that, the benefits to the median high and low income individual appear to be about the same, at least for this data.

5.3.5 Directions for future research

The smaller variance in the MWTP distribution is a promising aspect of the WTP-space mixed logit model because it reduces the incidence of the extreme outliers that make the MWTP distribution from preference-space mixed logit less usable. It is a newer method however and many small issues have not been investigated. There are primarily two methods featured in the current literature that are used for estimating a WTP-space model: a modified GMNL method and Bayesian methods directly programmed. Results from both have been compared to preference-space models, but not too each other. This is an avenue of interest given the slight difference in allowing for partial or completely correlated scale cost terms. In addition, the impact of separately estimating the scaled cost coefficient has implications that should be studied in more depth in order to reliably use point estimates.

5.4 Chapter 4

5.4.1 Gaps in the literature

Water utilities have used both price and non-price conservation policies to encourage efficient water use. Demand-side conservation policies encourage or require customers to reduce their water consumption. Research has studied quantity restrictions are an example of a non-price, demand-side policy, where households must reduce their water consumption by a target percentage, but can make their own decisions about how to achieve the reduction within their household. Evidence is mixed as to the impact and effectiveness of quantity restrictions. Some economists argue that price conservation policies that increase the price per unit of water at increasing block levels of use are more efficient and reduce overall welfare loss to households while achieving maximum flexibility of use. However equity issues between low- and high-income households can result from pricing conservation policies.

Water budgets are a relatively recent long-term conservation policy that combine aspects of quantity restrictions and block rate pricing. To my knowledge, only one paper examines the impact of water budgets in the context of residential customers. Chapter 4 focuses on the impact of a newly-designed water budget program for irrigation-only customers of ABCWUA over a six-year time frame.

5.4.2 Summary of major findings

Initially, the chapter examines differences in water consumption annually and over time between account site categories as well as public and private sector accounts with landscaped areas greater than and less than 100,000 feet^2. I find that private sector accounts appear to respond to the water budget program better than public sector accounts. In the first year of my data, there is no statistical difference between the average use of the two accounts. Each subsequent year, the average water consumption of private sector accounts is significantly less than public sector accounts. They also have a greater percentage of accounts that never exceed their water budget and a smaller percentage of accounts that consistently exceed their water budget.

Each account's annual water consumption is categorized in relation to their unique water budget by three levels: efficient, excess, and extreme. Results indicate that accounts that had efficient or extreme water consumption the previous year have a high probability of being in the same category of water consumption in the current year. Accounts with excess water consumption are the most likely the change their water consumption behavior. I find that elasticity of water demand is inelastic overall (-0.845), however differences in price responsiveness exist between subgroups. Parks, multi-family, and education accounts have the most inelastic demand of all site categories, while commercial, home owner associations, and govt accounts have elastic or nearly elastic demand. The size of the landscaping is more influential with regards to price responsiveness than public or private sector ownership. Large landscaped lots (described as having more than 100,000 feet^2 of area) are significantly more price inelastic than smaller lots. Finally, accounts that are in the lowest percentiles of percentage of water budget use are the most price responsive, the accounts in the highest percentiles are the least price responsive.

5.4.3 Contribution of this research

This paper contributes to the overall conservation literature by examining water budgets, which are a relatively new conservation policy. By focusing on the irrigation-only customer class I am able to examine the effects of the water budget program alone because, unlike with residential customers, there are no competing conservation policies that affect this group. In addition, outdoor water use and elasticity of demand for outdoor water use has been examined for residential customers, with outdoor water use typically found to be less inelastic than indoor use. However it is being estimated in the context of individuals who are simultaneously using both. Irrigation-only customers do not have indoor use, so estimated elasticities represent price responsiveness for outdoor water demand only. I estimate an overall elasticity of demand, as well as the elasticity of various subgroups based on site categories, ownership and landscape size categories, and the percentile of water budget use. This has not been done in previous studies.

5.4.4 Policy implications

This paper is the first analysis of the effectiveness of the water budget program for irrigation-only customers. My results show that the average private sector account has significantly lower water consumption in comparison to the average public sector account. In addition, findings indicate that commercial, HOA, and govt accounts, accounts with landscapes under 100,000 feet^2 and those who are in the lower percentiles of water budget use are the most price responsive. The least price responsive are accounts with large landscapes, multi-family, parks and education accounts, and those in the 85th percentile or higher of water budget use. ABCWUA might want to focus on these groups to increase efficient irrigating and or increase the surcharge prices to a level that these accounts find relevant. Accounts in the highest percentile of water budget users are the most extreme water consumers, so decreasing their water consumption levels might have the most immediate response.

A final area of focus for ABCWUA is accounts that had excess water consumption the past year. These accounts have the greatest probability of behavior change in comparison to accounts who already irrigate efficiently or those who are extreme water consumers. If ABCWUA can get those accounts to reduce water consumption to an efficient level, there is a high probability that the following year they will again be efficient water consumers. Focusing on the surcharge, the utility probably needs to increase the surcharge to cause a behavior change in the extreme water consumers. The recently enacted third surcharge block for use above 200% is a step in the right direction.

5.4.5 Directions for future research

This chapter indicates the importance of studying this type of conservation policy for encouraging optimal outdoor water consumption. As the program continues with more accounts are added and at least a third tier of surcharges, future research will have the benefit of a longer time series panel with more price variation. Research can look at the short-term and long-term responsiveness to the program, explicitly model differences between account categories, and examine the effect of multiple surcharge blocks. For maximum effectiveness, ABCWUA needs to understand at what price signals each account type responds so they can accordingly adjust their policy. Also, greater research into the movement of accounts between surcharge blocks is called for so the utility has an improved understanding of the characteristics that impact reduced water consumption behavior over the long run.

5.5 Final remarks

In my dissertation, I have taken a look at two separate, but concurrent issues facing water utilities today. Economists often look at the effect of a change in a variable, *ceteris paribus*, but water utilities do not have that luxury. Distribution infrastructure is constantly deteriorating, easily accessed water supplies are dwindling, and droughts may occur more frequently. Water utilities must use both revenues and water resources optimally; greater consideration of their customers' preferences for projects could be valuable. In the absence of these actions by the water utility, it may be more difficult to realistically argue in favor of rate increases to support needed investments while at the same time encouraging conservation, which decreases revenues and, customers assume, leads to lower monthly bills. This series of papers has attempted to look at some of these questions.

Appendices

Appendix A

Derivation of λ_n

In the WTP-space specification, the variable λ_n is the heterogeneous cost and scale parameter. Both cost and scale are allowed to be heterogeneous. The coefficient must be positive; to achieve this, $\lambda_n = (\overline{\lambda} + \tau\omega)$ is estimated in exponential form. Here $\overline{\lambda}$ is the mean while the standard deviation, τ, is multiplied by a draw from the standard normal distribution, $\omega \sim N(0, 1)$.

$$\lambda_n = exp(\overline{\lambda} + \tau\omega) \tag{A.1}$$

λ_n normalizes the other constants in the WTP-space equation. To ensure that this condition is met, the expectation of λ_n is set equal to one and then the coefficients inside the parentheses are solved for.

$$E(\lambda_n) = E[exp(\overline{\lambda} + \tau\omega)] \tag{A.2}$$

$$E(\lambda_n) = E[exp(\overline{\lambda})exp(\tau\omega)] \tag{A.3}$$

$$E(\lambda_n) = exp(\overline{\lambda})E[exp(\tau\omega)] \tag{A.4}$$

The only random variable is the ω. To calculate the expectation, use the moment generating function for a random variable with a standard normal distribution. This is the probability density function for the standard normal distribution:

$$f(\omega) = N(\omega; 0, 1) = \frac{1}{\sqrt{2\pi}} e^{-\frac{\omega^2}{2}} \tag{A.5}$$

