COME HELL OR HIGH WATER PRICES:

A HOUSEHOLD-LEVEL ANALYSIS OF RESIDENTIAL WATER DEMAND IN TUCSON, AZ

by

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STATEMENT BY AUTHOR

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Abstract

Given the potential impacts of climate change and the recent decline in household water consumption across the Southwest, the importance of accurate water demand forecasting is evident. Using household-level panel data from Tucson, AZ, and a unique set of control variables, we estimate demand via a Stone-Geary specification. The Stone-Geary functional form advantageously allows price elasticity of demand to vary with quantity consumed and enables estimation of a threshold level of consumption below which demand is considered perfectly price inelastic. Our results indicate that not all outdoor water use is price elastic. We also assess the sensitivity of water consumption to potential climate change using downscaled projections from the Coupled Model Intercomparison Project (CMIP5). We find that, without substantial socioeconomic or technological change, climate change could result in significant increases in water consumption year-round, including an average annual increase in peak demand of up to 15% above study period levels.

1. Introduction

1.1 Study Context

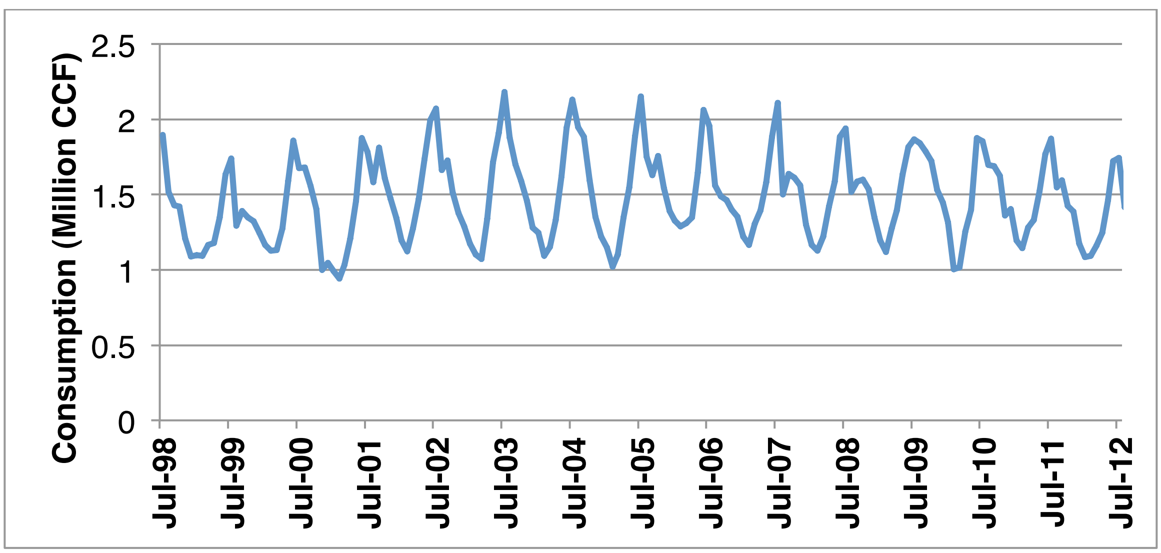
In an environment such as the American Southwest, the importance of water resource management cannot be underestimated. Water utilities are tasked with the responsibility of providing this critical resource to consumers in a way that both satisfies current demand and ensures the viability of the resource in the long run. In the city of Tucson, Arizona, the public utility Tucson Water fills this role for roughly 712,700 people through approximately 227,000 metered connections in its service area (Tucson Water 2015).

In the sun-belt state of Arizona, rapid population growth has historically increased demand for water and put pressure on utilities to ensure sufficient, reliable water supplies. Between 1980 and 2000, the population of Arizona grew by 88%, while the total U.S. population grew by 24.2% over the same period. Between 2000 and 2009, the total population of Arizona increased again by 28.6% (McConnell 2013). Much of this population growth has been concentrated in the major metropolitan areas of Phoenix and Tucson, and these cities continue to expand even today. For utilities like Tucson Water, meeting the demands of these ever-increasing urban populations has required substantial investment in new infrastructure and reliable forecasts of future demand levels.

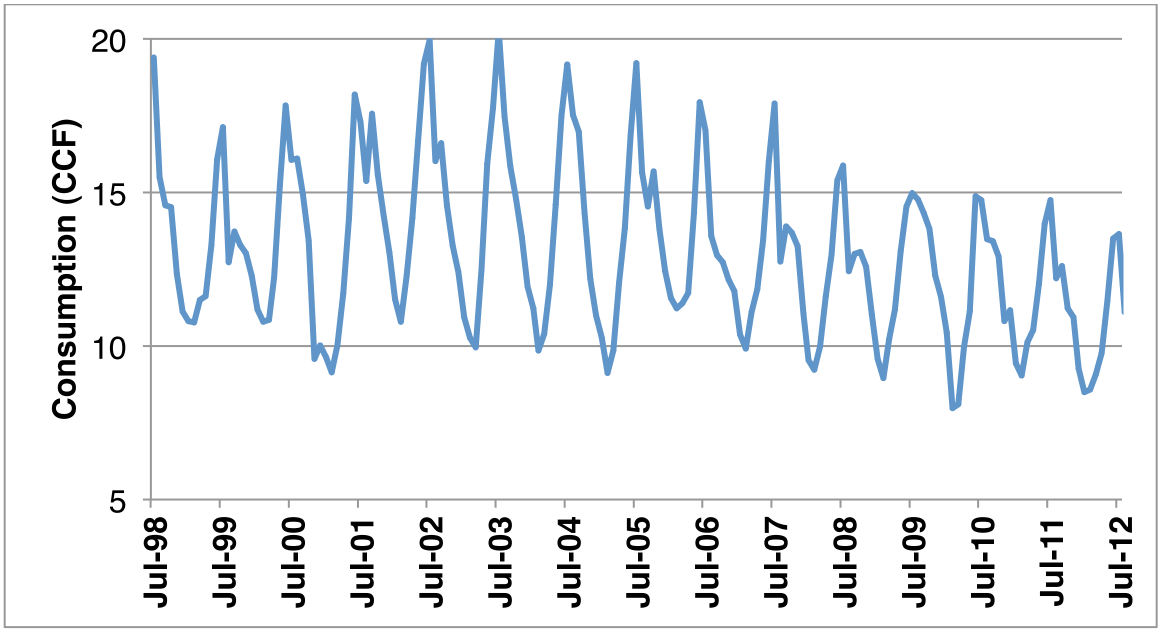
Using demand-forecasting models that take into account major determinants of water demand including population growth and weather variability, Tucson Water projected total water demand in their service area to rise from about 136,000 acre-feet (AF) in 2007 to 175,000 AF by 2020 – an increase in water consumption of almost 29% (Tucson Water 2009). However, despite continued growth in the number of households served, water utilities across the Southwest have observed a declining trend in total household water consumption over the past several decades that may render these projections inaccurate. As shown in Figure 1, aggregate (total) water use among single-family residential (SFR) customers in Tucson Water's service area has been declining since about 2006, and per household SFR water use has been on the decline since at least 2002, if not before. (Note: These consumption data were taken from our final dataset, which does not include all SFR households serviced by Tucson Water. Actual levels of total consumption are higher, but the trends are similar.) Since SFR customers make up about 80% of Tucson Water's customer base and consume 56% of the potable water supplied by the utility, these trends have nontrivial impacts on the utility's revenue stream and corresponding financial stability (Klawitter 2014). A better understanding of household decision-making in regard to water consumption behavior is needed to ensure that future demand for water can be met.

Figure 1: Tucson SFR Water Consumption Over Time

a) Aggregate SFR Consumption



b) SFR Consumption per Household



At the same time, increasing uncertainty regarding the reliability of water supplies in this region presents challenges for water management going forward. In Arizona, the Colorado River represents the primary renewable water supply source for the major metropolitan areas of Phoenix and Tucson. Colorado River water is delivered to these urban areas via a massive aqueduct system called the Central Arizona Project (CAP). In an effort to ensure more sustainable water supplies, in recent years Tucson Water has moved away from its use of local groundwater and toward reliance on CAP supplies (Tucson Water 2009). While severing dependence on non-renewable groundwater resources is certainly a step toward more sustainable water supplies, threats of shortage along the Colorado River make even this supposedly renewable source of water less reliable. Colorado River flows could be reduced by 10 to 20% in coming decades (Gammage, et al. 2011). Because of the “junior” status of Arizona’s water rights, the CAP’s allocation of Colorado River flows could be reduced in a shortage situation. And while a reduction in the CAP’s allocation would only affect recharge and agricultural rights holders at first, more extreme shortage situations could lead to reductions in Tucson Water’s annual allocation (CAP 2014).

Additionally, climate models from the International Panel on Climate Change (IPCC) are predicting increasing temperatures and higher variability in rainfall in Arizona (Gammage, et al. 2011). This increases the likelihood of a shortage situation on the Colorado River, compounding the uncertainty associated with future supplies. It also affects future demand. Since water demand already tends to be highly seasonal, increased weather variability associated with future climate could increase the variation in intra-annual water demand as well.

1.2 Purpose of Study

The purpose of this analysis is to examine the household-level decision-making process regarding water consumption and its relationship with aggregate water demand in Tucson, AZ. It is impossible to assess whether available water supplies will be sufficient or reliable enough to meet future demands if current demand patterns are not well understood. Given that declining levels of total and average household water demand in many Southwestern cities have not been adequately explained by current demand forecasting models, we would expect the accuracy of future projections to depend on our ability to better account for the data generating process at work.

In this study, we emphasize the fact that the price elasticity of water demand for a given household increases in magnitude with quantity consumed. While this fact has long been discussed in the literature, there has been little emphasis on the use of demand models that account for it. To put the concept more simply, a household is more likely to respond to price increases by cutting back consumption when they are already consuming a sizable amount of water. Likewise, households will respond less to price increases at lower levels of water consumption, all else constant. Extending this logic, the implication is that each household has some minimum level of water consumption below which changes in price will not influence their consumption choices – a “perfectly inelastic” portion of their demand function. A practical definition of this minimum level of consumption in the literature proves elusive. Typically, the term “subsistence” level of water consumption is used, but since American households typically do not lack access to water for basic biological needs this term is not applicable in our context. Some have assumed that this minimum level corresponds to water consumption for indoor use, while water for outdoor use represents a more discretionary or luxury level of consumption (Howe and Linaweaver 1967). However, given that each household is unique and may have different preferences regarding what the water they purchase is used for, this assumption may be too strong. Others have considered the difference between “base” and “seasonal” use, taking consumption in the winter months to reflect the “necessary” portion of household consumption (Maidment, Miaou and Crawford 1985; Miaou 1990). This is a more realistic assumption, so long as it allows for the possibility that “base” use may vary between households or over time. We prefer to use the term developed by Gaudin, Griffin, and Sickles (2001), after whose work much of our analysis is patterned. They refer to this minimum level of water consumption as the “conditional water use threshold” to emphasize that its level is dependent on the household and time period considered. Regardless of the nomenclature, however, the significance of this fact is clear. Failure to account for this aspect of household decision-making in a water demand model could lead to erroneous conclusions about the responsiveness of water demand to changes in price, and therefore bias projections regarding future water consumption levels.

We utilize a Stone-Geary demand specification to allow the estimation of this conditional water use threshold empirically. Unlike many reduced form models, this demand specification is consistent with utility theory, which assumes the maximization of utility subject to a budget constraint. The Stone-Geary model is also advantageous in that it requires the estimation of only a few parameters. One of these parameters is the “subsistence level” of consumption, which specifies the amount below which consumption is unresponsive to price (inelastic). A practical simplification suggested by Gaudin, Griffin, and Sickles (2001) allows us to abstract away from the concept of “subsistence” in the context of water demand to focus on the conditional water use threshold.

In our empirical analyses, we utilize panel data on SFR consumption at the household level for the period July 1998 – June 2012. To the best of our knowledge, no study has been conducted to date using panel data at the household level to estimate a Stone-Geary demand function. Since SFR households, unlike most other customer classes, tend to be primarily owner-occupied, these consumers have the greatest latitude in appliance and landscape choice (Klawitter 2014). These two types of choices tend to have a substantial impact on the amount of household water consumption for indoor and outdoor use, respectively. As mentioned earlier, SFR users also represent the largest proportion of consumers and total consumption among Tucson Water customer classes. Thus, they represent the best subset of customers to examine in order to understand consumer decision-making behavior related to water consumption.

We also recognize that our understanding of household water consumption behavior today must be conditioned on our expectations regarding the future in order to provide valuable information for future projection efforts. The potential impacts of future climate will need to be taken into account, since weather patterns represent a major source of seasonal variation in urban water consumption. We evaluate the impact of alternative climate scenarios on aggregate water consumption in Tucson using climate projections from global climate models (GCMs) utilized in the Coupled Model Intercomparison Project (CMIP5).

The remainder of this thesis is organized as follows. Chapter 2 presents a review of the literature surrounding municipal water demand, with an emphasis on studies that attempt to examine the issue of variable price elasticity of demand. Chapter 3 details our theoretical demand model, which is a Stone-Geary specification adopted from Gaudin, Griffin, and Sickles (2001). Chapter 4 describes the data collected for empirical demand estimation. Chapter 5 details the empirical demand estimation process and summarizes the results we obtain, including the results of our analysis of the sensitivity of water consumption to potential climate change. Finally, Chapter 6 concludes and discusses the policy implications of our research.

2. Literature Review

This literature review places our analysis of residential water demand in Tucson, AZ, in its appropriate historical, theoretical, and methodological context. The review attempts to show how the literature surrounding municipal water demand has evolved, demonstrate the value of such studies for informing water policy decisions, and lay the foundation for our analysis of residential water demand in Tucson, AZ, and its potential contributions to the literature and to water policy in the Southwest.

The literature on municipal water demand is rich and goes back more than half a century. As early as 1967, Howe and Linaweaver compared the price elasticities of indoor and outdoor or “sprinkling” uses of water in municipalities in the western and eastern United States. Studies of water demand began to proliferate after the publication of Taylor’s 1975 article on estimating electricity demand under multi-step block rate structures. His work, modified by Nordin (1976), provided the foundation for a continuing debate over the appropriate specification of the price variable in estimating water demand under increasing block rate structures. Due to data and computing constraints, most of these models examined changes in aggregate, municipal water demand over time or focused on differences in water consumption across households or multiple municipalities at fixed points in time. Then, with Danielson’s 1979 analysis of trends in indoor and outdoor water consumption at the household level in Raleigh, NC, empiricists began to examine water demand both over time and among disaggregated user groups to account for user heterogeneity. As statistical software has become more advanced and data collection and maintenance has grown in priority, the number of water demand studies has grown dramatically, as has the size, scope, and resolution of the datasets used. However, despite the growing diversity in the design and application of municipal water demand studies, trends in the explanatory variables and statistical models used in previous studies are apparent. A summary of these trends is attempted here. Additionally, a review of the subset of water demand studies aimed at distinguishing between specific types of water consumption is included.

2.1 Explanatory Variables

In empirical models of water demand, price is almost always a key explanatory variable. This is one of the few factors influencing water consumption behaviors that a utility has control over. Most economic studies of water demand focus on estimating a price elasticity of demand for water, which is inherently complicated by the price structures and billing procedures utilities use.

Particularly in the southwestern United States, utilities commonly implement increasing block rate (IBR) structures, which raise the per-unit price of water with consumption at specified intervals, called blocks (Griffin 2006). Increasing block rates eliminate the possibility of setting a single, optimal marginal price for all users, making elasticity calculations difficult (Klawitter 2014). The other confounding factor in any analysis of water demand is the lack of information that consumers have regarding their marginal price or their consumption level at any given moment (Nataraj and Hanemann 2011). For one, consumers are also typically only informed of their usage when their bill is mailed, since water meters are typically located outside and out of sight. Second, IBRs impose non-constant marginal prices, which, aside from being difficult for most consumers to readily grasp, require consumers to have information about their consumption level in order to know what price they are currently facing. This presents a problem of simultaneity when modeling demand for water as a function of price. Finally, many utilities use billing cycle lengths as well as start and end dates that are asynchronous – that is, they vary across consumers and over successive billing periods. During longer billing cycles, consumers may face higher marginal prices if their additional consumption in extra days causes them to move into a higher tier in their utility's IBR structure. This sends conflicting price signals to consumers (Foster and Beattie 1979; Nataraj and Hanemann 2011; Klawitter 2014). Thus, consumers are typically ill-equipped to make water consumption decisions at the margin.

In light of these challenges, the literature reflects much debate regarding the appropriate specification of the price variable in water demand studies. Traditional practice was to use either the pure marginal price for the last units consumed or the average price on all units consumed (Young 1973). However, with the advent of IBR structures, these methods have been shown to be inadequate. Taylor (1975) argues that models using average price present instances of simultaneity, while models using marginal price fail to account for the different price paid by the consumer for inframarginal units (those not at-the-margin). Nordin (1976), building on Taylor's argument, proposes a price specification that includes both the marginal price and an expenditure differential variable. This differential variable, which hereafter will be referred to as the Taylor-Nordin difference, is equal to the difference between what a given consumer would have paid had all units of water been charged at the marginal price and the amount that customer would actually pay given the imposed rate structure. This price specification satisfies the theoretical requirements related to IBR structures to incorporate information about consumption thus far and specify the price the consumer faces on the last units of water consumed. Many water demand studies over the years have continued to use the Taylor-Nordin method of estimating marginal price (Agthe and Billings 1980; Coleman 2009; Martinez-Espiñeira and Nauges 2004; Dharmaratna and Harris 2012).