The moment generating function for a continuous distribution is:

$$M_\omega(\tau) = E(e^{\tau\omega}) = \int_{-\infty}^{\infty} e^{\tau\omega} f(\omega) d\omega \tag{A.6}$$

$$E(e^{\tau\omega}) = \int_{-\infty}^{\infty} e^{\tau\omega} \frac{1}{\sqrt{2\pi}} e^{(-\frac{\omega^2}{2})} d\omega \tag{A.7}$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{(\tau\omega - \frac{\omega^2}{2})} d\omega \tag{A.8}$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \underbrace{e^{-\frac{1}{2}(-2\tau\omega + \omega^2)}} d\omega \tag{A.9}$$

Focusing on the exponentiated section with the underbracket:

$$= -\frac{1}{2}(-2\tau\omega + \omega^2) \tag{A.10}$$

$$= -\frac{1}{2}[(\omega - \tau)(\omega - \tau)] \tag{A.11}$$

$$= -\frac{1}{2}[(\omega^2 - 2\tau\omega + \tau^2) - \tau^2] \tag{A.12}$$

Substitute back into Equation A.9

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}[(\omega^2 - 2\tau\omega + \tau^2) - \tau^2]} d\omega \tag{A.13}$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}[(\omega - \tau)^2 - \tau^2]} d\omega \tag{A.14}$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{[-\frac{1}{2}(\omega - \tau)^2 + \frac{1}{2}\tau^2]} d\omega \tag{A.15}$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{(-\frac{1}{2}(\omega - \tau)^2)} e^{(\frac{1}{2}\tau^2)} d\omega \tag{A.16}$$

$$= e^{(\frac{\tau^2}{2})} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{(-\frac{1}{2}(\omega - \tau)^2)} d\omega \tag{A.17}$$

The integral is the pdf of a standard normal random variable with $\mu = \tau$ and $\sigma^2 = 1$. A pdf integrated equals one. Therefore,

$$E[exp(\tau\omega)] = e^{\frac{\tau^2}{2}} \tag{A.18}$$

and, substituting into Equation A.4:

$$E(\lambda_n) = exp(\overline{\lambda}) exp(\frac{\tau^2}{2}) \tag{A.19}$$

$$E(\lambda_n) = exp(\overline{\lambda} + \frac{\tau^2}{2}) = 1 \tag{A.20}$$

Q.E.D.

Appendix B

Descriptive statistics by annual household income

Appendix B. Descriptive statistics by annual household income

Table B.1: Descriptive statistics by annual household income category

Attribute	Description	Low income Mean (S.d.)	Mid income Mean (S.d.)	High income Mean (S.d.)
Age	Age of respondent, (years); continuous	58 (18)	52 (15)	52 (12)
Female	Respondent is female; 1=yes, 0=no	0.65 (0.48)	0.52 (0.50)	0.44 (0.50)
Hispanic	Respondent is Hispanic; 1=yes, 0=no	0.45 (0.50)	0.34 (0.47)	0.17 (0.37)
HSDiploma	Highest education is HS diploma or GED; 1=yes, 0=no	0.33 (0.47)	0.10 (0.30)	0.02 (0.13)
AA	Highest education: some yrs college or an AA degree; 1=yes, 0=no	0.40 (0.49)	0.31 (0.46)	0.16 (0.37)
BA	Highest education: a B.A. degree or higher; 1=yes, 0=no	0.27 (0.44)	0.59 (0.49)	0.82 (0.38)
HomeOut[a]	Respondent had a home, outage 2004-09; 1=yes, 0=no	0.35 (0.48)	0.32 (0.47)	0.29 (0.46)
TractOut[b]	Pipe breaks in Census tract 2004-09; continuous	15.2 (13.6)	13.3 (14.7)	11.3 (13.5)
Water0	0% pct watered in typical summer month; 1=yes, 0=no	0.04 (0.19)	0.05 (0.21)	0.01 (0.10)
Water50	1-25% pct watered in typical summer month; 1=yes, 0=no	0.87 (0.49)	0.82 (0.50)	0.78 (0.50)
Water100	51-100% pct watered in typical summer month; 1=yes, 0=no	0.09 (0.28)	0.13 (0.34)	0.21 (0.41)
Children	Children live in household; 1=yes, 0=no	0.22 (0.41)	0.32 (0.47)	0.41 (0.49)
HH[c]	Household has aytpical water use; 1=yes, 0=no	0.48 (0.50)	0.34 (0.47)	0.34 (0.48)
NM	Years lived in NM; continuous	37 (22)	32 (18)	28 (16)
Address	Years lived in current home; continuous	19 (17)	13 (11)	13 (15)
Westside	Lives west of Rio Grande River; 1=yes, 0=no	0.30 (0.46)	0.31 (0.47)	0.13 (0.34)
South	Lives in south Albuquerque; 1=yes, 0=no	0.30 (0.46)	0.21 (0.41)	0.22 (0.41)
North	Lives in north Albuquerque; 1=yes, 0=no	0.40 (0.49)	0.47 (0.50)	0.65 (0.48)
Total		227	356	187

[a] Self reported at least one outage at home between 2004-2009

[b] Pipe breaks reported by the water utility for time period 2004-2009, aggregated by Census Tract

[c] Water outages at home may affect certain sub-populations differently, i.e. a stay-at-home parent, a home business, or someone with a sensitive health issue.

Appendix C

Percentage of water budget used by site category

These figures indicate water budget use by site category.

Figure C.1: Percent water budget used by Commercial site category per year

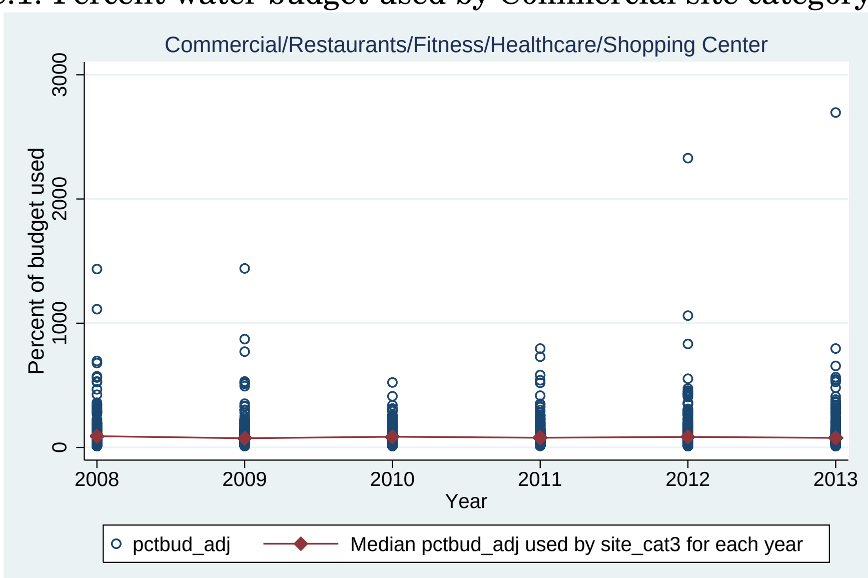


Figure C.2: Percent water budget used by Parks site category per year

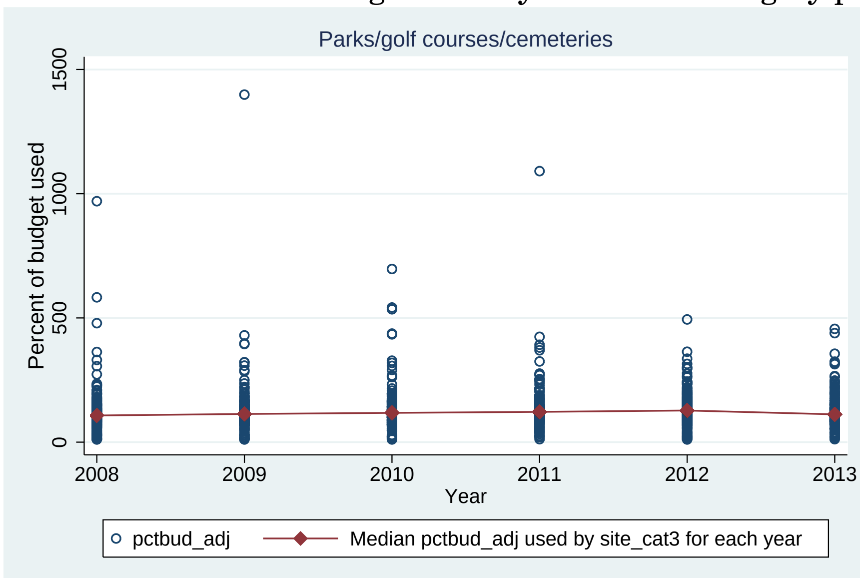


Figure C.3: Percent water budget used by HOA category per year

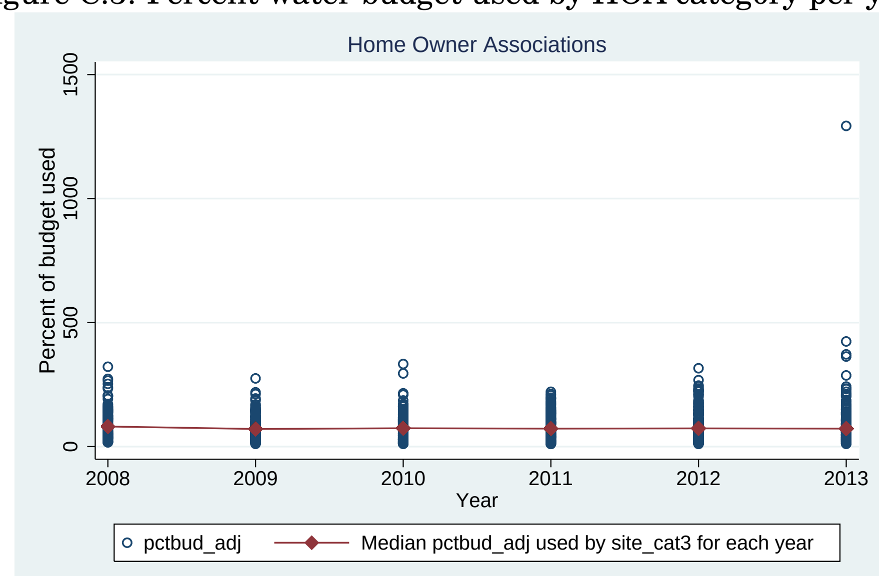


Figure C.4: Percent water budget used by Street Medians category per year

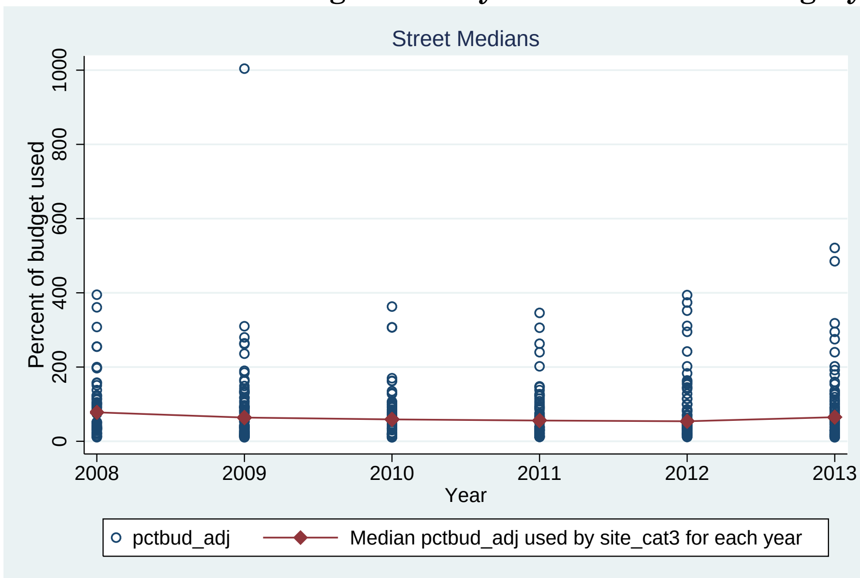
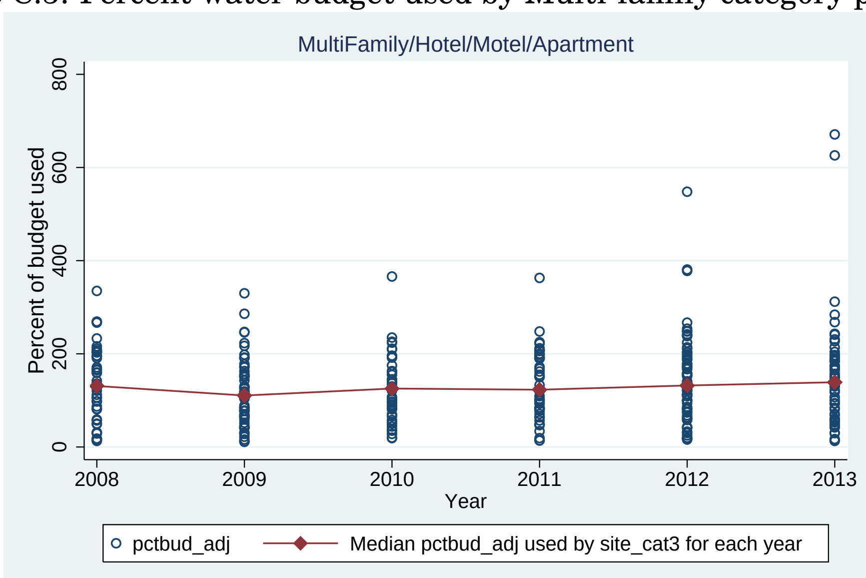