However, the Taylor-Nordin marginal price specification has been criticized for being too theoretical in its assumption that consumers have perfect information about the marginal price they face at the time of consumption (Foster and Beattie 1979,1981). Arguing that the traditional economic theory of utility maximization using marginal prices to make consumption decisions is not applicable given the lack of clarity consumers have regarding their marginal price for water they face, Foster and Beattie (1981) suggest that consumers will respond to changes in average price. They also argue that the lack of substantively different elasticity estimates in the literature between studies using Taylor-Nordin marginal price specifications and average price specifications makes the decision of which price specification to use an empirical rather than a theoretical problem. Charney and Woodard (1985) agree that the average price specification best represents consumer behavior, but only when lagged average price – the average price per unit from the previous billing period – is considered. Since consumers have little information about the price they face during a given billing cycle, they are likely to rely on their last bill for information about price in the current billing period. An added benefit to this price measure is that, because it is not determined within the current billing period, simultaneity is no longer an issue.

Several studies have attempted to empirically assess which measure of price is more appropriate for demand estimation in the case of IBR structures. Billings and Day (1989) find that demand models using average price have strong explanatory power when consumers' incomes are high relative to the price of water, but that as water prices increase relative to incomes, marginal price becomes the more useful variable for estimating demand. More recent studies using sophisticated regression discontinuity techniques have provided evidence that consumers do in fact correspond to marginal price, or even to the marginal price they *expect* to face (Olmstead, Hanemann, and Stavins 2007; Nataraj and Hanemann 2011). Ray (2012) compares lagged average price to the Taylor-Nordin marginal price specification and finds no clear empirical evidence for the superiority of either measure.

Despite the debate over the appropriate price specification for water demand estimation, the literature strongly supports the notion that urban water demand is price inelastic, regardless of the price specification. A meta-analysis of the residential water demand literature by Espey, Espey, and Shaw (1997) indicates that the average price elasticity estimate is -0.5. A more recent meta-analysis by Worthington and Hoffman (2008) similarly finds that price elasticity estimates from water demand studies tend to range from 0 to -0.5 in the short-run, and from -0.5 to unity in the long-run. Consumers' lack of clear price information at the time of consumption and the low proportion of income represented by the cost of water consumption are frequently cited as the main reasons for such low price responsiveness (Klawitter 2014).

Other than price, the only other tools at utilities' disposal to influence water consumption patterns are demand management strategies. In recent years, several studies have been directed at assessing the effectiveness of various demand management strategies, such as water use restrictions, water quantity allocations, water-saving practices and technology, and public education campaigns, in encouraging water conservation (Renwick and Archibald 1998; Michelsen, McGuckin, and Stumpf 1999; Martinez-Espiñeira and Nauges 2004; Coleman 2009; Mansur and Olmstead 2012; Garcia-Valiñas, et al. 2014). Due to the low price elasticity of demand for water, these studies typically find non-price demand management strategies to be more effective at reducing water consumption than price-related strategies, though their associated costs can potentially outweigh the conservation benefits. Notably, Coleman (2009) focuses on the price elasticity of demand for water in summer, when much of residential water use tends to be discretionary, such as for landscaping. He finds summer water demand to be relatively elastic and concludes that price-related demand management is more effective than the city's public information campaigns, particularly in the summer when reduced consumption is most desirable.

All other factors of water demand are outside of the control of water utilities. Non-price independent variables in water demand models can include demographic data about the consumer base, structural information about the characteristics of houses or properties, and weather and climate patterns.

Relevant demographic characteristics include household income, number of persons per household, household age distribution, household ethnic or cultural background, and levels of educational attainment among household members.

Virtually all water demand studies include some sort of income variable, whether a direct estimate or some proxy such as assessed home value, due to the emphasis of economic theory on the notion of utility maximization subject to a budget constraint (Foster and Beattie 1979; Billings and Agthe 1980; Harlan, et al. 2009; Mansur and Olmstead 2012; Ray 2012). Klawitter (2014) uses a novel transformation of Census tract median household income estimates to more closely approximate this variable. He weights the median household income for each census tract in each year by a home value index to get a unique estimate of household income for each customer. His home value index is constructed as the ratio of each individual household’s assessed home value to the average assessed home value in the corresponding census tract.

Household size, age distribution, and educational attainment have also been found to influence household water consumption. Harlan, et al. (2009) create individual dummy variables for each number of persons per household in their self-reported household size data and find the expected positive and significant effect for each dummy. Ray (2012) uses Census estimates of household size and generally finds the expected positive effect, though it varies in sign and significance across municipalities in the Phoenix metro area. He finds similar positive relationships between the proportion of the population of non-working age or with a Bachelor’s degree in certain Phoenix suburbs. Most studies that include such variables do so in an attempt to control for cross-sectional user heterogeneity.

Cultural norms or other unobservables may distinguish the water consumption behaviors of certain cultural or ethnic groups as well. Several studies have found water use among Hispanic or Latino households to be different from that of other groups (Gaudin, Griffin, and Sickles 2001; Balling, Gober, and Jones 2008; Ray 2012).

In addition to demographic variables, heterogeneity in physical house or property characteristics can contribute to differences in water consumption between households. The size of a house as well as whether the house has an evaporative cooling system have been found to be positively related with water consumption (Balling, Gober and Jones 2008; Coleman 2009; Harlan, et al. 2009; Ray 2012; Wang 2014; Klawitter 2014; Yoo, et al 2014; Halper, et al. 2015). Measures of the age of a house based on its construction year have been used to explain household water use as well (Harlan, et al. 2009; Ray 2012; Halper, et al. 2015). However, expectations as well as findings about its sign are unclear. Harlan, et al. (2009) hypothesize a negative relationship, while Ray (2012) includes a squared term to account for a possible parabolic relationship. Unlike Harlan, et al. (2009), Ray (2012) does find significance with his parabolic relationship; however, the signs alternate depending on the municipality within the Phoenix metro area that he examines.

Since much residential water consumption is aimed at maintaining outdoor landscapes, variables such as lot size and the presence or size of a pool have been included in models of water demand (Wentz and Gober 2007; Balling, Gober, and Jones 2008; Harlan, et al. 2009; Halper, et al. 2015). More recently, remotely-sensed (satellite or aerial) imagery has been used been used to explain outdoor irrigation behavior by approximating parcel greenness via vegetation indices such as the normalized difference vegetation index (NDVI) and the soil-adjusted vegetation index (SAVI) (Harlan, et al. 2009; Halper, et al. 2015). Both NDVI and SAVI have been shown to have a positive, significant, and substantial influence on household water consumption. It is expected that the use of remotely-sensed data will continue to increase in the literature and could represent a valuable new source of information for water managers.

Particularly in terms of water consumption for outdoor use, it is important to consider the effects of weather and climate patterns in models of water demand. The literature consistently supports the notion that water consumption increases as the environment becomes hotter and drier (Agthe and Billings 1980; Balling, Gober, and Jones 2008; Coleman 2009; Harlan, et al. 2009; Ray 2012; Klawitter 2014; Yoo, et al. 2014). However, the variables used to capture these weather phenomena are not uniform across studies.

Mean maximum daily temperature has been used to compare trends in weather at the hottest part of the day across months (Harlan, et al. 2009; Klawitter 2014), and has been found to have the expected positive and significant relationship with water use. Mean monthly temperature (Balling, Gober, and Jones 2008; Yoo, et al. 2014) and minimum monthly temperature (Klaiber, et al. 2014) have also been used, but only Yoo, et al. econometrically demonstrate a significant and positive relationship with water consumption, as expected.

Evapotranspiration (ET) has also been used as a comprehensive measure of weather conditions in urban water demand studies, since it includes information regarding temperature, solar radiation, vapor pressure, and wind speed. ET approximates the evaporative demand of the landscape for a particular reference crop, typically cool-season grass or alfalfa (Brown 2005). (See Appendix 7 for a more complete description of the ET calculation.) Agthe and Billings (1980) find a positive relationship between water consumption and evapotranspiration for Bermuda grass minus rainfall in Tucson, AZ. Likewise, Coleman (2009) found ET measured by the Blaney-Criddle method to have the expected positive and significant relationship with water consumption in Salt Lake City. In a novel application, Ray (2012) and Wang (2014) interacted potential ET with yard size and pool size in the Phoenix area and found a statistically significant and positive relationship with water consumption.

Precipitation has been shown to have a negative relationship with water use (Balling, Gober, and Jones 2008; Harlan, et al. 2009; Klaiber, et al. 2014). Harlan, et al. 2009 demonstrate a nonlinear relationship using a squared term. In addition to total monthly precipitation, mean monthly precipitation (Coleman 2009; Yoo, et al. 2014) and mean daily precipitation (Klawitter 2014) have been used, and the negative relationship has been confirmed. The impact of rainfall events, rather than levels of rainfall, on water consumption has also been examined (Maidment, Miaou, and Crawford 1985; Miaou 1990; Ray 2012; Klaiber, et al. 2014; Wang 2014). Some studies have even attempted to account for seasonal variation in response to precipitation (Billings and Day 1989;

Maidment, Miaou, and Crawford 1985; Miaou 1990; Klawitter 2014). This proves especially useful in the Southwest, where summer monsoonal rainfall tends to be more scattered, brief, and intense than winter rainfall.

The effects of broader climate trends on water consumption behaviors have also been explored (Balling and Gober 2007; Balling, Gober and Jones 2008; Balling and Cubaque 2009). Higher water consumption has been linked to drought as well as increases in urban heat island effects.

2.2 Model Choice

The choice of statistical model to use in an analysis of water demand depends on the level of data aggregation, the temporal scale of the analysis, and the hypotheses to be tested.

Many water demand studies have been conducted at both the aggregate, municipal level and the user (often household) level. Interestingly, despite the increased precision of studies using disaggregated data, Worthington and Hoffman's (2008) meta-analysis of water demand studies finds little difference between price elasticity estimates from studies using either aggregated or disaggregated data. Nonetheless, data disaggregated to the user level is typically preferred since it can be used to account for user heterogeneity in models. Advancements in statistical software in recent years have facilitated the proliferation of water demand studies using disaggregated data. Aggregated data is typically analyzed using time-series models, but can be used in panel models to compare water consumption behaviors across multiple municipalities. Disaggregated data, on the other hand, can be used in cross-sectional models or panel models depending on the time frame of data collection.

Time series models are useful in that they can explain variation in water consumption over time and can be used to forecast such behavior. However, as mentioned above, they are limited in their ability to capture user heterogeneity. Cross-sectional models, on the other hand, can explain well how user attributes influence their water consumption, but cannot predict how this behavior will change over time. Panel models can both account for user heterogeneity and forecast trends in user water consumption. As such, panel models are typically favored by water managers and policymakers. However, they have much higher data requirements than either time-series or cross-sectional models and require more sophisticated statistical techniques to run.

The econometric models typically used to estimate demand from time-series data include ordinary least-squares (OLS) and feasible generalized least-squares (FGLS) regression (Young 1973; Agthe and Billings 1980; Martinez-Espiñeira and Nauges 2004). These techniques have been used to forecast water consumption behavior in the short-run, examine the impact of changes in weather and demographics on water consumption, and compare the effectiveness of price and non-price demand management strategies.

When cross-sectional data are involved, OLS is still one of the most common regression frameworks used (Foster and Beattie 1981; Schefter and David 1985; Nieswiadomy 1992). These cross-sectional models have been used to test whether consumers respond to average or the marginal price as specified by Taylor (1975) and Nordin (1976), as well as to compare price elasticities across user classes in various municipalities. Also, since cross-sectional data are often spatial in nature, geocoded data have been used within spatially-explicit OLS or geographically-weighted regression (GWR) models to identify clusters of high and low water consumption while correcting for spatial autocorrelation (Wentz and Gober 2007; Balling, Gober, and Jones 2008). Recently, Hewitt and Hanemann (1995) and Olmstead, Hanemann, and Stavins (2007) have used cross-sectional data within the discrete-continuous choice (DCC) maximum-likelihood (ML) framework to account for the piecewise-linear budget constraint created by the non-constant marginal price water consumers face under IBR structures. Despite the fact that the DCC model offers the most theoretically sound approach to approximating the marginal price faced by consumers under IBRs, it has not produced price elasticity estimates that are significantly different from those of prior studies using simpler techniques, such as multiple stage-least squares (2SLS or 3SLS) or instrumental variables (IV).

Panel regression techniques have also been used more and more frequently in the literature, as the use of disaggregated data has become more common. Many of the econometric techniques described above, such as OLS FGLS, 2SLS, and IV models, have been adapted to the panel context. Two types of panel regression techniques have been effectively coupled with such models to account for the effects of time-invariant data: fixed effects (FE) panel models and random effects (RE) panel models. FE panel models average out time-invariant unobserved effects. In the water demand literature, FE techniques have been combined with IV models (FE-IV) to account for simultaneity of price (Arbués, Barberán, and Villanúa 2004; Kenney, et al. 2008; Coleman 2009). RE techniques allow parameters to be estimated for time-invariant effects. RE techniques have also been implemented in the context of IV models (RE-IV), as well as in GLS estimation (RE-GLS) of Tobit demand models and Generalized Cobb-Douglas and Stone-Geary demand functions (Gaudin 2001; Coleman 2009; Mansur and Olmstead 2012).

Ultimately, the choice of model for a water demand study depends on the research question being asked. For testing different types of hypotheses, the literature highlights two types of model structure: structural form models and reduced form models. Structural form models are based on deductive theories of the economy and are typically selected to address research questions regarding price response and user consumption decision behavior. (It should be noted that much of the variation in the type of model used in water demand studies comes from different structural approaches to addressing the problem of the simultaneity of price and quantity under IBR structures and not from issues of data aggregation or temporal scope. This simultaneity problem renders OLS estimation less than ideal in most water demand studies.) Examples of structural form models include those using a Taylor-Nordin marginal price specification (Agthe and Billings 1980; Foster and Beattie 1981; Coleman 2009; Martinez-

Espiñeira and Nauges 2004; Dharmaratna and Harris 2012), DCC models (Hewitt and Hanemann 1995; Olmstead, Hanemann, and Stavins 2007), regression discontinuity (RD) models (Nataraj and Hanemann 2011), and models specified by Stone-Geary and Generalized Cobb-Douglas demand functions (Al-Qunaibet and Johnston 1985; Gaudin, Griffin, and Sickles 2001; Martinez-Espiñeira and Nauges 2004; Monteiro and Roseta-Palma 2011; Dharmaratna and Harris 2012; Garcia-Valiñas, et al. 2014). On the other hand, research questions regarding the effects of exogenous shocks on water consumption behavior, such as weather and climate or demographics, are generally addressed via reduced form models (Wentz and Gober 2007; Balling, Gober, and Jones 2008; Ray 2012).

2.3 Discriminating Between Types of Water Consumption

Within the body of literature surrounding municipal water demand, a select group of studies has focused on discriminating between different types of residential water use. Essentially, these studies have attempted to examine how price elasticity of demand for water varies with quantity consumed. Despite consensus in the literature that demand for water is, on the whole, inelastic to price, researchers and water managers alike have noted that water demand is highly seasonal. Thus, there is a portion of total water consumption that is considerably more price responsive. Since residential water demand generally peaks in the summer months when temperatures are higher and rainfall is scarcer, many have correlated the seasonal component of water consumption with additional irrigation water used to maintain outdoor landscaping. However, because water providers measure only total water consumption, distinguishing between “base” and “seasonal” or “indoor” and “outdoor” water use is inherently challenging. Yet for water managers interested in reducing water consumption or promoting water conservation, such information could be very valuable.

Several water demand studies model indoor and outdoor or base and seasonal water use in a reduced form manner as separate functions of unique exogenous variables (Howe and Linaweaver 1967; Maidment, Miaou, and Crawford 1985; Miaou 1990; Mansur and Olmstead 2012). Mansur and Olmstead (2012) exploit data from flow sensors installed in sample households' meters that distinguish "flow signatures" of various household appliances and fixtures. In this way, they are able to distinguish between indoor and outdoor uses of water. They then model indoor and outdoor water demand separately, constructing outdoor demand as a Tobit model censored from below at zero to account for periods of no outdoor use. In most water demand studies, however, indoor and outdoor water use cannot be measured directly. In such cases, indoor or base use is typically assumed to be equal to some measure of average use in the winter months (December-February), since these months often see the lowest water consumption. Then, only outdoor use is modeled as a function of weather variables (Howe and Linaweaver 1967; Maidment, Miaou, and Crawford 1985; Miaou 1990).