Figure C.5: Percent water budget used by Multi-family category per year



Appendix C. Percentage of water budget used by site category

Figure C.6: Percent water budget used by Education category per year

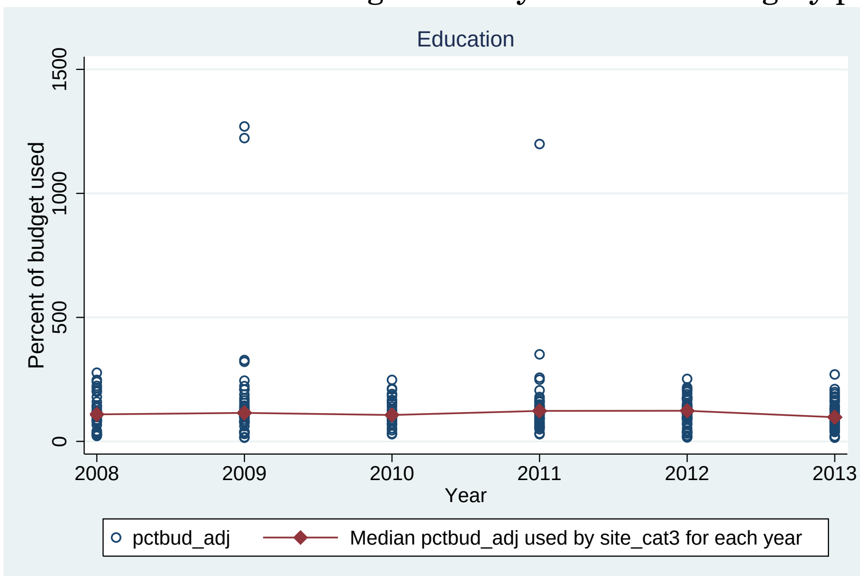
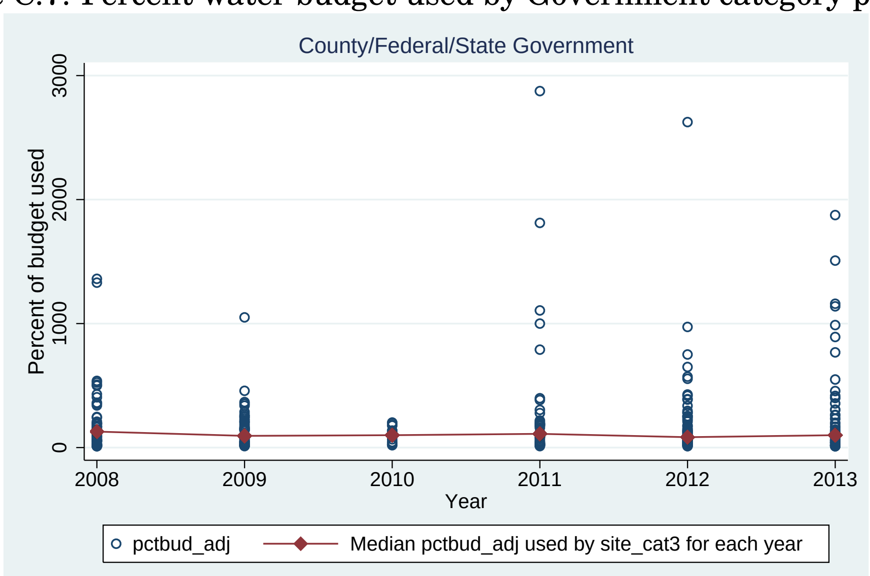
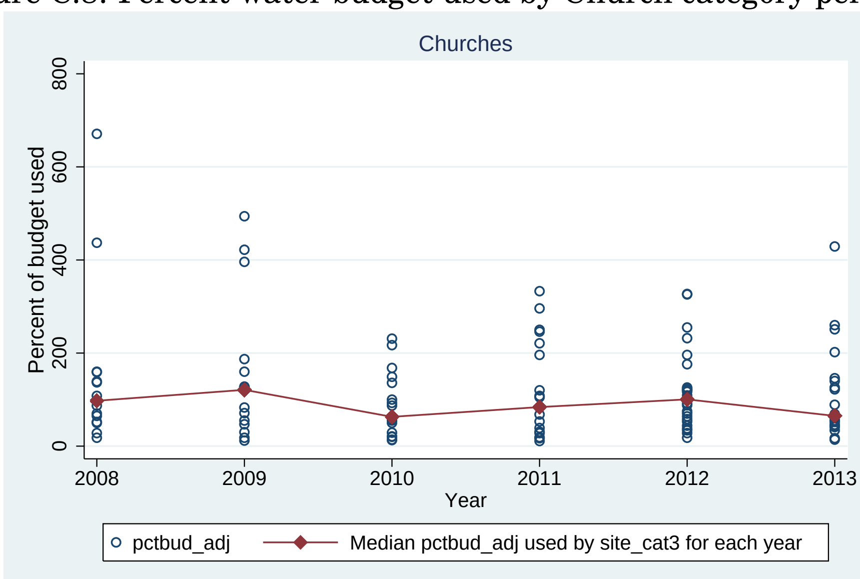


Figure C.7: Percent water budget used by Government category per year



Appendix C. Percentage of water budget used by site category

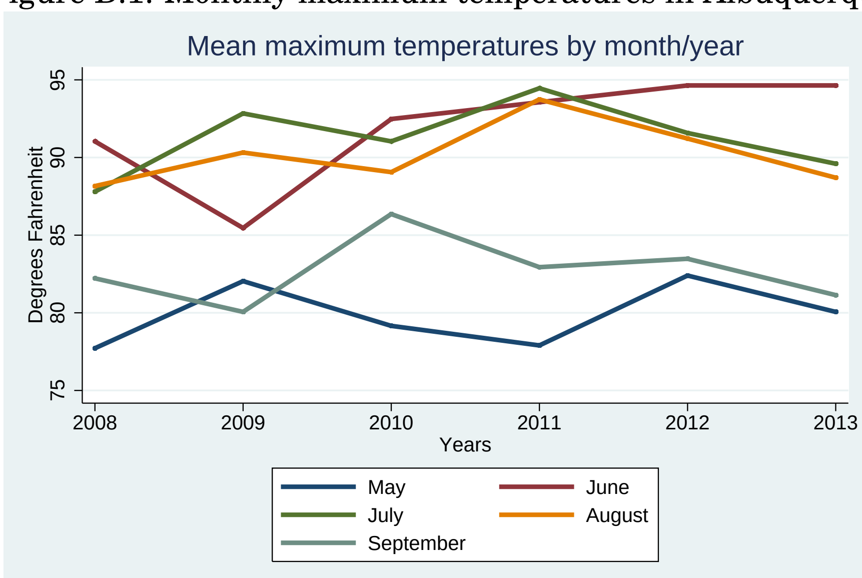
Figure C.8: Percent water budget used by Church category per year



Appendix D

Public and private sector accounts, consumption differences

Figure D.1: Monthly maximum temperatures in Albuquerque



Appendix D. Public and private sector accounts, consumption differences

Table D.1: Descriptive statistics by ownership and irrigable square feet

	PubSmall	PubLarge	PrivSmall	PrivLarge
Area, mean	38,214 ft^2	452,680 ft^2	25,355 ft^2	398,360 ft^2
Area, min	54 ft^2	101,291 ft^2	556 ft^2	101,086 ft^2
Area, max	99,748 ft^2	6,516,926 ft^2	99,598 ft^2	7,435,090 ft^2
Trees	4,588 ft^2	17,618 ft^2	3,021 ft^2	14,317 ft^2
Xeric	12,733 ft^2	36,447 ft^2	13,823 ft^2	141,649 ft^2
Turf	24,888 ft^2	257,497 ft^2	5,656 ft^2	125,806 ft^2
Athletic	7,448 ft^2	149,459 ft^2	0	0
Elevation5000	29%	18%	22%	11%
Elevation5300	66%	74%	27%	76%
Elevation5700	6%	8%	6%	13%
Percent IWB, mean	144%	103%	110%	106%
Percent IWB, min	11%	11%	11%	13%
Percent IWB, max	1,875%	263%	2,696%	424%
Surcharge, mean	$417	$1,858	$217	$2,139
Commercial	0	0	58% (314)	31% (26)
HOA	0	0	27% (147)	35% (30)
Park	36% (109)	75% (132)	0.2% (1)	4% (3)
StreetMedian	26% (80)	11% (19)	0	0
Multi	0	0	9% (51)	27% (23)
Education	12% (36)	11% (19)	1% (6)	0
Government	26% (80)	4% (7)	0	0
Church	0	0	4% (21)	4% (3)
Observations	311	177	540	85

Table D.2: X^2 test for differences in water consumption level in a given year for public and private sector accounts

Variable	All Priv/Pub	2009 Priv/Pub	2010 Priv/Pub	2011 Priv/Pub	2012 Priv/Pub	2013 Priv/Pub
Improved	354/413	27/50	50/75	80/87	97/103	100/98
No change (0)	2,127/1,740	309/290	275/264	291/259	462/287	405/257
Worsened	427/400	60/53	76/63	66/75	82/85	143/124
X^2_2 statistic	21.1621	7.8951	6.4391	2.4322	16.8017	9.3271
$Pr(\|T\| > \|t\|)$	0.000	0.019	0.040	0.296	0.000	0.009
Observations	5,461	789	803	858	1,116	1,127

Unit of observation is one year of movement between tiers for one account. Accounts must have at least 2 consecutive years of irrigation data to calculate tier movement.

Appendix E

Stata Code

E.1 Chapter 1 code

E.1.1 Kernel density graphs

twoway (kdensity n2c_grn, lcolor(orange) lwidth(thick)) (kdensity n2u_grn, lcolor(black) lwidth(thick) lpattern(dash)),xline(0.134, lcolor(green) lwidth(thick)) yline(2, lcolor(gray) lwidth(medthick)) xtitle(Dist. of MWTP for an additional 1% of green energy used by the utility, size(small)) ytitle(Density)

E.1.2 Kernel density with text box in graph

twoway (kdensity n1u_reu, lcolor(black) lwidth(medthick) lpattern(longdash) legend(label(1 "RPL1_uncorr"))) (kdensity n1c_reu, lcolor(black) lwidth(thick) lpattern(tight_dot) legend(label(2 "RPL1_corr"))) (kdensity n3u_reu, lcolor(black) lwidth(medthick) lpattern(dash_3dot) legend(label(3 "RPL2_uncorr"))) (kdensity n3c_reu, lcolor(black) lwidth(medthick) lpattern(solid) legend(label(4 "RPL2_corr"))), text(3.5 -0.25 "Median MWTP Reuse: 0.17(MNL1), 0.07(1c), 0.08(2c)", place(ne)box

```
just(left) margin(l+4 t+1 b+1) width(90)) xlabel( -0.50 0 0.08 0.17 0.50 1) xtitle(MWTP per month) ytitle(Density)
```

E.1.3 Mixed logit models, normal distribution

```
* uncorrelated model
mixlogit choice Notify_sqpct FreqLen_cntr, rand(Reuse_sqpct Green_sqpct Length_sqpct Freq_sqpct Cost) group(newid) id(userid2) nrep(500) robust

    mixlbeta Notify_sqpct FreqLen_cntr Reuse_sqpct Green_sqpct Length_sqpct Freq_sqpct Cost userid2, saving(N10unc_basic_beta500d)

    * save vector of betas
matrix b = e(b)

    * starting values for correlated model to speed things up
matrix start = b[1,1..8],0,0,0,0,b[1,9],0,0,0,b[1,10],0,0,b[1,11],0,b[1,12]

    * Correlated model using starting values from uncorrelated model
mixlogit choice Notify_sqpct FreqLen_cntr, rand(Reuse_sqpct Green_sqpct Length_sqpct Freq_sqpct Cost) group(newid) from(start,copy) id(userid2) nrep(500) robust corr

    * obtain the covariance matrix
mixlcov

    * calculate the standard deviations
```

mixlcov, sd

* save conditional individual betas

mixlbeta Notify_sqpct FreqLen_cntr Reuse_sqpct Green_sqpct Length_sqpct Freq_sqpct Cost userid2, saving(N10corr_basic_beta500d)

E.2 Chapter 2 code

E.2.1 Scatter plot graphs

Scatter plot F1, N1, L1, W1 models, minimum 30 MWTP values

* Code for ordered distribution of MWTP values at positive and negative endsd to highlight outliers. Each model has unique symbols (i.e. smplus, or smtriangle_hollow)

twoway (scatter negfreq_n1u id_negfreqn1u if id_negfreqn1u > 3 & id_negfreqn1u ⩽ 30, mcolor(black) msymbol(smplus) legend(label(1 “N1 Cost normal”))) (scatter w1ns_Freq id_w1ns_Freq if id_w1ns_Freq > 0 & id_w1ns_Freq ⩽ 30, mcolor(black) msymbol(smtriangle_hollow) legend(label(2 “W1 wtp-space”))) (scatter negfreq_c1u id_negfreqc1u if id_negfreqc1u > 0 & id_negfreqc1u ⩽ 30, mcolor(black) msymbol(smsquare_hollow) legend(label(3 “C1 Cost lognormal”))) (scatter negfreq_f1u id_negfreqf1u if id_negfreqf1u > 0 & id_negfreqf1u ⩽ 30, mcolor(black) msymbol(smx) legend(label (4 “F1 Cost fixed”))),xtitle(Observations sort by MWTP, size(small)) ytitle(MWTP in dollars)

Appendix E. Stata Code

* Scatter plot F1, N1, L1, W1 models, maximum 30 MWTP values

twoway (scatter negfreq_n1u id_negfreqn1u if id_negfreqn1u > 819 & id_negfreqn1u ⩽ 847, mcolor(black) msymbol(smplus) legend(label(1 “N1 Cost normal”))) (scatter w1ns_Freq id_w1ns_Freq if id_w1ns_Freq > 819 & id_w1ns_Freq ⩽ 850, mcolor(black) msymbol(smtriangle_hollow) legend(label(2 “W1 wtp-space”))) (scatter negfreq_c1u id_negfreqc1u if id_negfreqc1u > 819 & id_negfreqc1u ⩽ 850, mcolor(black) msymbol(smsquare_hollow) legend(label(3 “C1 Cost lognormal”))) (scatter negfreq_f1u id_negfreqf1u if id_negfreqf1u > 819 & id_negfreqf1u ⩽ 850, mcolor(black) msymbol(smx) legend(label (4 “F1 Cost fixed”))),xtitle(Observations sort by MWTP, size(small)) ytitle(MWTP in dollars)

* Scatter plot F1 and W1 models, minimum and maximum 60 MWTP values

twoway (scatter w1ns_Freq id_w1ns_Freq if id_w1ns_Freq > 0 & id_w1ns$_{Freq}$⩽ 60, mcolor(black) msymbol(smtriangle_hollow) legend(label(1 “W1 wtp-space”))) (scatter negfreq_f1u id_negfreqf1u if id_negfreqf1u > 0 & id_negfreqf1u ⩽ 60, mcolor(black) msymbol(smx) legend(label (2 “F1 Cost fixed”))),xtitle(Observations sort by MWTP, size(small)) ytitle(MWTP in dollars)

twoway (scatter w1ns_Freq id_w1ns_Freq if id_w1ns_Freq > 789 & id_w1ns_Freq ⩽ 850, mcolor(black) msymbol(smtriangle_hollow) legend(label(1 “W1 wtp-space”))) (scatter negfreq_f1u id_negfreqf1u if id_negfreqf1u > 789 & id_negfreqf1u ⩽ 850, mcolor(black) msymbol(smx) legend(label (2 “F1 Cost fixed”))),xtitle(Observations sort by MWTP, size(small)) ytitle(MWTP in dollars)

E.2.2 Graphs comparing distributions of MWTP by binary characteristics

twoway (kdensity w1un_l if HM0409_high==0, lcolor(red) lwidth(thick) legend(label(1 “15 or fewer outages”)))(kdensity w1un_l if HM0409_high==1, lcolor(black) lwidth(thick) legend(label(2 “16-64 outages”))),xtitle(MWTP to avoid one hour longer average outage by ABCWUA outages w/i 0.5 miles of home, size(small)) ytitle(Density)

* box-and-whisker graph

graph box w1un_f, over(HM0409_high) ytitle(MWTP Frequency) title(MWTP to avoid 1 additional outages by ABCWUA outages) xla(1 “15 or fewer” “outages w/i 0.5 miles” 2 “16-64 outages” “w/i 0.5 miles, 2004-09”)

* box-and-whisker graph of all obs by income category

graph box f1u_wtpr n1u_wtpr c11u_wtpr w1un_r, over(inc_cat, relabel(1”$39,999 or less$”2”40,000 to $99,999$”3”100,000 or more”)) box(1,fcolor(gs1) lcolor(gs1)) box(2,fcolor(gs3) lcolor(gs3)) box(3,fcolor(gs6) lcolor(gs6)) box(4,fcolor(gs2) lcolor(gs2)) ytitle(MWTP in dollars) noout legend(col(1) label(1 “Model F1 (cost fixed)”) label(2 “Model N1 (cost normal)”) label(3 “Model C1 (cost lognormal)”) label(4 “Model W1 (wtp-space)”))

E.2.3 WTP-space model

```
* fixed coefficients, following presentation by A. Hole

gen const = 1

constraint 1 [Mean]negCost = 1

constraint 2 [tau]_cons = 0

matrix start = 1,0,0,0,0,0,0,0,0

gmnl choice negCost FreqLen_cntr Notify_sqpct Reuse_sqpct Green_sqpct Length_sqpct Freq_sqpct , group(newid) id(userid2) het(const) constraint(1 2) from(start,copy) nrep(300)

nlcom (price: -exp([Het]const))

* with random coefficients

matrix b = e(b)
matrix start2 = b,0.1,0.1,0.1,0.1,0.1,0.1

gmnl choice negCost FreqLen_cntr Notify_sqpct, group(newid) id(userid2) rand(Reuse_sqpct Green_sqpct Length_sqpct Freq_sqpct) het(const) constraint(1 ) from(start2,copy) nrep(100) gamma(0)
```

nlcom (price_mean: [Het]const - [tau]_cons$^2/2$)

gmnlbeta Notify_sqpct FreqLen_cntr Reuse_sqpct Green_sqpct Length_sqpct Freq_sqpct negCost userid2, saving(w1betas$_{n}oscale)noscale$