Other studies have taken a more structural approach, using the Stone-Geary functional form to identify the portion of total water consumption that is not responsive to price (Al-Qunaibet and Johnston 1985; Gaudin, Griffin, and Sickles 2001; Martinez-Espiñeira and Nauges 2004; Monteiro and Roseta-Palma 2011; Dharmaratna and Harris 2012; Garcia-Valiñas, et al. 2014). Al-Qunaibet and Johnston (1985) conduct one of the earliest studies of water demand using the Stone-Geary demand specification. Per the structure of the Stone-Geary demand function, the model includes as parameters 1) an intercept, which represents the subsistence level of water consumption, 2) a coefficient for the ratio of income to the price of water, which indicates the share of total income spent on water and 3) a coefficient for the ratio of the "cost of living" to the price of water, which indicates the relative consumption levels of water and all other essential goods. The authors also add to their structural model a term to control for the effects of relative humidity on water consumption. Using national data from Kuwait, Al-

Qunaibet and Johnston (1985) compare the Stone-Geary model to 5 other demand specifications used in the literature and find that, unlike most other demand specifications, the Stone-Geary function predicts subsistence levels of consumption high enough to actually sustain life.

Subsequent water demand studies using the Stone-Geary demand specification have abstracted away from subsistence levels of water consumption and expenditures on all other goods essential to life (Gaudin, Griffin, and Sickles 2001; Martinez-Espiñeira and Nauges 2004; Monteiro and Roseta-Palma 2011; Dharmaratna and Harris 2012; Garcia-Valiñas, et al. 2014). Following the example of Gaudin, Griffin, and Sickles (2001), later studies consider only the share of supernumerary income – income in excess of necessary living expenses – spent on water and the level of water consumption below which short-run water use is not responsive to price: the "conditional water use threshold." Thus, instead of having three necessary parameters, as in Al-Qunaibet and Johnston (1985), these modified Stone-Geary water demand models require only two. Moreover, the conditional water use threshold can be seen as a proxy for indoor or base use. While some studies have held this parameter fixed (Dharmaratna and Harris 2012), most have allowed it to vary over time by modeling it as a function of control variables (Gaudin, Griffin, and Sickles 2001; Martinez-Espiñeira and Nauges 2004; Garcia-Valiñas, et al. 2014).

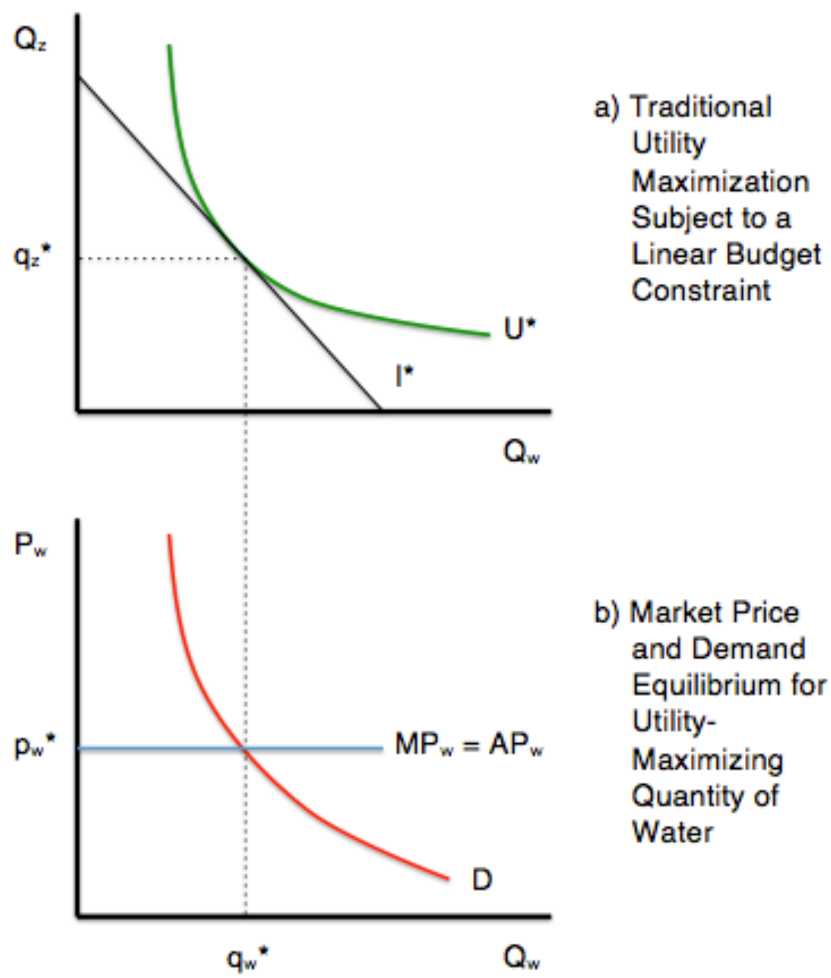
Martinez-Espiñeira and Nauges (2004) and Dharmaratna and Harris (2012) note that modification of the Stone-Geary function for water demand as implemented by Gaudin, Griffin, and Sickles (2001) restricts price and income elasticities to be of the same magnitude and opposite sign. This implies that price and income affect consumption through their relative levels only. Martinez-Espiñeira and Nauges (2004) argue that this restriction should not be too strong due to similar results found in the water demand literature with demand specifications other than the Stone-Geary. Nonetheless, studies that have compared this modified Stone-Geary functional form to other demand models have generally found that the Stone-Geary model predicts a smaller absolute value of price elasticity, or in other words, more inelastic demand (Gaudin, Griffin, and Sickles 2001; Monteiro and Roseta-Palma 2011).

This review of the literature on water demand estimation was used to inform the selection of variables and model specification for our analysis of residential water use in Tucson, AZ. The final model specifications will be discussed in subsequent chapters.

3. Theoretical Model

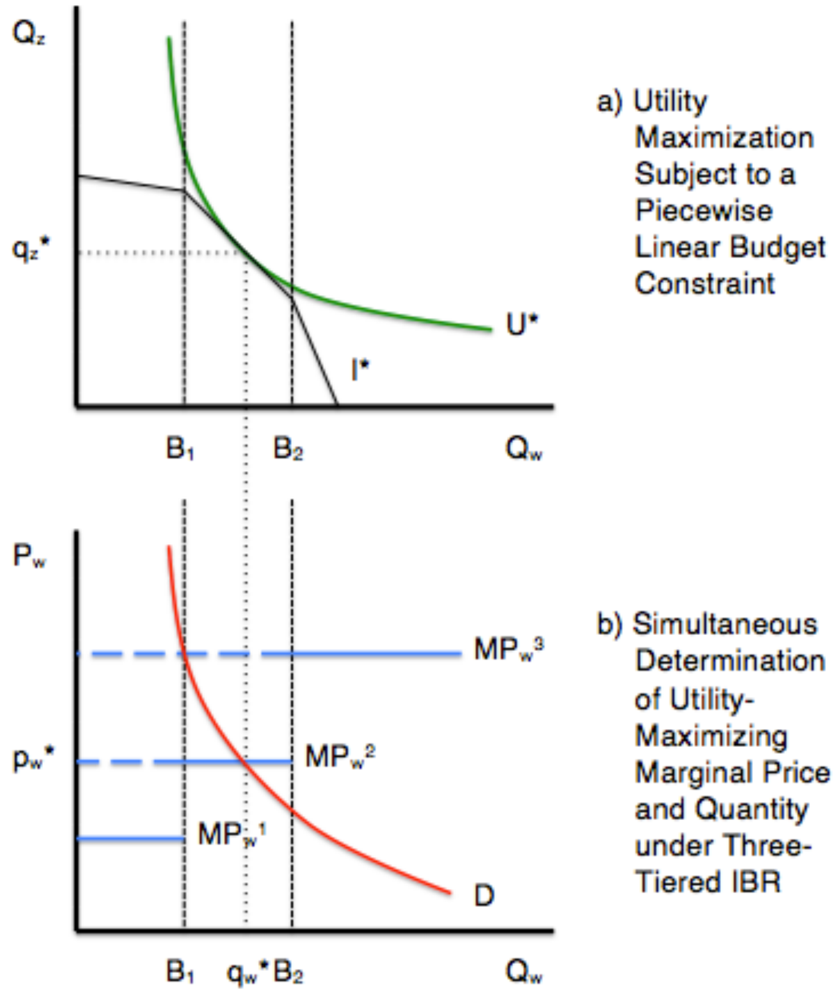
This chapter discusses the economic theory pertaining to consumption behavior that underpins the econometric analysis of this thesis. It provides the conceptual context to estimate demand for water based on the decision-making process of consumers facing an increasing block rate (IBR) structure. The theoretical model described here provides the basic functional form for our empirical model specification discussed in Chapter 5.

Figure 2: Traditional Utility Maximization and Demand Derivation



In a conceptual sense, consumer decision-making with regard to municipally-supplied water is generally similar to that of other normal goods. Consumers attempt to maximize their utility by consuming combinations of water and all other goods (represented collectively by z) subject to a budget (or income) constraint, as shown in Figure 2. However, pricing water according to an IBR structure, such as the one maintained by Tucson Water, presents challenges for demand estimation. The first is that IBRs cause the budget constraint faced by consumers of municipally-supplied water to be piecewise-linear, as opposed to the linear form presupposed by most demand specifications commonly used in empirical work (Taylor 1975). However, Klawitter (2014) has shown that piecewise-linear budget constraints derived from IBRs nonetheless satisfy the convexity requirement for utility maximization (see Figure 3a). The more significant challenge presented by IBR structures is the issue of simultaneity. The whole premise of demand estimation is to explain quantity consumed of a particular good as a function of exogenous factors – in particular the good's own price. Yet, because an IBR by definition allows a utility to charge higher per-unit prices as consumption of water increases, customers facing IBRs select the marginal price of water they face and the quantity of water they consume simultaneously. In other words, marginal price is no longer exogenous to quantity consumed. The simultaneous determination of marginal price and quantity under IBR structures is shown in Figure 3b.

Figure 3: Utility Maximization and Demand Derivation under IBR



To account for these two issues related to the non-constant marginal prices imposed by IBRs, the utility-maximization process for water consumption has been conceptualized as a two-step process, wherein the consumer first selects a block in which to consume and then selects a level of consumption within that block. This process has been modeled using discrete-continuous choice (DCC) models (Hewitt and Hanemann 1995; Olmstead, Hanemann, and Stavins 2007). For the sake of brevity and focus, a detailed description of the consumption decision-making process and demand derivation in a DCC framework is avoided here. For a thorough review of these issues, see Klawitter (2014). Though the DCC approach addresses the issue of non-constant marginal prices under IBR structures in the manner most consistent with the traditional economic theory of utility maximization, the DCC model has limited empirical application. Its complex structure restricts its analytical capacity to small, cross-sectional datasets. Additionally, critics have questioned whether the assumptions of traditional economic theory regarding perfect information and response to marginal price are valid in the case of water demand under IBR structures (Foster and Beattie 1981).

As mentioned in the previous chapter, critics of water demand models using marginal price specifications, such as the DCC model, have typically favored average price demand specifications for practical reasons. Under IBR structures, consumers have to know how much water they are consuming before they can know the price they face. Yet since most utilities install water meters outside dwellings and under a metal plate, most customers never know how much water they are consuming until they receive their bill (Klawitter 2014). On top of that, many utilities, including Tucson Water, still use human meter readers for most of their customer base, which means that billing cycle length and start and end dates vary from billing cycle to billing cycle. This makes it almost impossible for consumers to know how much water they are using during their current billing cycle, even if they make an effort to do so. And since water costs typically do not constitute a significant portion of household income, most consumers do not bother to seek any information about their water consumption not provided in their water bill. Thus, it is expected that consumers will respond to the more tractable average price per unit of water consumed.

For the demand model in this analysis, we select an average price specification. This practical simplification eliminates the problem of accounting for the piecewise linear budget constraint IBR structures create. However, average price specifications do not address the issue of simultaneity per se. In studies that have not utilized a DCC model to separate the utility maximization decision process into two steps, the issue of simultaneity has been addressed using a myriad of empirical methods, such as two- or three-stage least-squares (2SLS or

3SLS) and instrumental variables (IV) estimation. An alternative to these empirical methods is to consider average price from a consumer's previous bill, also called the lagged average price (Charney and Woodard 1984). Since consumers do not receive their water bills until after they have already chosen how much to consume, most consumers likely refer to the average price they faced from their last bill in order to determine how much to consume in the current billing cycle. While there may be substantial autocorrelation between lagged average price and current period consumption, the problem of simultaneous price and quantity determination is avoided. For this analysis, we utilize a lagged average price to account for simultaneity since this approach appears to best mirror the actual decision-making process of water consumers.

Addressing the issue of price specification under IBR structures establishes the budget constraint portion of our consumption model. However, to estimate a demand function for municipally-supplied water, we must also specify a utility function that reflects the decision-making process involved in the consumption of water. Utility functions reflect consumers' preferences, which are slightly more complicated in the case of water than many other normal goods. Because water is necessary for life and because municipally-supplied water has few effective substitutes, there is a certain portion of water consumption that consumers will not be willing to forgo, even if the price of water skyrockets or the prices of all other goods fall dramatically. This portion of water consumption can be said to be perfectly inelastic to price (see Figure 4). Most scholars that have attempted to address this issue have referred to this portion of water use as "base" or "indoor" use, while "seasonal" or "outdoor" use is seen as much more responsive to price. To estimate demand in our analysis, we select a utility function that accommodates this peculiarity of water consumption: the Stone-Geary model. As discussed in the previous chapter, several econometric studies of water demand have utilized the Stone-Geary model because of its ability to incorporate the perfectly inelastic portion of municipal water consumption. (Al-Qunaibet and Johnston 1985; Gaudin, Griffin, and Sickles 2001; Martinez-

Espiñeira and Nauges 2004; Monteiro and Roseta-Palma 2011; Dharmaratna and Harris 2012; Garcia-Valiñas, et al. 2014). The remainder of this discussion will focus on demand estimation within the Stone-Geary framework for water demand, as adapted from Gaudin, Griffin, and Sickles (2001).

According to Gaudin, Griffin, and Sickles (2001), the Stone-Geary utility function assumes additive utilities, but does not require homotheticity. It is a generalization of the simple Cobb-Douglas model, taking the following form:

$$\ln U = \sum_{i=1}^{n} \beta_i \ln(q_i - \gamma_i),$$

Where $\sum_{i=1}^{n} \beta_i = 1$, and:

U : Utility

q_i : Quantity of good *i*

γ_i : Subsistence level of consumption of good *i*

β_i : Marginal budget share allocated to good *i*

A compelling feature of this functional specification is its elegant simplicity. The model requires only two parameters: the marginal budget share devoted to each good (β_i), and the subsistence level of consumption of each good (γ_i). Conveniently for this analysis, this subsistence level parameter (γ_i) represents the level of consumption of each good that is necessary for survival and therefore unresponsive to price. This model suggests a consumption process in which a consumer first purchases a minimum level of each good, and then allocates his or her remaining income, called their “supernumerary income,” between each good in fixed proportions denoted by the marginal budget share associated with each good. These marginal budget shares are determined by consumers’ preferences, while the purchase of subsistence levels of each good is needs-based.

Since this analysis is aimed solely at water consumption, we simplify to a two-good world; that is, we assume that consumers allocate their income between municipally-supplied water and some aggregate of all other goods (z). Maximization of such a utility function subject to a budget constraint yields the following ordinary demand function:

$$Q_w = \gamma_w + \beta \frac{I - P_w \gamma_w - \gamma_z}{P_w}$$

Where:

Q_w : Quantity of water consumed

P_w : Price of water

I : Income

γ_w : Subsistence level of water consumption

γ_z : Expenditure on subsistence level of all other goods

β : Marginal budget share allocated to water

Based on this demand function, own-price elasticity of demand and income elasticity of demand can be calculated as:

$$\varepsilon_w^p = -\beta \frac{(I - \gamma_z)}{P_w Q_w}$$

$$\varepsilon_w^I = \beta \frac{I}{P_w Q_w}$$

According to Gaudin, Griffin, and Sickles (2001), the Stone-Geary model only allows for inelastic demand, and can only be used to analyze normal goods. However, neither of these restrictions appears inappropriate in the case of water. Additionally, unlike its parent function, the Cobb-Douglas, the Stone-Geary model does not impose constant price elasticity of demand but instead allows price elasticity of demand to vary with price – a distinct advantage for modeling water demand.

There is one practical drawback to the Stone-Geary water demand model, however. The fact that information is required about expenditures on the subsistence level of consumption of some aggregation of all goods other than water is theoretically plausible, but finding data to approximate this in empirical work is difficult. Al-Qunaibet and Johnston (1985) use a cost of living index for Kuwait to address this issue, but in most cases no acceptable metric exists. To overcome this limitation, Gaudin, Griffin, and Sickles (2001) abstract away from expenditures on all other goods by considering supernumerary income as income over and above *total* expenditures on all such goods. Since γ_z is not pertinent to this analysis, this abstraction is not only simpler, but also more focused. The simplified demand function is as follows:

$$Q = \gamma + \beta \frac{I^*}{P}$$

Where:

Q : Quantity of water consumed

P : Price of water

I^*: Supernumerary income

γ : Conditional water use threshold

β : Marginal budget share allocated to water

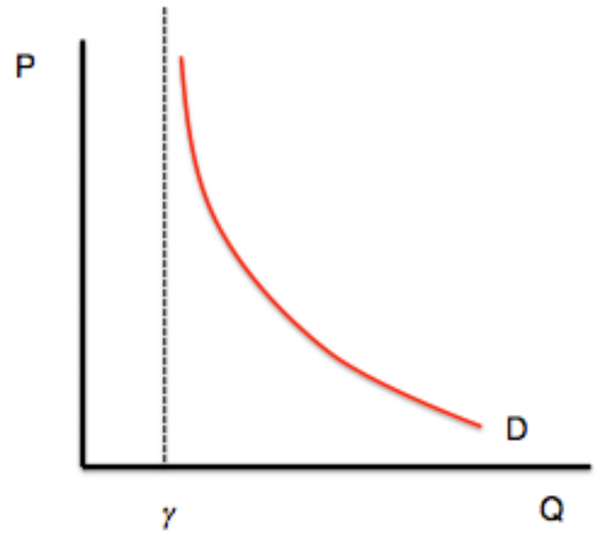
Price and income elasticities are also simplified accordingly:

$$\varepsilon_p = -\beta \frac{I^*}{PQ}$$

$$\varepsilon_I = \beta \frac{I^*}{PQ}$$

This simplification has many advantages. First, Gaudin, Griffin, and Sickles (2001) rename γ as the “conditional water use threshold” to emphasize that the amount of water referred to here is not what is needed to survive, but rather the amount below which consumption is perfectly inelastic to price. This interpretation of γ is more appropriate in the case of municipally supplied water in developed countries such as the United States. Additionally, abstracting away from the consumption of all other goods allows both γ and β to be modeled as linear functions of exogenous control variables.

Figure 4: Stone-Geary Demand Model



One limitation of this simplified Stone-Geary model is that price and income elasticities are equal in magnitude and opposite in sign (Martinez-Espiñeira and Nauges 2004). Though Martinez-Espiñeira and Nauges (2004) argue that this restriction should not be too strong due to similar results found in the water demand literature with demand specifications other than the Stone-Geary, it is worth noting the implication that price and income affect consumption through their relative levels only. In other words, we do not expect household water consumption to change in response to a price increase if their income rises proportionally to the change in prices. Only when prices increase such that a given household is forced to allocate more of its supernumerary income to water expenditures than before in order to consume the same amount of water as before do we expect to see total household water consumption decline.

This simplified Stone-Geary demand model provides the functional form for our empirical estimation of water demand in Tucson, AZ, discussed in Chapter 5.

4. Description of Data

4.1 Single Family Residential Water Consumption Data

Water consumption data for this analysis were provided by Tucson Water under a confidentiality agreement with the Department of Agricultural and Resource Economics at the University of Arizona. These data consist of single-family residential (SFR) billing records for individually metered households over the 16 years from 1997 to 2012. Based on these data, we conduct a panel analysis of household water consumption over time as well as a time-series analysis of aggregated SFR water use. (Please note that, from this point forward, the terms “household”, “user”, “customer”, and “consumer” are all meant to refer to the individual entity billed by Tucson Water, regardless of the number of people who may live in a single SFR household. Additionally, water “consumption”, water “use”, and water “usage” are all used interchangeably.)

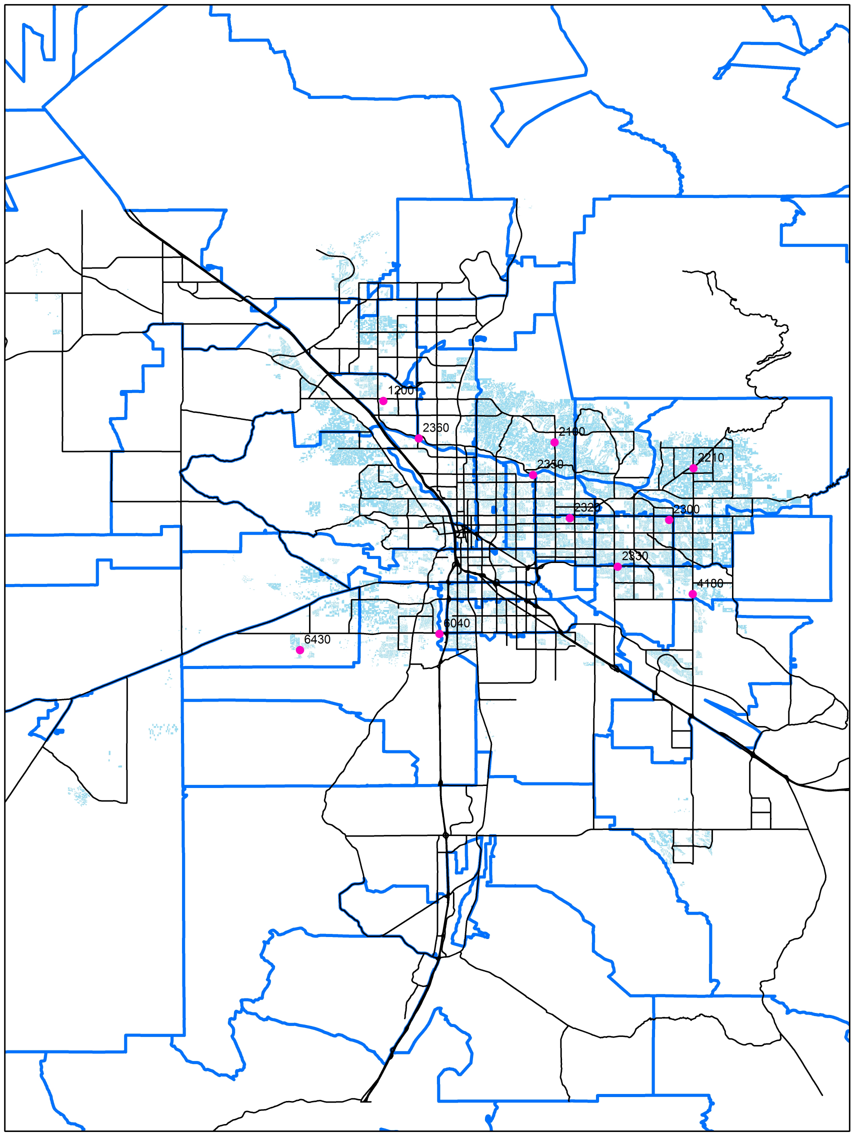
Due to our interest in changes in consumption behaviors over time, we attempt to preserve as long of a time-series as possible for the final analyses. For our household analysis, data availability forced us to limit our study to the 10-year period from July 2001 to June 2011. For our aggregate analysis, which involves fewer control variables, we are able to examine the 13-year period spanning July 1998 to June 2011. In both cases, we limit our analyses to consecutive fiscal years because Tucson Water adjusts its rate structure at the beginning of the fiscal year (July).

Because Tucson Water uses human meter readers that must visit each meter every billing cycle, billing cycle lengths as well as start and end dates are asynchronous – that is, they vary across households. Tucson Water does not account for discrepancies in billing cycle length when billing customers; customers who have longer billing cycles may face higher marginal prices if their additional consumption in extra days causes them to move into a higher tier in Tucson Water’s increasing block rate structure. For this reason, in our household analysis, an effort is made to measure all variables over the exact length of each household's billing cycle whenever possible. On the other hand, in our aggregate analysis, potable water deliveries across customers in the SFR rate class are aggregated into monthly totals based on the "period-ending month" of each billing cycle. The period-ending month is the month to which Tucson Water assigns each household's billing cycle to ensure that only one bill is recorded per month. For our aggregate analysis, all independent variables are matched to consumption data by period-ending month. Since billing cycles have asynchronous lengths and dates, it is important to note that aggregate monthly totals do not reflect the exact billing cycle lengths or dates of the individual households whose consumption is being aggregated.

In order to match household water consumption data from Tucson Water to data from other sources, Tucson Water provided a database linking their internal customer identifier codes with unique parcel identifiers in the Pima County Geographic Information System (Pima GIS) database. These parcel identifiers are used by the Pima County Assessor's office to record housing characteristics, which we make use of in our analysis. Via a geodatabase developed by the Advanced Resource Technologies (ART) GIS Lab at the University of Arizona, these parcel identifiers were also associated with the zip codes and census geographies that correspond to the location of each parcel.

The initial Tucson Water dataset contained water consumption data for 284,993 SFR customers that could be matched to 259,646 unique Pima GIS parcel identifiers (25,347 parcels had more than one metered SFR connection). Before conducting our analysis, we eliminate households with insufficient or nonsensical data, reducing the number of SFR customers to 127,644 and the number of unique parcels to 127,291. The process of and rationale for eliminating households from our dataset is described in detail in Appendix 1. Figure 5 shows the geographical distribution of the 127,291 parcels in our final dataset by zip code. In our aggregate analysis, we use consumption records of this subset of SFR households to generate our aggregate monthly usage and average price estimates. However, in our household analysis, the computational burden of estimating panel regression models on a dataset of such considerable cross-sectional and temporal breadth prompts us to take a representative sample of manageable size. To avoid biasing our results by altering the geographic distribution present in our dataset, we draw a random sample of 2,000 households without replacement from the final set of 127,644 metered SFR connections with complete data, stratifying by zip code in a manner that preserves the proportion of households in each of the 31 zip codes in our study area. These sample households are then linked back to their monthly usage records for analysis, producing a dataset with 246,049 records. If each household has a single usage record for each of the months in our study period, which is not the case because of gaps in meter reads and new construction, the final number should be 264,000. However, even within this dataset, a few issues remain regarding period-ending months with multiple bills. For a description of how these data are cleaned, see Appendix 2. The final number of observations in our household dataset for the period July 2001 to June 2012 is 240,224, and after removing July 2011 to June 2012 this number drops to 216,456 observations of 1,994 households.

Figure 5: Distribution of Studied SFR Households by Zip Code

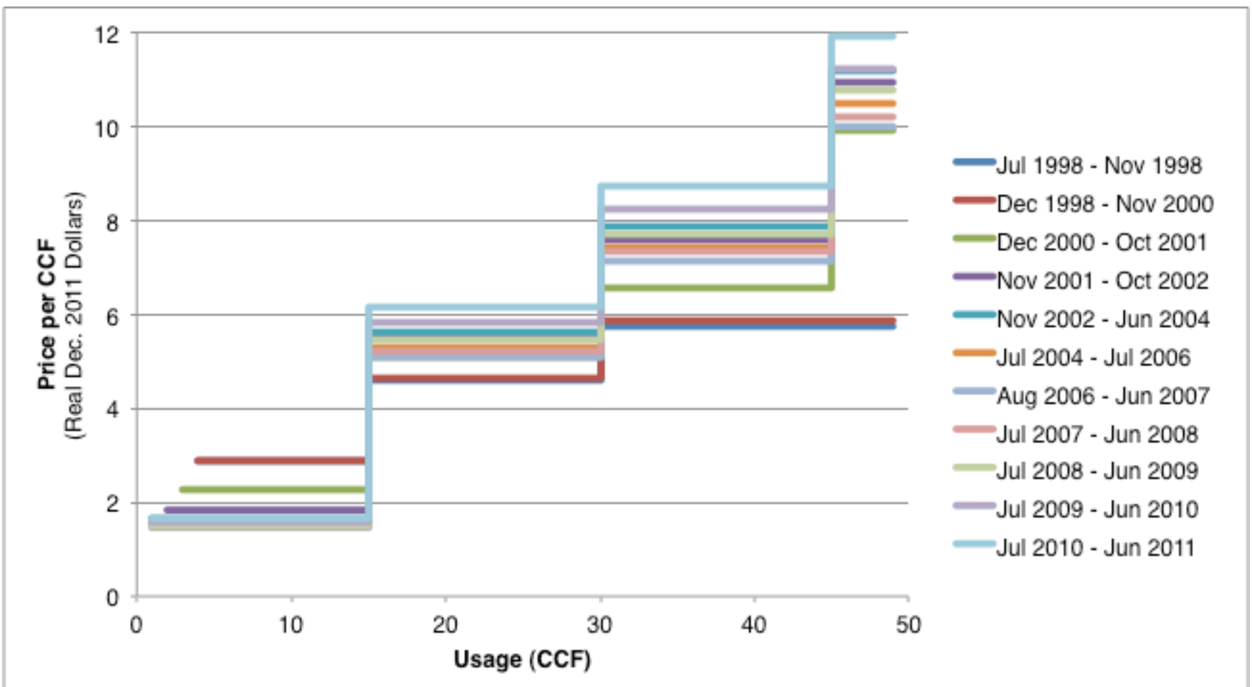


4.2 Rate Structure Data

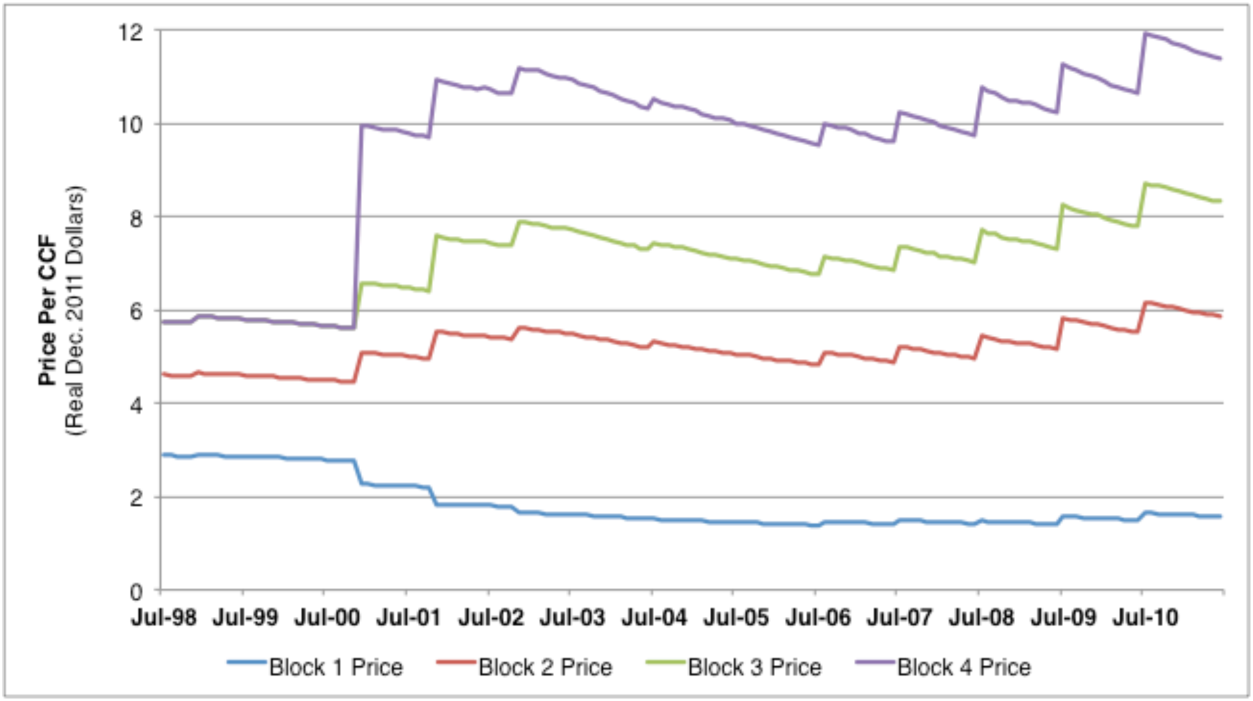
Along with the SFR billing records, Tucson Water also provided information about its pricing structure over the entire period from 1997 to 2012. Tucson Water uses a four-tiered increasing block rate (IBR) structure to determine the volumetric component of its charges for potable water deliveries. The tier breakpoints over the period of our analyses remained constant at 15 hundred cubic feet (CCF), 30 CCF, and 45 CCF (1 CCF = 748 gal). Over the period from July 1998 to June 2011, the price levels of the 3 highest tiers were adjusted 10 times, and the price of the lowest tier was adjusted 9 times. The price levels (in real Dec. 2011 dollars) of each of the four tiers (blocks) over the study period are shown in Figure 6 below.

Figure 6: Tucson Water's Increasing Block Rate Structure

a) Increasing Block Rate Schedule (July 1998 – June 2011)



b) Increasing Block Rate Prices by Block (July 1998 – June 2011)



While Tucson Water's per-unit or volumetric charges for potable water deliveries are determined by their IBR structure, Tucson Water also bills customers for four other types of water-related charges. The first is the meter surcharge, which is determined by the size of each customer's meter. SFR customers have meters of 5 distinct sizes, measured in inches: 5/8, 3/4, 1, 3/2, and 2. Meter surcharges for the each of the meter sizes (except 3/4 inches) were raised 5 times between July 1998 and June 2011. (The 3/4-inch meter size was not available to Tucson Water SFR customers until July 2011.) In July 2010, Tucson Water also implemented a groundwater protection fee associated with meter size.

The other two water-related charges in a Tucson Water bill are per-unit surcharges. The first is the CAP charge, which is intended to offset the costs to Tucson Water of purchasing water from the Central Arizona Project (CAP). This charge increased 3 times over the study period. The second is the conservation surcharge, which was implemented in July 2008 to encourage customers to consume less water. This charge increased twice over the study period.