* correlated

matrix start2 = b[1,1..9],0,0,0,b[1,10],0,0,b[1,11],0,b[1,12..13]

gmnl choice negCost FreqLen_cntr Notify_sqpct, group(newid) id(userid2) rand(Reuse_sqpct Green_sqpct Length_sqpct Freq_sqpct) het(const) constraint(1) from(start,copy) nrep(100) corr gamma(0)

E.3 Chapter 3 code

E.3.1 Graphs

* Histograms of water consumption behavior over time. Divides them by different variables and includes the entire population graph as the very last one.

histogram status if last==1, discrete fraction addlabels ylabel(0(.15).90) xlabel(0(1)4, valuelabel) ylabel(0(0.25)0.75) by(site_cat3, total legend(off) style(compact) note("")) addlabopts(yvarformat(%4.2f)) histogram status if last==1, discrete fraction addlabels ylabel(0(.15).90) xlabel(0(1)4, valuelabel) ylabel(0(0.15)0.6) by(pp_size, total legend(off) style(compact) note(“”)) addlabopts(yvarformat(%4.2f))

* bar graph of water budget consumption levels by surcharge tier and year, levels are stacked

graph bar T0 T1 T2, percent bar(1, color(navy)) bar(2, color(forest_green)) bar(3, color(maroon)) ytitle(“Percent”) legend(label(1 “Efficient, ¡=100% of IWB”) label (2 “Excess, 101-150% of IWB”) label (3 “Extreme, ¿150% of IWB”)) over(year) stack blabel(bar, position(inside) format(%9.1f) color(white))

* line graph of mean and median water budget used for each year
line pctbud_meanall year, lwidth(thick) sort || line pctbud_medianall year, lwidth(thick) sort ||, title(“Percent of water budget used by year”) xtitle(“Year”) ytitle(“Percent of water budget”) legend(label(1 “Mean”) label(2 “Median”))

* bar graph with side by side bars, slightly overlapping
graph bar tier_yr1 tier_yrlast if yrsdata_1213==1, over(site_cat3, label(alt)) bargap(-30) legend(label(1 ”Tier, First Year”) label (2 ”Tier, Last Year”))

* Line graph of mean maximum temperatures each year

line maymmxt year, lwidth(thick) sort || line junemmxt year, lwidth(thick) sort || line julymmxt year, lwidth(thick) sort || line augmmxt year, lwidth(thick) sort || line septmmxt year, lwidth(thick) sort || , title(”Mean maximum temperatures by month/year”) xtitle(”Years”) ytitle(”Degrees Fahrenheit”) legend(label(1 ”May”) label(2

”June”) label(3 ”July”) label(4 ”August”) label(5 ”September”))

* Graph of percent water budget for each account (all dataset or by category) each year stacked vertically using hollow circles and then the median percent budget use connected by a red line from year to year

* first generate the median variable for each year
bysort pp_size year: egen pb_medppsize = median(pctbud_adj)
label var pb_medppsize ”Median pct budget used by pp_size variable”

twoway scatter pctbud_adj year if pp_size==0, msymbol(circle_hollow) || connected pb_medppsize year if pp_size==0 , msymbol(diamond) sort || , title(Percent budget used by year and median for Public ownership under 100000 sq ft.,size(small)) ytitle(“Percent of budget used”, size(small)) xtitle(“Year”)

* graphs all accounts pct bud use plus median for pp_size across years twoway scatter pctbud_adj year if pp_size==0, msymbol(circle_hollow) || connected pb_medppsize year if pp_size==0 , msymbol(diamond) sort || , title(Public sector small landscape accts,size(medium)) ytitle(“Percent of budget used”, size(medium)) xtitle(“Year”)

twoway scatter pctbud_adj year if pp_size==1, msymbol(circle_hollow) || connected pb_medppsize year if pp_size==1 , msymbol(diamond) sort || , title(Public sector large landscape,size(medium)) ytitle(“Percent of budget used”, size(medium)) xtitle(“Year”)

twoway scatter pctbud_adj year if pp_size==2, msymbol(circle_hollow) || connected pb_medppsize year if pp_size==2 , msymbol(diamond) sort || , title(Private sector small landscape accts,size(medium)) ytitle(“Percent of budget used”, size(medium)) xtitle(“Year”)

twoway scatter pctbud_adj year if pp_size==3, msymbol(circle_hollow) || connected pb_medppsize year if pp_size==3 , msymbol(diamond) sort || , title(Private sector large landscape,size(medium)) ytitle("Percent of budget used", size(medium)) xtitle("Year")

* example graph all accounts pct bud use plus median for each site category across years

twoway scatter pctbud_adj year if site_cat3==4, msymbol(circle_hollow) || connected pctbud_median3 year if site_cat3==4, msymbol(diamond) sort || , title(MultiFamily/Hotel/Motel/Apartment,size(medium)) ytitle("Percent of budget used", size(medium)) xtitle("Year")

E.3.2 Models

E.3.3 Ordered logit

* null is that there is no difference in coefficients between models (that is Tier2 vs. Tier1tier0 or Tier0 vs. Tier1Tier2)
data4 variable just means this model was run with accounts that had at least 4 years of data

omodel logit tieradj tieradjL1 elevation5700 elevation5000 soil_water ownsize2 ownsize3 ownsize4 daa_mayaug days90_firlst if data4==1

brant, detail

* if brant test rejects null, use partial proportional odds model
gologit2 tieradj tieradjL1 elevation5700 elevation5000 soil_water i.pp_size daa_mayaug days90_firlst, autofit lrforce
to calculate marginal effects for each observation, preferred by Greene (2003)
predict p0 p1 p2 if e(sample)

E.3.4 Model analyzing percentage of budget used

* random effects analysis of percentage of budget used

dependent variable: pctbud_adj

let Stata know it is panel data set

xtset acct_id year

Test for autocorrelation

* Test 1 for autocorrelation using procedure in Beck's presentation

xtreg res lagres soil_water elevation5000 elevation5700 drought_see moddrght daa_mayaug i.pp_size if data4==1, re

xtreg pctbud_adj soil_water elevation5000 elevation5700 days90_firlst daa_mayaug i.pp_size if data4==1, re

predict res, e
gen lagres = L1.res

xtreg res lagres soil_water elevation5000 elevation5700 days90_firlst daa_mayaug i.pp_size if data4==1, re

xtreg pctbud_adj L1.pctbud_adj soil_water elevation5000 elevation5700

```
days90_firlst daa_mayaug i.pp_size if data4==1, re
```

Durbin's alternative statistic for autocorrelation, manual

```
xtreg pctbud_adj L1.pctbud_adj soil_water elevation5000 elevation5700 days90_firlst
daa_mayaug i.pp_size if data4==1, re
```

Step 1. calculate r

```
predict res, e
gen lagres = L1.res
gen elage = res*lagres
gen e2 = res^2
egen sum_elage = sum(elage)
egen sum_e2 = sum(e2)
gen rho = sum_elage / sum_e2
di rho
```

Step 2. calculate square root portion of h-statistic

```
gen T = 6
matrix V = e(V)
matrix list V
gen varL1pbud = .00018604
```

Step 3. calculate h

```
gen h = rho * sqrt(T(1-T*varL1pbud))
```

E.3.5 Hausman test, fixed or random effects

```
xtreg pctbud_adj L1.pctbud_adj soil_water elevation5000 elevation5700 days90_firlst daa_mayaug i.pp_size if data4==1, fe

estimates store fixed

xtreg pctbud_adj L1.pctbud_adj soil_water elevation5000 elevation5700 days90_firlst daa_mayaug i.pp_size if data4==1, re

estimates store random
hausman fixed random
```