In addition to water-related charges, Tucson Water bills contain Pima County sewer fees and, since August 2004, have contained City of Tucson waste disposal (garbage) fees. Sewer fees are charged to all Tucson Water customers who live within the city limits. Two sewer charges exist: a flat service charge for all users within the city limits and a commodity charge based on average water use in the most recent winter quarter (December-February). The commodity charge was increased 16 times over the study period, while the flat service charge was instituted in January 2000 and subsequently raised 11 times over the study period. The garbage charge also applies to all customers who live within the Tucson city limits; it is a flat fee that has been raised once since 2004.

In both the aggregate and household analyses, these various charges are incorporated into a single price variable for econometric modeling. The specification of this price variable will be discussed in Chapter 5. These prices are inflated to December 2011 real dollars using the seasonally-adjusted, U.S. city average monthly consumer price index (CPI) for sewer, water, and trash services obtained from the U.S. Bureau of Labor Statistics (BLS) to facilitate comparison of monetary amounts over time.

4.3 Income Data

Economic theory emphasizes the importance of income and budget constraints in influencing utility-maximizing consumption decisions. For both of our analyses, we attempt to collect estimates of income that most closely correspond to our temporal and spatial units of analysis.

4.3.1 Household-Level Income Data

Approximating individual household incomes is not as straightforward as it might sound. Past studies have often used either assessed home value or Census Bureau income estimates at the census block or census tract level, since these data are typically available. They make reasonable proxies, but neither is ideal. Assessed home values fluctuate with the market and probably better approximate a household's wealth than their monthly income. Census income estimates, on the other hand, probably better approximate actual income, but only vary decennially and do not account for income heterogeneity within census tracts or blocks.

Klawitter (2014), who used the same Tucson Water household billing data as in this analysis, attempts to circumvent these drawbacks by combining the two measures of income. He first interpolates annual census tract median household income estimates over his study period 2007-2011. To do so, he uses 2011 median household income estimates at the census tract level from the 2011 5-year American Community Survey (ACS) and applies the Census Bureau's estimate of the real median income growth rate for the state of Arizona over that period. In this way, he is able to utilize the best measure of income at the census tract level. Then, in order to capture the heterogeneity in income within each census block, he weights the median household income by a home value index calculated for each household using data from the Pima County Assessor's office. The home value index is calculated simply as the ratio of an individual home's actual assessed value to the average assessed value of all homes within the same census tract in a given year. In this way, the census tract income estimates are scaled to the household level.

For our household-level analysis, we likewise collect data on annual assessed home values from the Pima County Assessor's office for the years 2002-2012. However, instead of using Census tract median household income estimates, we procure annual Internal Revenue Service (IRS) tax return data on adjusted gross income (AGI) by zip code for the years 1998, 2001, and 2004-2012. While census tract income estimates are more spatially specific than IRS zip code data, they are not available annually as IRS income estimates are (with the exception of the years 1999-2000 and 2002-2003). Using the seasonally-adjusted, U.S. city average monthly CPI for water, sewer, and trash services, assessed home values and IRS AGI estimates are inflated to December 2011 real dollars.

We use Klawitter's (2014) method of approximating annual household income, substituting IRS AGI estimates for Census tract median household income estimates. To do so, we first interpolate linearly the missing IRS average AGI estimates for the years 2002-2003 for each zip code in our dataset. Then, we calculate a home value index for each household by dividing each household's annual assessed home value by the average annual assessed home value in its corresponding zip code. The home value index calculation is shown below:

$$HomeValueIndex_{i,y} = \frac{ActualAssessedValue_{i,y}}{AvgAssessedValue_{z,y}}$$

Where:

i : 1,…, n

y : Year

z : Zip code

We then weight the average monthly income estimates for each zip code by a unique home value index for each household to capture income heterogeneity within zip codes, as shown below:

$$RealHouseholdInc_{i,y} = RealAvgAGI_{z,y} \times HomeValueIndex_{i,y}$$

Finally, we divide the annual real income estimates by 12 in order to approximate available household income in each period-ending month. It is important to note that these downscaled monthly estimates still do not correspond exactly to each household's relevant billing cycle, but since data even at a monthly time-step are not available, they represent the closest available proxy.

4.3.2 Aggregate Income Data

In our analysis of aggregate SFR water consumption, we collect annual income estimates for the years 1998-2012 from the Bureau of Economic Analysis for the Tucson Metropolitan Statistical Area (MSA), since the MSA corresponds closely to the Tucson Water service area. However, since our analysis is conducted at a monthly time-step, we downscale these annual estimates to correspond to the period-ending months of our consumption data. This is accomplished by assuming a constant growth rate of income between annual estimates. Each observation of monthly income is calculated as the previous month's income plus the difference in current and prior years' annual income estimates weighted by the annual growth rate. This calculation is shown below:

$$Inc_m = Inc_{m-1} + (BEAInc_{y+1} - BEAInc_y) \times \frac{(BEAInc_{y+1} - BEAInc_y)}{12}$$

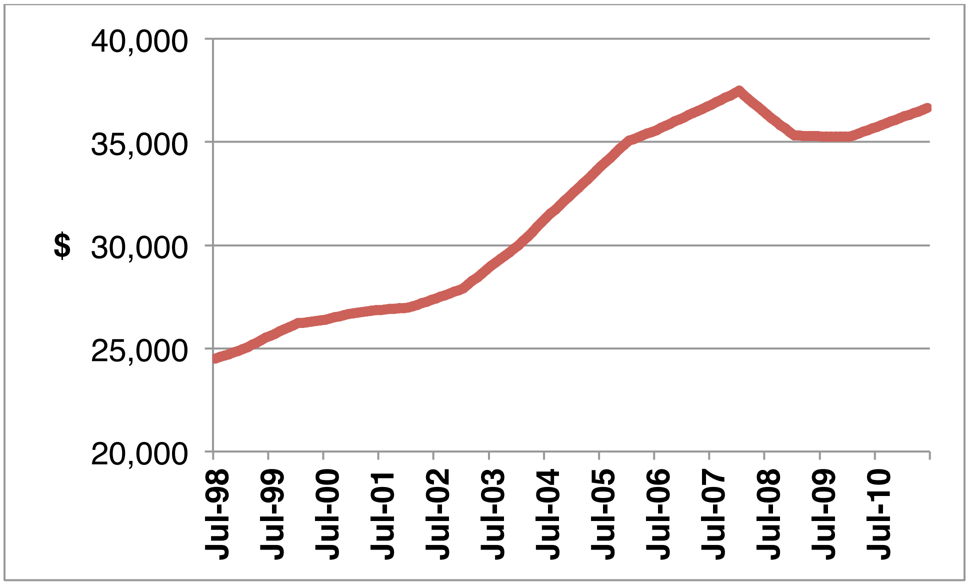
Where:

y : Year

m : Month

All income and per capita income estimates for the aggregate analysis are inflated to December 2011 real dollars using the seasonally-adjusted, U.S. city average monthly CPI for sewer, water, and trash services. The monthly trend of per capita income is shown below in Figure 7. With the exception of the 2008 recession, per capita income increased over the study period.

Figure 7: Per Capita Income over the Study Period



4.4 Demographic Data

Another set of factors expected to influence SFR water consumption in Tucson is the number and type of people living in households in the Tucson Water service area. Both annual and seasonal variation in demographic characteristics of the studied households can significantly affect the amount of water demanded.

4.4.1 Household Demographic Data

All demographic data for the household analysis described below are obtained from the U.S. Census Bureau at the tract level. Since tracts tend to correspond roughly to neighborhoods, they do not represent household-specific characteristics precisely. Nonetheless, they represent the best available proxy and can still be considered reliable in most cases since neighborhoods tend to be relatively homogeneous in terms of their demographic composition.

As previously mentioned, even though Tucson Water only bills individual meters, the number of people living in a SFR household varies across the Tucson area. Naturally, larger households will consume more water, ceteris paribus. We use Census estimates of average household size by Census tract to attempt to capture some of this heterogeneity. Such estimates were available from the 2000 and 2010 decennial Census. Since average household size is not expected to vary significantly within census tracts from year to year, values for intermediate years (2001-2009) are interpolated linearly, whereas values for 2011 and 2012 are assumed to be equivalent to 2010. Average household size is assumed to be constant throughout each year.

Not only do we expect the number of people in a household to affect household water use, but we also anticipate that the type of people in each household will affect consumption behavior. Previous studies have shown that differing age distributions, levels of education, and ethnic/cultural norms across households can lead to different water consumption behavior (Gaudin, et al. 2001; Balling, Gober, and Jones 2008; Ray 2012). The age of household occupants is expected to influence water consumption in terms of the efficiency of water use. Working age adults are expected to use less water since they tend to be around the house less and have less time for bathing or swimming. On the other hand, households with young children may use more water to bathe with, or may require additional pool water to compensate for their children's splashing, households with teenagers may use more water for the "15 minute showers" their adolescents take, and retirees may use more water for leisure activities such as swimming or landscaping. For our analysis, household age distribution is approximated by the percentage of people in each Census tract in various age brackets, including under the age of 5, 5 to 9, 10 to 14, 15 to 19, under 18, and over 65. These data are obtained from the 2000 and 2010 decennial Census.

Differences in educational attainment across households are expected to influence water consumption in terms of differing views or levels of knowledge regarding water conservation as well as differing amounts of time spent at home.

The higher the education level, the lower the expected level of water consumption. To account for educational differences across households, we use estimates of the percentage of the over-25 population in each Census tract with a Bachelor's as well as the proportion with a graduate or professional degree. These data are available from the 2000 decennial Census, but not from the 2010 decennial Census. Therefore, 5-year estimates from the 2010 American Community Survey (ACS) conducted by the U.S. Census Bureau are obtained instead.

Finally, because of the significant Hispanic population in Tucson, we use 2000 and 2010 decennial Census estimates of the percentage of Hispanic or Latino residents (of any race) in each census tract to account for ethnic or cultural differences that could influence water consumption behavior. Previous studies have shown that the proportion of Hispanic or Latino residents in an area tends to be inversely related to water consumption (Gaudin, Griffin, and Sickles 2001; Balling, Gober, and Jones 2008; Ray 2012). The rationale for such behavior may be that Hispanic residents who have emigrated from Mexico tend to consume bottled water for many potable uses rather than tap water, since the quality of municipal water in Mexico is often highly suspect. Ethnicity may thus represent a proxy for immigrant status.

Values for age, education, and percent Hispanic variables in years for which data are not available (2001-2009, 2011-2012) are assigned in the same manner as that used for household size estimates. It is also important to note that, as in the case of the household-level income data, these demographic variables are not measured over the exact billing cycle dates of each household. Instead, they are downscaled to the closest available proxy: the period-ending month of each billing cycle.

4.4.2 Aggregate Population Data

In terms of water consumption across the Tucson Water service area, the variation in total population living in the area will significantly influence the amount of water consumed. Tucson Water did provide data on the number of metered connections in the SFR rate class; however, the number of people living in a SFR household varies across the Tucson Water service area. To account for this variation, annual population estimates for the Tucson MSA are obtained from the Census Bureau. These estimates provide a reasonably clear picture of how the number of people in the Tucson Water service area is growing over time. However, such estimates do not capture seasonal variation in population. This variation can be substantial in Tucson, since the mild winter climate attracts a considerable number of snowbirds who live in Tucson for only a few winter months out of the year. The presence of the University of Arizona also creates seasonal population trends; college students tend to leave for breaks during the summer and on specific holidays. Annual census estimates are thus downscaled to the monthly level to correspond to the period-ending months of Tucson Water's billing cycles in a manner designed to account for seasonal population trends. This process, which was adapted from Chandrasekharan and Colby (2013), is described below.

Since Census annual population estimates are calculated in July of each year, the value of each annual Census population estimate is assigned to July of each year. For every other month, the population value is interpolated. The difference between each annual estimate is calculated to determine the annual growth or decline in population. Then, for every year, the population in each month after July is calculated as the prior month's population plus the amount of annual growth or decline attributable to that month. In other words, the annual population difference is weighted for each month and then added to the previous month's estimate, as shown below:

$$Pop_{m,y} = Pop_{m-1,y} + (CensusPop_{y+1} - CensusPop_{y}) \times PopWeight_{m,y}$$

Where:

y : Year

m : Month

Appropriate weights for each month are determined using monthly 5-day average traffic count data for 6 major roadways throughout Tucson provided by the Pima County Department of Transportation (DOT). For each month of each year, the appropriate population weight is calculated by dividing the monthly average traffic count for all 6 roadways by the annual sum of the monthly average traffic counts for all 6 roadways, as shown below:

$$AvgTrafficCount_{m,y} = \frac{\sum_{n=1}^{6} (TrafficCount_{n})_{m,y}}{6}$$

$$PopWeight_{m,y} = \frac{AvgTrafficCount_{m,y}}{\sum_{m=1}^{12} AvgTrafficCount_{m,y}}$$

Where:

y : Year

m : Month

n : Region of Tucson represented by DOT traffic counters

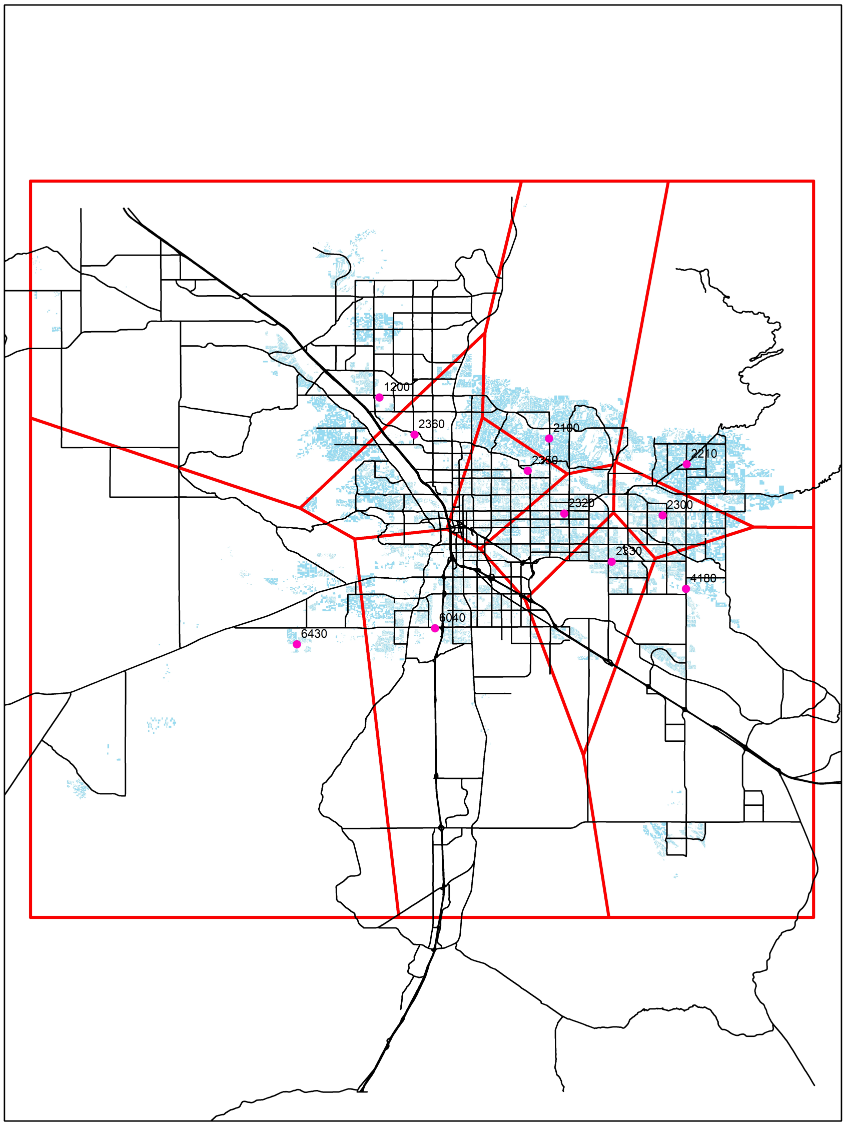
24 percent of the traffic counter data for the years 1998-2012 are missing; these values are filled using averages. Traffic counts reflect the number of people actually present in an area at a time, rather than simply estimating how many live there. Nevertheless, traffic counts provide an indication of seasonal population ebbs and flows.

4.5 Weather Data

4.5.1 Current Period Data

Weather and climate patterns may also affect water consumption, particularly outdoor uses of water such as landscape irrigation. All weather data for the period 1998-2012 are collected at a daily time step. Data on potential evapotranspiration (ET) are obtained from the Arizona Meteorological Network (AZMET), and data on total precipitation are obtained from both AZMET and the Pima County Regional Flood Control District (RFCD). AZMET data are collected at a single weather station in central Tucson, whereas RFCD maintains a network of rainfall and streamflow gauges across Pima County. For reference, AZMET records of total precipitation, number of rainy days, total ET, and mean temperature are tabulated by month and year in Appendix 3. Since variation in ET across a municipal area tends to be very little, we deem AZMET data for potential ET to be appropriate for both the aggregate and household analyses. AZMET precipitation data are also used in the aggregate analysis. However, because precipitation in Tucson tends to be highly localized, particularly during the summer monsoon, AZMET precipitation data will not accurately reflect rainfall conditions at all households in our study area. Instead, 11 RFCD precipitation gauges spatially distributed across the Tucson metropolitan area are selected for use in the household analysis. Households are matched to the nearest gauge using a geodatabase developed by the University of Arizona's ART GIS Lab. Figure 8 shows the distribution of the studied SFR households in relation to each rain gauge, as well as the areas of the city assigned to each rain gauge.