E.3.6 2SLS-IV model

Generate instruments

Marginal price per 1000 gallons for next unit of water, (Wichman et al., 2014)

```
gen mprice200 = ppu_tier0 if budg100 >200
replace mprice200 = ppu_tier1 if budg100 <200 & budg150 > 200
replace mprice200 = ppu_tier2 if budg150 ⩽ 200
label var mprice200 "Marginal price for next unit of water after 200 units, acct j"

gen mprice400 = ppu_tier0 if budg100 >400
replace mprice400 = ppu_tier1 if budg100 <400 & budg150 > 400
replace mprice400 = ppu_tier2 if budg150 ⩽400
```

label var mprice400 “Marginal price for next unit of water after 400 units, acct j”

```
    gen mprice600 = ppu_tier0 if budg100 >600
replace mprice600 = ppu_tier1 if budg100 <600 & budg150 > 600
replace mprice600 = ppu_tier2 if budg150 ⩽600
label var mprice600 “Marginal price for next unit of water after 600 units, acct j”

    gen mprice800 = ppu_tier0 if budg100 >800
replace mprice800 = ppu_tier1 if budg100 <800 & budg150 > 800
replace mprice800 = ppu_tier2 if budg150 ⩽800
label var mprice800 “Marginal price for next unit of water after 800 units, acct j”

    gen mprice1000 = ppu_tier0 if budg100 >1000
replace mprice1000 = ppu_tier1 if budg100 <1000 & budg150 > 1000
replace mprice1000 = ppu_tier2 if budg150 ⩽1000
label var mprice1000 “Marginal price for next unit of water after 1000 units, acct j”

    gen mprice1250 = ppu_tier0 if budg100 >1250
replace mprice1250 = ppu_tier1 if budg100 <1250 & budg150 > 1250
replace mprice1250 = ppu_tier2 if budg150 ⩽1250
label var mprice1250 “Marginal price for next unit of water after 1250 units, acct j”

    gen mprice1500 = ppu_tier0 if budg100 >1500
replace mprice1500 = ppu_tier1 if budg100 <1500 & budg150 > 1500
replace mprice1500 = ppu_tier2 if budg150 ⩽1500
label var mprice1500 “Marginal price for next unit of water after 1500 units, acct j”
```

```
gen mprice1800 = ppu_tier0 if budg100 >1800
replace mprice1800 = ppu_tier1 if budg100 <1800 & budg150 > 1800
replace mprice1800 = ppu_tier2 if budg150 ⩽1800
label var mprice1800 “Marginal price for next unit of water after 1800 units, acct j”

gen mprice2100 = ppu_tier0 if budg100 >2100
replace mprice2100 = ppu_tier1 if budg100 <2100 & budg150 > 2100
replace mprice2100 = ppu_tier2 if budg150 ⩽2100
label var mprice2100 “Marginal price for next unit of water after 2100 units, acct j”

gen mprice2400 = ppu_tier0 if budg100 >2400
replace mprice2400 = ppu_tier1 if budg100 <2400 & budg150 > 2400
replace mprice2400 = ppu_tier2 if budg150 ⩽2400
label var mprice2400 “Marginal price for next unit of water after 2400 units, acct j”

gen mprice2700 = ppu_tier0 if budg100 >2700
replace mprice2700 = ppu_tier1 if budg100 <2700 & budg150 > 2700
replace mprice2700 = ppu_tier2 if budg150 ⩽2700
label var mprice2700 “Marginal price for next unit of water after 2700 units, acct j”

gen mprice3000 = ppu_tier0 if budg100 >3000
replace mprice3000 = ppu_tier1 if budg100 <3000 & budg150 > 3000
replace mprice3000 = ppu_tier2 if budg150 ⩽3000
label var mprice3000 “Marginal price for next unit of water after 3000 units, acct j”

gen mprice3400 = ppu_tier0 if budg100 >3400
replace mprice3400 = ppu_tier1 if budg100 <3400 & budg150 > 3400
replace mprice3400 = ppu_tier2 if budg150 ⩽3400
```

```
label var mprice3400 "Marginal price for next unit of water after 3400 units, acct j"

    gen mprice3800 = ppu_tier0 if budg100 >3800
replace mprice3800 = ppu_tier1 if budg100 <3800 & budg150 > 3800
replace mprice3800 = ppu_tier2 if budg150 ≤3800
label var mprice3800 "Marginal price for next unit of water after 3800 units, acct j"

    gen mprice4500 = ppu_tier0 if budg100 >4500
replace mprice4500 = ppu_tier1 if budg100 <4500 & budg150 > 4500
replace mprice4500 = ppu_tier2 if budg150 ≤4500
label var mprice4500 "Marginal price for next unit of water after 4500 units, acct j"

    gen mprice5000 = ppu_tier0 if budg100 >5000
replace mprice5000 = ppu_tier1 if budg100 <5000 & budg150 > 5000
replace mprice5000 = ppu_tier2 if budg150 ≤5000
label var mprice5000 "Marginal price for next unit of water after 5000 units, acct j"

    gen mprice6000 = ppu_tier0 if budg100 >6000
replace mprice6000 = ppu_tier1 if budg100 <6000 & budg150 > 6000
replace mprice6000 = ppu_tier2 if budg150 ≤6000
label var mprice6000 "Marginal price for next unit of water after 6000 units, acct j"

    gen mprice7000 = ppu_tier0 if budg100 >7000
replace mprice7000 = ppu_tier1 if budg100 <7000 & budg150 > 7000
replace mprice7000 = ppu_tier2 if budg150 ≤7000
label var mprice7000 "Marginal price for next unit of water after 7000 units, acct j"
```

```
gen mprice8000 = ppu_tier0 if budg100 >8000
replace mprice8000 = ppu_tier1 if budg100 <8000 & budg150 > 8000
replace mprice8000 = ppu_tier2 if budg150 ⩽8000
label var mprice8000 "Marginal price for next unit of water after 8000 units, acct j"

gen mprice9000 = ppu_tier0 if budg100 >9000
replace mprice9000 = ppu_tier1 if budg100 <9000 & budg150 > 9000
replace mprice9000 = ppu_tier2 if budg150 ⩽9000
label var mprice9000 "Marginal price for next unit of water after 9000 units, acct j"

gen mprice10000 = ppu_tier0 if budg100 >10000
replace mprice10000 = ppu_tier1 if budg100 <10000 & budg150 > 10000
replace mprice10000 = ppu_tier2 if budg150 ⩽10000
label var mprice10000 "Marginal price for next unit of water after 10000 units, acct j"

gen mprice11000 = ppu_tier0 if budg100 >11000
replace mprice11000 = ppu_tier1 if budg100 <11000 & budg150 > 11000
replace mprice11000 = ppu_tier2 if budg150 ⩽11000
label var mprice11000 "Marginal price for next unit of water after 11000 units, acct j"

gen mprice12000 = ppu_tier0 if budg100 >12000
replace mprice12000 = ppu_tier1 if budg100 <12000 & budg150 > 12000
replace mprice12000 = ppu_tier2 if budg150 ⩽12000
label var mprice12000 "Marginal price for next unit of water after 12000 units, acct j"

gen mprice13000 = ppu_tier0 if budg100 >13000
replace mprice13000 = ppu_tier1 if budg100 <13000 & budg150 > 13000
replace mprice13000 = ppu_tier2 if budg150 ⩽13000
```

```
label var mprice13000 "Marginal price for next unit of water after 13000 units, acct j"

    gen mprice15000 = ppu_tier0 if budg100 >15000
replace mprice15000 = ppu_tier1 if budg100 <15000 & budg150 > 15000
replace mprice15000 = ppu_tier2 if budg150 ⩽15000
label var mprice15000 "Marginal price for next unit of water after 15000 units, acct j"

    gen mprice18000 = ppu_tier0 if budg100 >18000
replace mprice18000 = ppu_tier1 if budg100 <18000 & budg150 > 18000
replace mprice18000 = ppu_tier2 if budg150 ⩽18000
label var mprice18000 "Marginal price for next unit of water after 18000 units, acct j"

    gen mprice21000 = ppu_tier0 if budg100 >21000
replace mprice21000 = ppu_tier1 if budg100 <21000 & budg150 > 21000
replace mprice21000 = ppu_tier2 if budg150 ⩽21000
label var mprice21000 "Marginal price for next unit of water after 21000 units, acct j"

    gen mprice25000 = ppu_tier0 if budg100 >25000
replace mprice25000 = ppu_tier1 if budg100 <25000 & budg150 > 25000
replace mprice25000 = ppu_tier2 if budg150 ⩽25000
label var mprice25000 "Marginal price for next unit of water after 25000 units, acct j"

    gen mprice30000 = ppu_tier0 if budg100 >30000
replace mprice30000 = ppu_tier1 if budg100 <30000 & budg150 > 30000
replace mprice30000 = ppu_tier2 if budg150 ⩽30000
label var mprice30000 "Marginal price for next unit of water after 30000 units, acct j"
```

```
gen mprice35000 = ppu_tier0 if budg100 >35000
replace mprice35000 = ppu_tier1 if budg100 <35000 & budg150 > 35000
replace mprice35000 = ppu_tier2 if budg150 ⩽35000
label var mprice35000 "Marginal price for next unit of water after 35000 units, acct j"

gen mprice40000 = ppu_tier0 if budg100 >40000
replace mprice40000 = ppu_tier1 if budg100 <40000 & budg150 > 40000
replace mprice40000 = ppu_tier2 if budg150 ⩽40000
label var mprice40000 "Marginal price for next unit of water after 40000 units, acct j"

gen mprice50000 = ppu_tier0 if budg100 >50000
replace mprice50000 = ppu_tier1 if budg100 <50000 & budg150 > 50000
replace mprice50000 = ppu_tier2 if budg150 ⩽50000
label var mprice50000 "Marginal price for next unit of water after 50000 units, acct j"

gen mprice60000 = ppu_tier0 if budg100 >60000
replace mprice60000 = ppu_tier1 if budg100 <60000 & budg150 > 60000
replace mprice60000 = ppu_tier2 if budg150 ⩽60000
label var mprice60000 "Marginal price for next unit of water after 60000 units, acct j"

gen mprice70000 = ppu_tier0 if budg100 >70000
replace mprice70000 = ppu_tier1 if budg100 <70000 & budg150 > 70000
replace mprice70000 = ppu_tier2 if budg150 ⩽70000
label var mprice70000 "Marginal price for next unit of water after 70000 units, acct j"

gen mprice80000 = ppu_tier0 if budg100 >80000
replace mprice80000 = ppu_tier1 if budg100 <80000 & budg150 > 80000
replace mprice80000 = ppu_tier2 if budg150 ⩽80000
```

```
label var mprice80000 “Marginal price for next unit of water after 80000 units, acct j”

    gen mprice100000 = ppu_tier0 if budg100 >100000
replace mprice100000 = ppu_tier1 if budg100 <100000 & budg150 > 100000
replace mprice100000 = ppu_tier2 if budg150 ⩽100000
label var mprice100000 “Marginal price for next unit of water after 100000 units, acct j”

    gen mprice120000 = ppu_tier0 if budg100 >120000
replace mprice120000 = ppu_tier1 if budg100 <120000 & budg150 > 120000
replace mprice120000 = ppu_tier2 if budg150 ⩽120000
label var mprice120000 “Marginal price for next unit of water after 120000 units, acct j”

    gen mprice140000 = ppu_tier0 if budg100 >140000
replace mprice140000 = ppu_tier1 if budg100 <140000 & budg150 > 140000
replace mprice140000 = ppu_tier2 if budg150 ⩽140000
label var mprice140000 “Marginal price for next unit of water after 140000 units, acct j”

    gen mprice160000 = ppu_tier0 if budg100 >160000
replace mprice160000 = ppu_tier1 if budg100 <160000 & budg150 > 160000
replace mprice160000 = ppu_tier2 if budg150 ⩽160000
label var mprice160000 “Marginal price for next unit of water after 160000 units, acct j”

    gen mprice180000 = ppu_tier0 if budg100 >180000
replace mprice180000 = ppu_tier1 if budg100 <180000 & budg150 > 180000
```