Figure 8: Assigning SFR Households to the Nearest Rain Gauge



For the aggregate analysis, total monthly precipitation and total monthly ET, as well as the number of rainy days in each calendar month, are calculated so as to correspond to the period-ending months of Tucson Water's billing cycles. Number of rainy days is calculated because studies by Maidment, Miaou, and Crawford (1985) and Miaou (1990) suggest that the occurrence of rainfall may have a more substantial effect on household irrigation decisions than the level of rainfall. For the household analysis, the same variables are calculated over the exact dates of each household's billing cycle. This is possible because, as opposed to the cases of the household-level income and demographic variables, our weather data are measured at a daily time step.

4.5.2 Counterfactual Climate Scenarios

In our aggregate analysis, we attempt to evaluate the sensitivity of water consumption behavior among SFR customers in Tucson to potential climate change. While making long-term projections regarding Tucson's socioeconomic conditions is beyond the scope of this thesis, we are able to investigate how water consumption patterns over our study period might have differed under alternate weather conditions. To do so, we construct counterfactual climate scenarios using regionally downscaled projections from the global climate models (GCMs) in the Coupled Model Intercomparison Project's phase 5 (CMIP5) multi-model ensemble. CMIP5 was developed by the World Climate Research Programme's Working Group on Coupled Modelling and was used to inform the Intergovernmental Panel on Climate Change's Fifth Annual Report (IPCC AR5). Substituting these projections for our weather variables from AZMET and Pima County RFCD, we examine how differently our model suggests water consumption patterns would look if the weather from July 1998 to June 2011 had actually resembled what CMIP5 models project Tucson weather conditions will be from July 2085 to June 2099. We also compare these projections-based scenarios to a hypothetical scenario in which historical weather data from the study period is altered to reflect somewhat hotter and drier summer conditions. This scenario, which we call the More Intense Summer Scenario (MISS), is adapted from Chandrasekharan and Colby (2013) and assumes an increase in daily minimum, mean, and maximum temperatures of 4ºC (7.2ºF) from May to September of each year, and a 2.5ºC (4.5ºF) increase in minimum, mean, and maximum temperatures in the remaining months of each year. Additionally, the number of rainy days occurring in the months of May to September throughout the study period is reduced by 50%. The values of these weather variables under the MISS scenario are tabulated in Appendix 6.

To obtain projections data for our counterfactual climate scenarios, we first determine the most appropriate CMIP5 GCM to use as well as which IPCC-defined emissions scenarios, or “representative concentration pathways” (RCPs), to consider. In selecting a GCM, we want to ensure that the projections we use will closely reflect the climate phenomena relevant to Tucson. In particular, we focus on the GCMs’ ability to model the North American Monsoon, since this phenomenon has a substantial impact on outdoor water use patterns in the American Southwest. According to Sheffield, et al. (2013), three GCMs have been shown to perform most effectively in modeling both the timing and the duration of North American monsoon. The first, the Hadley Centre Coupled Model, version 3 (HadCM3) model, produced by the U.K. Meteorological Office, was part of the Coupled Model Intercomparison Project’s phase 3 (CMIP3) ensemble. The other two are from CMIP5: the second generation Canadian Earth System Model (CanESM2), developed by the Canadian Centre for Climate Modelling and Analysis (CCCma), and the Hadley Centre Global Environment Model 2 - Earth System (HadGEM2-ES), also developed by the U.K. Met Office. Of the 17 CMIP5 GCMs evaluated by Sheffield, et al. (2013), these three models are also shown to have minimal bias in projecting both winter and summer precipitation in Western North America. However, despite their reliability in representing precipitation patterns, it should be noted that these models do not necessarily outperform the others in representing all aspects of climate in Western North America. According to Sheffield, et al. (2013), these models demonstrate more bias than most of the evaluated GCMs in terms of projecting winter and summer temperature. For our analysis, we utilize projections from CCCma’s CanESM2 since downscaled daily projections are not available for the two Hadley Centre models.

Although CMIP5 projections were developed under 4 alternative emissions scenarios or RCPs, we select data from runs under only 2 of these emissions pathways: RCP 2.6 and RCP 8.5. According to Moss, et al. (2010), these two pathways represent the most extreme cases. Although under all RCPs emissions levels are projected to increase into the middle of the century, RCP 2.6 projects emissions levels less than current ones by 2100, while RCP 8.5 projects increases in emissions up to five times current levels over the same period. Since our goal is to assess the sensitivity of water consumption behavior in Tucson to climate change, examination of the most extreme cases should be most informative.

Regionally downscaled projections of daily minimum and maximum temperature and daily total precipitation generated by the first run of the CanESM2 model under RCP 2.6 and RCP 8.5 are collected from the Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections archive for the period July 2085 to June 2099. These projections are calculated as a spatial mean over the gridded region from latitude 31.9375 to 32.4375 N and longitude -111.1875 to -110.6875 E to approximate weather conditions over the Tucson metro area. Daily precipitation projections are aggregated to the monthly level, calculating both total monthly precipitation and number of rainy days per month, to replace the variables in our model for the period July 1998 to June 2011. In addition to these two precipitation variables, our model includes total monthly ET. Presently, ET projections are not part of the standard output requirements of CMIP5 GCM runs. However, according the equation for standardized reference ET used by AZMET (shown in Appendix 4), which is a slight simplification of the Penman-Monteith equation, we know that ET is a function of several weather variables (Brown 2005). And while approximations for many of these variables, such as net radiation, vapor pressure, wind speed, and mean daily temperature, could be obtained from CMIP5 GCM output, only temperature projections have been regionally downscaled for the Tucson area. Fortunately, temperature is likely to be a major source of long-term temporal variation in ET. Additionally, various formulas have been developed to approximate ET in ways that better fit specific regional contexts and are less data-intensive than the Penman-Monteith equation

(McKenney and Rosenberg 1993; Droogers and Allen 2002; McKellar and Crimmins 2015). Recent work by McKellar and Crimmins (2015) suggests that the formula developed by Hargreaves (1994) is particularly well-suited to estimating ET in southern Arizona. The advantage of the Hargreaves (1994) formula is that daily ET can be reliably approximated using data on simply daily minimum and maximum temperature and the arithmetic mean thereof (see Appendix 4). As shown in Appendix 5, we use the Hargreaves approach to determine the relationship between ET and temperature in the current period. Then, assuming the same relationship in the future, we use temperature projections from downscaled GCM output to project ET for the period July 2085 – June 2099 (see Appendix 5). We also use this Hargreaves ET formula to approximate ET under the MISS scenario.

Once we obtain daily values for ET under the MISS scenario as well as the CanESM2 projections, we calculate total monthly ET to replace the historical weather data in our model. Likewise, using daily total precipitation projections from the CanESM2 model, we approximate the number of rainy days per month from July 2085 – June 2099 for both RCPs. Values of these weather variables calculated from CanESM2 projections under both RCPs are tabulated by month and year in Appendix 7. Once we have number of rainy days per month and total monthly ET for all 3 counterfactual climate scenarios, we multiply the coefficients estimated in our original SGF and SGV model runs by these alternative weather data, assuming that prices and incomes do not change. This procedure allows us to project what water consumption would have looked like during our study period under these alternative weather conditions. The results of this sensitivity analysis are described in Chapter 5, while a comparison of weather variables in the current period with those in each of the 3 counterfactual climate scenarios is presented in Appendix 8.

4.6 Housing and Property Characteristics

For our household analysis, we also consider the impact that variation in housing and property characteristics may have on water consumption. Of particular interest is the amount of yard for which households must make landscaping (and therefore irrigation) decisions, which we will refer to as "landscapable area." We obtain records of parcel area (lot size) from the Pima County GIS database, while housing characteristics are collected from the Pima County Assessor's housing characteristics (MAS) database. In addition to assessed home value, MAS data include house square footage, number of stories, number of garage or carport parking spaces, and pool area, recorded annually from 2002 to 2012. Since our household analysis begins in 2001 and housing characteristics are not expected to change much year-to-year, we use 2002 values to approximate relevant housing characteristics for 2001 as well. These data are used to calculate an estimate of landscapable area (in sq. ft.) using the same method as in Klawitter (2014). The equation below summarizes this calculation:

$$LandscapableArea_{i,y} = L_{i,y} - \frac{A_{i,y}}{S_{i,y}} - (G_{i,y} \times 200) - P_{i,y}$$

Where:

i : 1,…, n

y : Year

L : Lot size in sq. ft.

A : Livable square footage of the house

S : Number of stories of the house

$(G \times 200)$: Approximate garage or carport area in sq. ft.

(Number of garage parking spaces times square footage required to park an average car)

P : Approximate pool surface area

4.7 Remotely-Sensed Data

Given our interest in explaining outdoor consumption trends, our household analysis includes estimates of the greenness of individual parcels. We expect that lots with more vegetative cover will typically require more water for irrigation than other lots. Previous studies have used remotely-sensed data to demonstrate a significant, positive relationship between vegetation indices representing parcel greenness and water consumption (Harlan, et al. 2009; Halper, et al. 2015). In this case, we model our approach after that of Halper, et al. 2015, who examine variations in water use patterns among households in the Tucson Water service area based on proximity to irrigated parks and public pools. They use 1 m· orthophotography from the National Agricultural Imagery Program (NAIP) of the U.S. Department of Agriculture to calculate a mean normalized difference vegetation index (NDVI) across the Tucson Water service area. NDVI provides an approximation of the greenness of a pixel; it is calculated as the ratio between the difference in infrared and red reflectance in a pixel and the sum of the infrared and red reflectance in a pixel, as shown below:

$$NDVI = \frac{(InfraredReflectance - RedReflectance)}{(InfraredReflectance + RedReflectance)}$$

Halper, et al. (2015) then average NDVI over each parcel to help explain outdoor water consumption. Similarly, Harlan, et al. (2009) calculate a neighborhood-level soil-adjusted vegetation index (SAVI) to explain water consumption in metropolitan Phoenix, AZ. SAVI is similar to NDVI but adjusts for terrain in which reflectance can occur because of the presence of exposed rock rather than vegetation. Since a majority of Tucson Water customers live in the central urban area of Tucson, we chose to use NDVI for our analysis.

With the support of the Arizona Remote Sensing Center at the University of Arizona, we calculate NDVI from remotely-sensed imagery of Tucson in the pre-monsoon summer months (May-June) – months which correspond to peak outdoor irrigation. Landsat satellite imagery at 30 m. resolution available from the

United States Geological Survey (USGS) for the years 2001-2011 is used. Based on our selection of one May-June image per year, NDVI is calculated for each 30 m. pixel in the Tucson Water service area in each year. The 30 m. pixels are then resampled to 1 m. resolution. By overlaying parcel boundaries on Landsat pixels in a geodatabase, a zonal mean NDVI value is calculated over the extent of each parcel. In this way, we obtain an average measure of parcel greenness in peak irrigation season for each parcel in each year.

The variables discussed in this chapter are used in the next chapter to empirically estimate demand for water.

5. Econometric Methods and Demand Estimation

This chapter details the econometric methods used to estimate a demand function for SFR water consumption in Tucson, AZ, and presents the results of our demand analysis. First, the construction of an appropriate price variable is discussed in light of the problem of simultaneity posed in Chapter 3. Then, the structure of the household and aggregate demand models are described, and the results of our estimation procedures summarized. Finally, the results of our analysis of the sensitivity of household water consumption to potential climate change are presented.

5.1 Constructing the Price Variable

As discussed in Chapter 3, we select an average price specification for our analysis in order to accurately model the data generating process involved in SFR household water consumption decisions. In both models, we choose to lag our price variable by one period-ending month, since consumers can only see their bill from the prior billing cycle when making decisions about their consumption in the current billing period. Theoretically, at least, this should overcome the simultaneity issue traditionally posed by the use of average price specifications in demand estimation; quantity in the current billing period is being explained by the average per unit price in the prior billing period. However, in practice the values of average price in the prior billing period may still be correlated with model errors since average price per unit tends not to vary much between billing cycles. Therefore, to avoid issues related to such correlation, we instrument lagged average price before including the price variable in our models. The process of calculating and estimating this instrumented price variable differs between our aggregate and household analyses, so these two procedures are discussed separately below.

5.1.1 Calculating Instrumented Price for Household Analysis

Calculating the average per-unit price faced by each household in each billing cycle is a straightforward procedure. The total bill for household *i* in a given billing cycle *t* is divided by the quantity consumed in *t*:

$$AP_{i,t} = \frac{TotalBill_{i,t}}{Q_{i,t}} ,$$

Where:

i : 1,…,2,000

t : 1,…,156

Lagged average price is calculated similarly, with the exception that the total bill and quantity consumed from the prior period are used:

$$AP_{i,t-1} = \frac{TotalBill_{i,t-1}}{Q_{i,t-1}}$$

Our preference would have been that this value for lagged average price enter the model directly. However, after performing a Durbin-Wu-Hausman test on a preliminary pooled OLS panel model containing this price variable, we reject the null hypothesis of the exogeneity of price at the 99% confidence level. Opaluch (1984) explains that the persistence of endogeneity here indicates a strong correlation between lagged average price and current period average price that results from the habitual nature of water usage. Therefore, we address this remaining endogeneity by using an instrumental variables (IV) approach to estimate lagged average price before including the price variable in our final model. This IV procedure involves regressing lagged average price on a series of explanatory (instrumental) variables and incorporating the predicted values into our final model as an instrument for lagged average price. The explanatory variables used in the IV regression resemble those used by Klawitter (2014). The IV model estimated is as follows:

$$AP_{i,t-1} = \beta_0 + \beta_1 IV_1 + \beta_2 IV_2 + \beta_3 IV_3 + \beta_4 IV_4 + \beta_5 IV_5 + \beta_6 IV_6 + \beta_7 IV_7 + \beta_8 IV_8 + \beta_9 IV_9 + \beta_{10} IV_{10} + u_i + \varepsilon_{i,t}$$

Where:

IV_1 : Total annual cost of water for each household

IV_2 : Block 1 price in real Dec. 2011 dollars

IV_3 : Difference in real price between Block 2 and Block 1

IV_4 : Difference in real price between Block 3 and Block 2

IV_5 : Difference in real price between Block 4 and Block 3

IV_6 : Conservation charge in real Dec. 2011 dollars

IV_7 : CAP charge in real Dec. 2011 dollars

IV_8 : Sewer commodity charge in real Dec. 2011 dollars

IV_9 : Sewer administrative fee in real Dec. 2011 dollars

IV_{10} : Garbage fee in real Dec. 2011 dollars

u_i : Individual-specific model error

$\varepsilon_{i,t}$: Model error resulting from measurement error

According to Wooldridge (2010), a strong instrumental variable is one that is highly correlated with the independent variable causing the endogeneity problem and uncorrelated with the error term of the final regression model. For this reason, the explanatory variables used in the IV regression resemble those used by Klawitter (2014). Klawitter argues that each of these variables except for IV_1 is determined by the utility and thus should not be correlated with quantity consumed in a given billing period. And while IV_1 is correlated with total annual consumption, it should not be highly correlated with consumption in any given billing cycle.

Using the equation above, a pooled ordinary least-squares (OLS) panel model is estimated to explain lagged average price. The results of this IV regression are shown below in Table 1. Despite the low R^2 value, the overall F-statistic indicates that the model has explanatory power at the 99% confidence level. Of the individual variables, all except IV_5 are shown to be significant at the 99% confidence level. However, since Klawitter (2014) estimates that the probability of any user consuming in Block 4 in a given billing cycle to be less than 2%, this result is not surprising. The overall significance of the model and the included regressors indicates that the IV estimates of lagged average price should be suitable for use in our final demand model.