replace mprice180000 = ppu_tier2 if budg150 ⩽180000
label var mprice180000 "Marginal price for next unit of water after 180000 units, acct j"

gen mprice200000 = ppu_tier0 if budg100 >200000
replace mprice200000 = ppu_tier1 if budg100 <200000 & budg150 > 200000
replace mprice200000 = ppu_tier2 if budg150 ⩽200000
label var mprice200000 "Marginal price for next unit of water after 200000 units, acct j"

gen lnmp200 = ln(mprice200)
gen lnmp400 = ln(mprice400)
gen lnmp600 = ln(mprice600)
gen lnmp800 = ln(mprice800)
gen lnmp1000 = ln(mprice1000)

gen lnmp1250 = ln(mprice1250)
gen lnmp1500 = ln(mprice1500)
gen lnmp1800 = ln(mprice1800)
gen lnmp2100 = ln(mprice2100)
gen lnmp2400 = ln(mprice2400)
gen lnmp2700 = ln(mprice2700)
gen lnmp3000 = ln(mprice3000)
gen lnmp3400 = ln(mprice3400)

gen lnmp3800 = ln(mprice3800)
gen lnmp4500 = ln(mprice4500)
gen lnmp5000 = ln(mprice5000)

```
gen lnmp6000 = ln(mprice6000)
gen lnmp7000 = ln(mprice7000)
gen lnmp8000 = ln(mprice8000)
gen lnmp9000 = ln(mprice9000)
gen lnmp10000 = ln(mprice10000)
gen lnmp11000 = ln(mprice11000)

    gen lnmp12000 = ln(mprice12000)
gen lnmp13000 = ln(mprice13000)
gen lnmp15000 = ln(mprice15000)
gen lnmp18000 = ln(mprice18000)
gen lnmp21000 = ln(mprice21000)
gen lnmp25000 = ln(mprice25000)
gen lnmp30000 = ln(mprice30000)

    gen lnmp35000 = ln(mprice35000)
gen lnmp40000 = ln(mprice40000)
gen lnmp50000 = ln(mprice50000)
gen lnmp60000 = ln(mprice60000)
gen lnmp70000 = ln(mprice70000)
gen lnmp80000 = ln(mprice80000)

    gen lnmp100000 = ln(mprice100000)
gen lnmp120000 = ln(mprice120000)
gen lnmp140000 = ln(mprice140000)
gen lnmp160000 = ln(mprice160000)
gen lnmp180000 = ln(mprice180000)
gen lnmp200000 = ln(mprice200000)
```

2SLS final basic model

xtivreg lnuse2 daa_mayaug days90_firlst ownsize2 ownsize3 ownsize4 (lnavgprice = mprice200 mprice400 mprice600 mprice800 mprice1000 mprice1250 mprice1500 mprice1800 mprice2100 mprice2400 mprice2700 mprice3000 mprice3400 mprice3800 mprice4500 mprice5000 mprice6000 mprice7000 mprice8000 mprice9000 mprice10000 mprice11000 mprice12000 mprice13000 mprice15000 mprice18000 mprice21000 mprice25000 mprice30000 mprice35000 mprice40000 mprice50000 mprice60000 mprice70000 mprice80000 mprice100000 mprice120000 mprice140000 mprice160000 mprice180000 mprice200000 site1 site2 site3 site4 site5 site6 site7 site8 lntrees lnturf lnathletic lnxeric elevation5000 elevation5700), re

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