Table 1: IV Panel OLS Regression Results, Dependent Variable: Lagged Average Price

Variable	Parameter Estimate (p-value)
Intercept	7.3022 (0.000)
IV_1	-0.0009 (0.000)
IV_2	-1.3256 (0.000)
IV_3	-3.0952 (0.000)
IV_4	4.1884 (0.263)
IV_5	-0.2902 (0.001)
IV_6	-5.4671 (0.000)
IV_7	-13.3899 (0.000)
IV_8	2.6823 (0.000)
IV_9	0.0691 (0.000)
IV_{10}	0.0727 (0.000)
R^2	0.1321
F-test	3657.19 (0.000)

5.1.2 Calculating Instrumented Price for Aggregate Analysis

Determining the appropriate price metric for an analysis of aggregated water use is less straightforward than in the household-specific case. Since Tucson SFR water consumers do not make consumption decisions collectively, it is useful to conceptualize the behavior of a "representative" SFR consumer, whose behavior reflects the average level of consumption of SFR households. For the same reasons given in the case of individual households, this representative consumer can be expected to respond to the average per-unit price faced by all SFR households. We calculate this average price as the total expenditure of all SFR consumers in our dataset in a given period-ending month divided by the total usage among all SFR customers in the same period ending month, shown below:

$$AP_t = \frac{\left(\sum_{i=1}^{n} TotalBill_i\right)_t}{\left(\sum_{i=1}^{n} Q_i\right)_t}$$

Where:

i : 1,…,127,644

t : 1,…,156

Just as in the household analysis, we expect that the representative SFR consumer will respond to the price they paid in their last billing period, so we lag our average price metric as follows:

$$AP_{t-1} = \frac{\left(\sum_{i=1}^{n} TotalBill_i\right)_{t-1}}{\left(\sum_{i=1}^{n} Q_i\right)_{t-1}}$$

Once again, we run a preliminary OLS regression utilizing a Durbin-Wu-Hausman test to determine whether lagged average price is correlated with the model errors. We reject the null hypothesis that lagged average price is exogenous at the 99% confidence level, and therefore turn to IV estimation methods to circumvent this issue. We use a simplified version of the IV model used to predict lagged average price for individual households. The only difference is that we ignore the variation in the fixed charges of the water bill, since we are not concerned with individual household differences and these charges tend to vary little over time. The model used to predict values of lagged average price for the aggregate analysis is shown below:

$$AP_{t-1} = \beta_0 + \beta_1 IV_1 + \beta_2 IV_2 + \beta_3 IV_3 + \beta_4 IV_4 + \beta_5 IV_5 + \varepsilon_t$$

Where:

IV_1 : Total annual cost of water for each household

IV_2 : Block 1 price in real Dec. 2011 dollars

IV_3 : Difference in real price between Block 2 and Block 1

IV_4 : Difference in real price between Block 3 and Block 2

IV_5 : Difference in real price between Block 4 and Block 3

ε_t : Random error

We estimate this model using OLS. Results are summarized in Table 2. Three of the variables are significant at the 99% confidence level, while IV_1 is significant at the 95% confidence level. Only IV_4 is not significant at any commonly accepted level of confidence. Nonetheless, the high R^2 value and the significance of the overall F-statistic at the 99% confidence level assure us that the predicted values of lagged average price will be sufficient to estimate water demand.

Table 2: IV OLS Regression, Dependent Variable: Lagged Average Price

Variable	Parameter Estimate (p-value)
Intercept	-1.076173 (0.170)

IV_1	0.0000000626 (0.032)
IV_2	77.7878 (0.001)
IV_3	358.9279 (0.001)
IV_4	-258.3305 (0.113)
IV_5	-92.76932 (0.000)
R^2	0.7093
F-test	79.04 (0.000)

5.2 Demand Estimation

Once we constructed appropriate price variables for both analyses, we proceeded to specify our model structures. As discussed in Chapter 3, we estimate demand functions of the Stone-Geary functional form, following closely the model of Gaudin, Griffin, and Sickles (2001). They show that while the Stone-Geary function is always nonlinear in the variables, it can be written as either linear or nonlinear in the parameters. While they argue that the linear model is likely to produce parameter estimates that are inefficient, they find little difference between the results of their linear and nonlinear estimation procedures. We estimate only linear demand models in this analysis and address the issue of efficiency ex post.

Gaudin, Griffin, and Sickles (2001) present two alternative formulations of the Stone-Geary demand function. The first, which we will refer to as the Stone-Geary Fixed (SGF) model assumes that the conditional water use threshold parameter (γ) is a linear function of the exogenous variables, while the marginal budget share (β) is fixed. This model takes the form:

$$Q = (1-\beta)(\alpha_0 + \sum_{i=1}^{k} \alpha_i C_i) + \beta \frac{I^*}{P}$$

Where:

C_i : Control variable *i*

k : Number of control variables

$$\gamma = \alpha_0 + \sum_{i=1}^{k} \alpha_i \bar{C}_i$$

To estimate this model linearly using OLS, the estimable function is:

$$Q = \alpha'_0 + \sum_{i=1}^{k} \alpha'_i C_i + \beta \frac{I^*}{P}$$

Where:

$$\alpha'_i = \frac{\alpha_i}{(1-\beta)}$$

$$\gamma = (1-\beta)(\alpha'_0 + \sum_{i=1}^{k} \alpha'_i \bar{C}_i)$$

The SGF model requires post-estimation calculation of γ , as shown above. The delta method is used to determine the standard error and assess the significance of this parameter. This process is detailed in Appendix 9.

The second formulation of the Stone-Geary model allows both γ and β to vary with the exogenous regressors. We refer to this model as the Stone-Geary Variable (SGV) model.

$$Q = [1-(\beta_0 + \sum_{i=1}^{k} \beta_i C_i)](\alpha_0 + \sum_{i=1}^{k} \alpha_i C_i) + (\beta_0 + \sum_{i=1}^{k} \beta_i C_i) \frac{I^*}{P}$$

Where:

C_i : Control variable *i*

k : Number of control variables

$$\gamma = \alpha_0 + \sum_{i=1}^{k} \alpha_i \bar{C}_i$$

$$\beta = \beta_0 + \sum_{i=1}^{k} \beta_i \bar{C}_i$$

For linear estimation, the estimable equation becomes:

$$Q = \alpha'_0 + \sum_{i=1}^{k} \alpha'_i C_i + (\beta_0 + \sum_{i=1}^{k} \beta_i C_i)\frac{I^*}{P}$$

Where:

$$\alpha'_i = \frac{\alpha_i}{(1-\beta)}$$

$$\beta = \beta_0 + \sum_{i=1}^{k} \beta_i \bar{C}_i$$

$$\gamma = (1-\beta)(\alpha'_0 + \sum_{i=1}^{k} \alpha'_i \bar{C}_i)$$

In the SGV case, both γ and β must be calculated outside of the linear estimation procedure, as well as their respective standard errors and significance levels. Appendix 9 details the procedure for calculating the standard errors of these parameters in order to determine their significance.

Both the SGF and SGV model formulations are estimated linearly in the aggregate and household analyses. In the sections that follow, we discuss demand estimation and results for the household and aggregate models.

5.2.1 Models of Household Water Demand

Aside from price and income, our household model includes several control variables. Because we have access to panel data, we are able to account for heterogeneity among SFR households within as well as between time periods. Weather variables are included primarily to control for seasonal and inter-annual variation in water consumption behavior, although spatially disaggregated precipitation measurements allow us to capture some cross-sectional heterogeneity. And while none of the variables in our household analysis can be considered strictly time-invariant, many of the remaining control variables, such as demographic, housing, and parcel characteristics, are included primarily to capture cross-sectional heterogeneity. The variables included in our household analysis are listed below in Table 3, along with their descriptive statistics.

Table 3: Household Variable Descriptive Statistics

Variable	Min	Mean	Max
Usage	0	12.22	288
Realinc	361.25	5,847.87	75,458.34
IV_price	1.91	6.60	8.97
IVinc_price	50.64633	957.20	16053.73
Tot_ET	0.7	6.66	20.28
LArea	0	17,148.27	646,685.4
IVNDVI	0.13	0.16	0.43
PoolArea	0	128.43	9999
ET_LArea_IVNDVI	0	19,829.67	2,206,306
PoolET	0	855.09	123,887.6
N_Rainy_Days	0	2.98	16
Daysinread	7	30.39	75
Hispanic	3	30.24	93.26
HHsize_avg	1.675	2.52	3.864
Per_under5	0.54	6.10	13.84
Per_65andover	0.8	14.40	65.86
IVinc_price_ ET_LArea_IVNDVI (millions)	0	38.9	33,500
IVinc_price_PoolET (millions)	0	1.36	399
IVinc_price _NRainyDays	0	2,929.156	138,580.2
IVinc_price_Days	1,441.89	29,094.88	520,884.3
IVinc_price_Hispanic	2,546.63	20,972.48	230,973.6
IVinc_price_HHsize	160.04	2,334.96	36,955.69
IVinc_price_under5	144.15	5,118.78	60,636.34
IVinc_price_65andover	164.74	15,497.65	383,438.2

Usage represents a particular household's total water consumption in a given billing cycle. This is the dependent variable in our household analysis.

Realinc is a particular household's monthly income in real Dec. 2011 dollars, calculated as described in Chapter 4, while *IV_price* represents the instrumented lagged average price we calculate in Section 5.1.1. It is worth noting that income and instrumented lagged average price are included in our model as a ratio ($\frac{I_{i,t}}{AP_{i,t-1}}$, denoted as *IVinc_price*) with a single coefficient rather than as two separate terms. This is characteristic of the Stone-Geary function and implies that price and income affect consumption through their relative levels only. We expect that, as income rises relative to price, water consumption will increase.

ET represents the total evapotranspiration measured over each billing period. We expect the effect of *ET* on water consumption to be positive; however, we expect the magnitude of this effect to vary with certain household characteristics. Since evapotranspiration measures the combined moisture evaporating from standing water bodies as well as transpiring from vegetation, we attempt to account for household-level differences in both of these processes by considering water use for both filling pools and irrigating landscapes. Evaporation from pools is a major contributor to household-level ET, so we interact ET with pool size (*PoolET*) to account for household-level differences in evaporation. To capture the effect of transpiration on household water demand, we consider both how much vegetation each yard contains – as measured by the greenness index NDVI in peak irrigation season (May-June) – and the size of the portion of each parcel that is available for landscaping. *LArea* corresponds to the landscapable area of a given parcel, while *NDVI* represents the average greenness of a given parcel in May or June of each year. During the development of our model, we received feedback that *NDVI* is likely to be dependent on the amount of water consumed for irrigation as well as the price of water. To test this, we conduct a Durbin-Wu-Hausman test for endogeneity and reject the null hypothesis of exogeneity with 99% confidence. Therefore, we instrument *NDVI* using house construction year, house assessed value, and parcel area (see Appendix 10). Once this endogeneity is accounted for, *ET*, *LArea*, and *IVNDVI* – the instrumented values of *NDVI* – enter our model as a triple interaction variable (*ET_LArea_IVNDVI*). We expect the signs of both *PoolET* and *ET_LArea_IVNDVI* to be positive.

N_Rainy_Days corresponds to the number of days in a given billing cycle for which some level of precipitation was measured at the nearest PCFCD rain gauge to a given household. We expect that households will cut back on outdoor irrigation on or around days with rainfall events, and thus anticipate that this variable will have a negative impact on total water consumption.

Daysinread represents the number of days in a given household's billing cycle in a particular period-ending month. Recall that, while billing periods are matched to unique period-ending months by Tucson Water, the length of each billing period may not necessarily correspond to the dates of its period-ending month, and in fact rarely does. We expect the length of a billing period to have a positive effect on the level of total consumption per household in a particular billing period.

Hispanic represents the percentage of the population in a given Census tract of Hispanic or Latino origin of any race. Previous studies have shown that a higher proportion of people of Hispanic or Latino origin in a given area can have a negative impact on water consumption (Gaudin, Griffin, and Sickles 2001; Balling, Gober, and Jones 2008; Ray 2012), possibly due to the correlation of ethnicity and immigrant status.

HHsize_avg is the average household size in a given Census tract. Households with more members are expected to consume more water.

Per_under5 and *Per_65andover* correspond to the percentage of the population in a given Census tract below the age of 5 and above the age of 65, respectively. These age brackets represent groups that typically spend more time at home and may consume more water there. Very young children are often not in school and typically take baths rather than showers, which may lead to higher water use. Likewise, we expect retirees to use more water than most working-age adults as they probably spend more time at home and may be more likely to have vegetation-intensive landscaping, such as gardens. We expect the sign on both of these variables to be positive.

The last set of variables in Table 3 – *IVinc_price_ET_LArea_IVNDVI*, *IVinc_price_PoolET*, *IVinc_price_NRainyDays*, *IVinc_price_Days*, *IVinc_price_Hispanic*, *IVinc_price_HHsize*, *IVinc_price_under5*, and *IVinc_price_65andover* – represent interaction variables in which the ratio of real household monthly income to instrumented lagged average price is multiplied by each of the control variables. They are included in the SGV model specification to allow β to vary with the control variables in the model as well as γ. In the SGV model formulation, the effect of each control variable on total water consumption is really a net of the relationship between each control variable and the levels of β and γ. In this case, the sign of individual coefficients on the control variables or their interactions with price are of little interest per se, but the net effect of each control variable on total water consumption should be roughly the same as that in the SGF model formulation.

Our household sample dataset is an unbalanced panel with observations from 1,994 households over the period July 2001 – June 2011, which corresponds to 10 years or a maximum of 120 monthly observations per household. The total number of observations in this dataset is 216,564. Table 4 summarizes this information. The panel is unbalanced for two reasons: 1) many households received bills at a less-than-monthly frequency, and 2) several households were added to the dataset throughout the study period due to new construction. We choose not to restrict our sample to households with billing cycles in each month of our study period since newly-constructed households tend to have more water-efficient fixtures, and we want to account for the effect of such fixtures on water consumption.

Table 4: Household Unbalanced Panel Dataset Summary

	Number of Observations	216,546
	Number of Households	1,994
Observations Per Household	Minimum	5
	Mean	108.6
	Maximum	120

The structure of our two household models is as follows. The SGF model takes the following form:

$$Usage_{i,t} = \alpha'_0 + \alpha'_1(ET\_LArea\_IVNDVI)_{i,t} + \alpha'_2(PoolET)_{i,t} + \alpha'_3(N\_Rainy\_Days)_{i,t}$$
$$+\alpha'_4(DaysinRead)_{i,t} + \alpha'_5(Hispanic)_{i,y} + \alpha'_6(HHsize\_avg)_{i,y} + \alpha'_7(Per\_under5)_{i,y}$$
$$+\alpha'_8(Per\_65andover)_{i,y} + \beta(IVinc\_price)_{i,t} + u_i + \varepsilon_{i,t}$$

Where:

i : 1,…,1994

t : 1,…,120

y : 2001,…,2011

u_i : Individual-specific model error

$\varepsilon_{i,t}$: Idiosyncratic error

The SGV model has a similar structure, except that terms for the interaction between *IVinc_price* and each of the control variables are included as well:

$$Usage_{i,t} = \alpha'_0 + \alpha'_1(ET\_LArea\_IVNDVI)_{i,t} + \alpha'_2(PoolET)_{i,t} + \alpha'_3(N\_Rainy\_Days)_{i,t}$$
$$+\alpha'_4(DaysinRead)_{i,t} + \alpha'_5(Hispanic)_{i,y} + \alpha'_6(HHsize\_avg)_{i,y} + \alpha'_7(Per\_under5)_{i,y}$$
$$+\alpha'_8(Per\_65andover)_{i,y} + \beta_0(IVinc\_price)_{i,t} + \beta_1(IVinc\_price\_ET\_LArea\_NDVI)_{i,t}$$
$$+\beta_2(IVinc\_price\_PoolET)_{i,t} + \beta_3(IVinc\_price\_NRainyDays)_{i,t} + \beta_4(IVinc\_price\_Days)_{i,t}$$
$$+\beta_5(IVinc\_price\_Hispanic)_{i,t} + \beta_6(IVinc\_price\_HHsize)_{i,t} + \beta_7(IVinc\_price\_under5)_{i,t}$$
$$+\beta_8(IVinc\_price\_65andover)_{i,t} + u_i + \varepsilon_{i,t}$$

Where:

i : 1,…,1994

t : 1,…,120

y : 2001,…,2011

u_i : Individual-specific model error

$\varepsilon_{i,t}$: Idiosyncratic error

Diagnostic tests are performed to determine the appropriate estimation procedure for each model formulation. Breusch-Pagan tests reveal the presence of heteroskedasticity in both of the model formulations. Likewise, we find evidence of autocorrelation in both models, using a STATA program developed by Drukker (2003) to implement Wooldridge's test for first-order serial correlation in panel data models (2010). Finally, a Hausman test is used to compare random-effects (RE) estimation to fixed effects (FE) estimation and test for the presence of household-specific fixed effects. However, the traditional formulation of the Hausman test has been shown to lead to invalid statistical inference in the presence of heteroskedasticity. Wooldridge (2010) details the implementation of a Hausman test via an auxiliary OLS regression procedure with panel-robust standard errors to correct for heteroskedasticity. We use a STATA program developed by Hoechle (2007) to implement this version of the Hausman test. In both the SGF and SGV models, the test favors FE specifications. Table 5 presents the results of these diagnostic tests.

Table 5: Household Model Diagnostics

	SGF		**SGV**	
Test	Test Statistic	Value (p-value)	Test Statistic	Value (p-value)
Breusch-Pagan	$\chi^2(9)$	5858.76 (0.000)	$\chi^2(25)$	6075.58 (0.000)
Wooldridge	F(1,1993)	729.19 (0.000)	F(1,1993)	737.86 (0.000)

Hausman	F(9, 216527)	20.62 (0.000)	F(17, 216511)	11.81 (0.000)

Both the SGF and SGV model formulations are estimated as fixed-effects (FE) unbalanced panel models via a feasible generalized least-squares (FGLS) procedure, and significance is determined using Huber/White/sandwich standard errors to account for heteroskedasticity. It should be noted that the Huber/White/sandwich approximation of the variance-covariance matrix does not account for the presence of autocorrelation in the estimated models, and we do not attempt to explicitly account for it. The most likely explanation for the occurrence of autocorrelation in these models is model misspecification, which we believe reflects more the limited availability of precise and complete household data than a lack of thorough consideration of the determinants of water demand on our part. Nonetheless, we do not expect the presence of autocorrelation to significantly alter inference from the model results given the adjustments already made for fixed effects and heteroskedasticity. The results of our estimation procedures are summarized in Table 6 below.

Table 6: Household Model Results

		SGF	**SGV**
Variable	Parameter	Estimate (p-value)	Estimate (p-value)
Intercept	α'_0	-6.4521 (0.147)	-1.7294 (0.686)
ET_LArea_IVNDVI	α'_1	0.0001 (0.000)	0.0001 (0.000)
PoolET	α'_2	0.0003 (0.000)	0.0002 (0.020)
N_Rainy_Days	α'_3	-0.0819 (0.000)	-0.1027 (0.000)
Daysinread	α'_4	0.3080 (0.000)	0.1965 (0.000)

Hispanic	α'_5	-0.1162 (0.001)	-0.1128 (0.004)
HHsize_avg	α'_6	2.9254 (0.036)	0.7106 (0.649)
Per_under5	α'_7	0.1713 (0.307)	0.6247 (0.013)
Per_65andover	α'_8	0.0682 (0.313)	0.1285 (0.127)
IVinc_price	β	0.0023 (0.000)	
IVinc_price	β_0		-0.0021 (0.378)
IVinc_price_ET_LArea_NDVI	β_1		2.43×10^{-9} (0.000)
IVinc_price_PoolET	β_2		0.0000 (0.222)
IVinc_price_NRainyDays	β_3		0.0000 (0.132)
IVinc_price_Days	β_4		0.0001 (0.000)
IVinc_price_Hispanic	β_5		0.0001 (0.001)
IVinc_price_HHsize	β_6		0.0012 (0.276)
IVinc_price_under5	β_7		-0.0005 (0.005)
IVinc_price_65andover	β_8		0.0000 (0.295)
	β	0.0023 (0.000)	0.0029 (0.000)
	γ	10.0163 (0.000)	9.6138 (0.000)
	F-test	244.01 (0.000)	Not Reported

From these results, we can see that many of our expectations regarding the relationships between the control variables and the dependent variable are confirmed. In both models, the coefficient on *ET_LArea_IVNDVI* is positive and highly significant. Consumers with larger, greener yards tend to use more water than other households when the evaporative demand of their landscaping is high.

Likewise, the sign of the *PoolET* coefficient indicates that consumers with larger pools tend to use more water when weather conditions result in substantial evaporation. Although these results are expected, they are particularly notable since their inclusion in a model of water demand is relatively novel.

Both models also suggest a highly significant negative relationship between the number of rainy days per month and total water consumption. It appears that households respond to the occurrence of rainfall, of any amount, by reducing water consumption, presumably for irrigation purposes. We did attempt to substitute total monthly precipitation for number of rainy days in both models, but number of rainy days outperformed this more precise metric in both cases. This is intuitively satisfying because it suggests that consumers rely more on simple heuristics than precise weather metrics when making their irrigation decisions. Since most households do not maintain their own precipitation gauges, they are more likely to rely on a glance out their window to see if it is raining than a precise measurement of rainfall when determining whether to reduce their irrigation demand.

Daysinread also has a highly significant impact on total household water consumption, according to both models, as we expect. Longer billing cycles result in significantly higher household consumption. This may seem obvious, but without controlling for the impact of billing cycle length, comparisons of price response across billing cycles would be biased.

The remaining control variables in both models represent demographic characteristics taken from the 2000 and 2010 Census. These variables are measured by Census tract rather than by household, so cross-sectional variation in observations is limited. Also, Census data are measured at 2 points in time and are interpolated annually for the remaining years, so temporal variation is minimal. Nonetheless, some significant results are found.

The SGF model suggests that the proportion of Hispanic or Latino residents in a given Census tract has a negative impact on household water consumption. This result is significant at the 99% confidence level in both models. Thus, the models provide support for the notion that cultural characteristics specific to Hispanic and Latino households, such as a potentially higher reliance on bottled water, may influence municipal water consumption.

The coefficient estimated for *HHsize_avg* is positive in both models, but is only significant at the 95% confidence level in the SGF model. This indicates that larger households tend to consume more water, as we would expect. Had the scale of data collection been improved, the significance of this coefficient may have been stronger in both models.

With regard to household age distribution, our model results are much weaker. The SGV model indicates that water consumption is higher in Census tracts with a higher proportion of children under age 5. However, this result is not significant in the SGF model. We expect that this discrepancy might disappear if the variables could be measured at a finer spatial and temporal scale. Similarly, while the coefficients on *Per_65andover* are positive in both models, neither model indicates a significantly higher level of water use in Census tracts with a higher proportion of elderly (age 65+) residents.

Despite all the discussion about the relationship between the control variables and total water consumption both here and in the literature, β and γ remain the parameters of primary interest in our study. In both models, these parameters are found to be significant at the 99% confidence level. As expected, β is positive, implying that an increase in household income relative to price should lead to higher household water consumption. Likewise, γ is positive and represents the level of consumption below which households will not respond to price.

Based on the estimated values of β and γ, the SGF demand model takes the form:

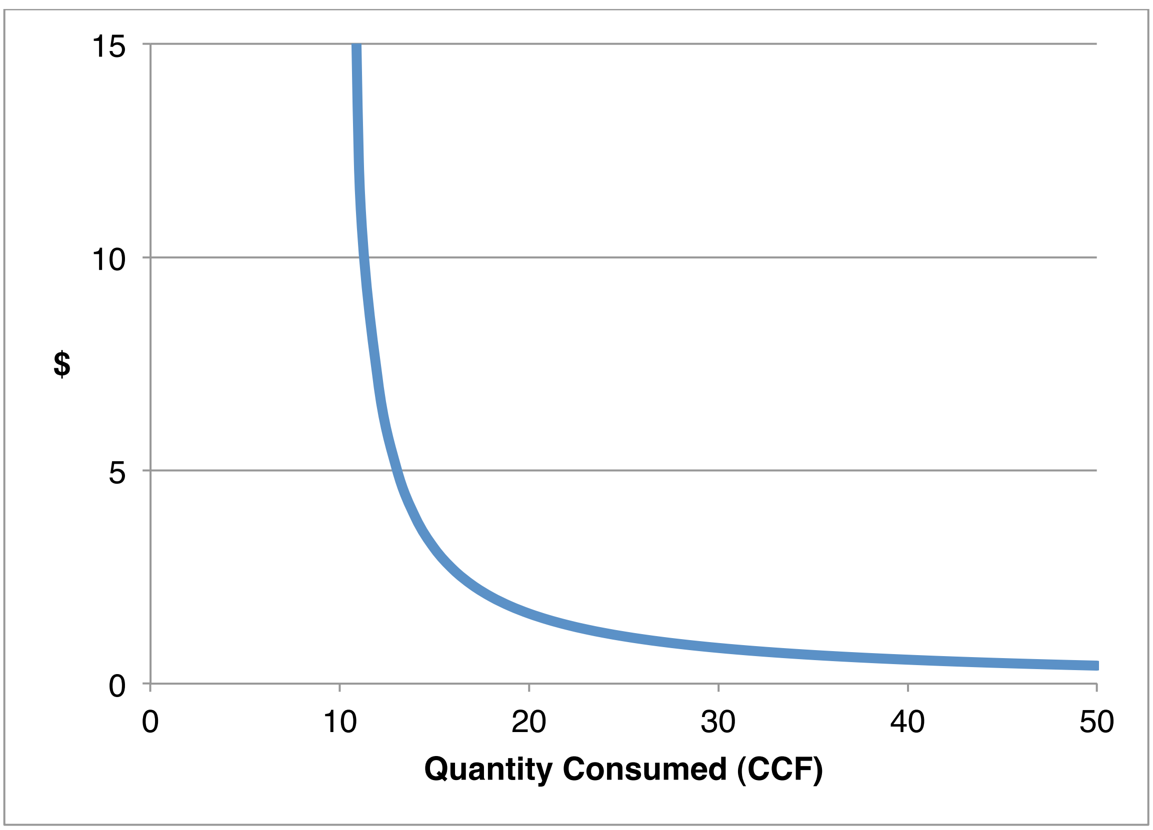
$$Q = 10.0163 + 0.0023\frac{I^*}{P}$$

The SGV demand model looks very similar, with a slightly higher estimated conditional water use threshold (γ) and a slightly larger marginal budget share (β) allocated to water:

$$Q = 9.6138 + 0.0029\frac{I^*}{P}$$

Since these two demand curves are so similar, we plot only the SGV demand function at mean income in Figure 9 below. Note the asymptotic behavior of the demand curve as it approaches the conditional water use threshold from the right.

Figure 9: Household Water Demand (SGV Model)



Like the values of the two Stone-Geary parameters, price and income elasticity of demand must also be calculated ex post. As described in Chapter 3, the Stone-Geary demand function restricts price and income elasticity of demand to be equal in magnitude and opposite in sign ($-\varepsilon_p = \varepsilon_I$). These calculations depend on the level of income, the quantity consumed, and the price faced by a given household. We calculate price and income elasticity at mean values for the control variables as well as mean values of household income, quantity consumed, and price. These estimates are displayed in Table 7. In every case, the SGV model provides elasticity values of slightly greater magnitude than the SGF model. Regardless, these elasticity estimates are similar to those typically found in the literature.

Table 7: Household Model Price and Income Elasticity Calculations

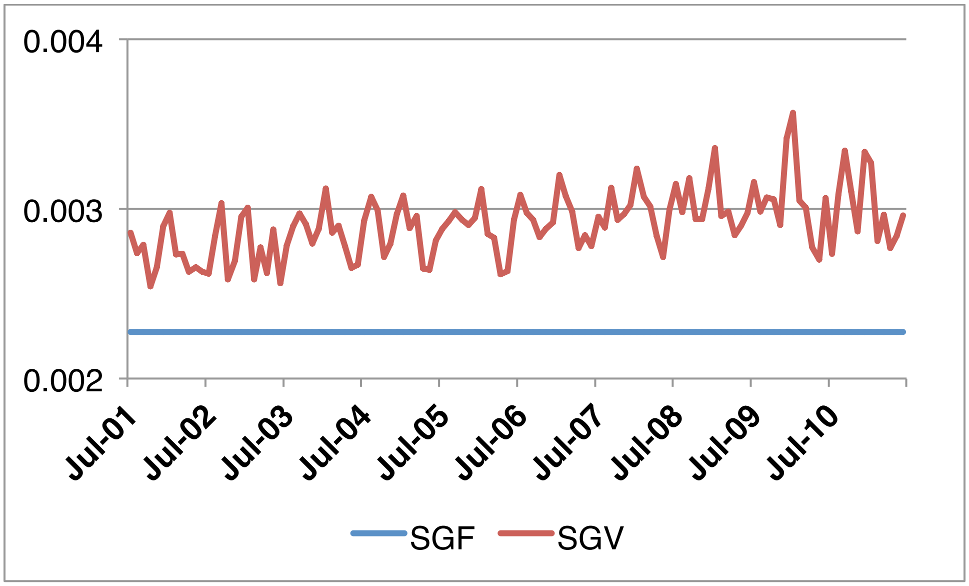
$$\varepsilon_p = \frac{-\beta I *}{PQ} \text{ and } \varepsilon_I = \frac{\beta I *}{PQ}$$

	SGF	SGV
ε_p	-0.165	-0.212
ε_I	0.165	0.212

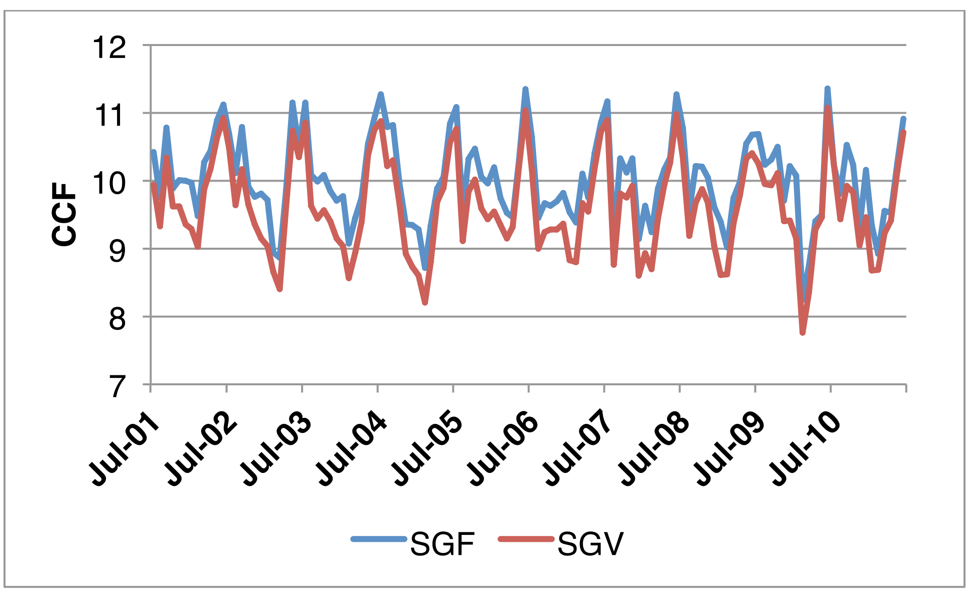
Perhaps more interesting than examining elasticity at a single average value of β and γ is to look at the variation in these two parameters and the corresponding price elasticity of demand over the study period. Although it would be too much to display the temporal variation in these parameters for each household in our sample, we can examine how the average values of the parameter and elasticity estimates change over time. Using sample values of each variable in each period-ending month, β, γ, and ε_p are calculated for each household. These values are then averaged across all households and plotted by period-ending month to show how they typically vary throughout the study period. Figure 10 shows the temporal variation in these parameter and price elasticity estimates for both models.

Figure 10: Temporal Variation in Mean β, γ, and ε_p

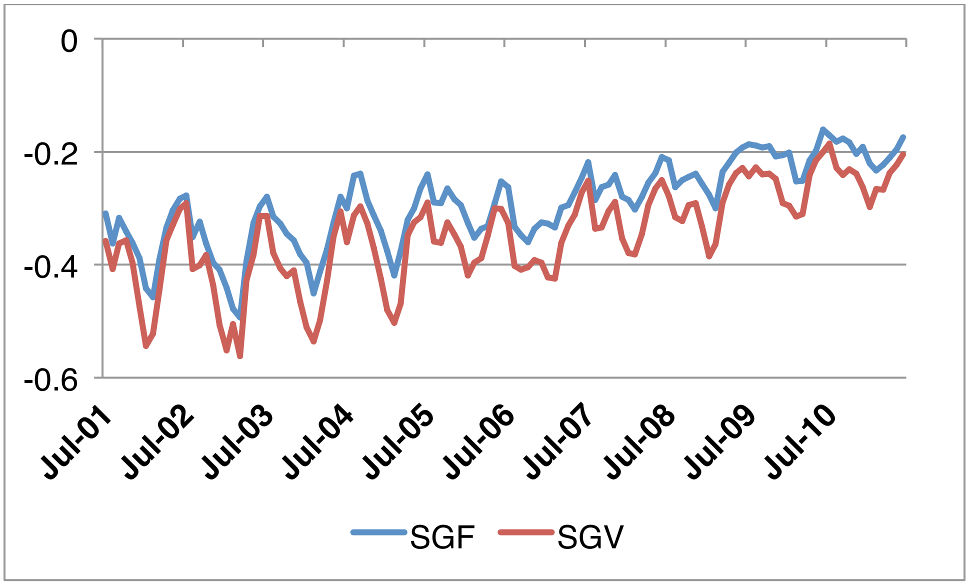
a) Temporal Variation in Mean β by Model Type



b) Temporal Variation in Mean γ by Model Type



c) Temporal Variation in Mean ε_p by Model Type



Note that β does not vary in the SGF calculations since the SGF model assumes β is fixed over time. Compare this to the SGV model, in which β absorbs some of the variation in γ. In the SGV model, variation in mean β is high and demonstrates an upward trend. In other words, the marginal budget share allocated to water appears to have increased over time for the typical Tucson SFR household.

And as the portion of monthly household income dedicated to water has increased, the level of water consumption the typical Tucson SFR household will not go without (γ) appears to have declined slightly. This level appears to fluctuate between roughly 8 and 12 CCF in a highly seasonal manner, owing to the significant influence of the weather control variables. Yet, if this seasonal variation is ignored, mean γ levels appear to trend slightly downward over time. The variation in γ in the early years of the study period appears to center roughly around 10 CCF, while in the latter years of the study period this variation centers closer to 9 CCF. Such trends would imply that, as water costs have taken up a larger portion of household income over time, households may have begun to question their assumptions about the amount of water they absolutely must consume. We test the significance of these temporal trends by regressing each Stone-Geary parameter (with the exception of β in the SGF model) on a 120-month time trend. The results, which are presented in Table 8, show that the upward trend in the marginal budget share in the SGV model is statistically significant at the 99% confidence level. However, the downward trend in the conditional water use appears more illusory than real; it is found to be significant only in the SGF model at the 90% confidence level.

Table 8: Significance of Household Stone-Geary Parameter Trends

Dependent Variable	Explanatory Variable	Coefficient (p-value)
β SGV	**Intercept**	-0.0002 (0.594)
	Date	0.0000001 (0.000)
γ SGF	**Intercept**	13.0937 (0.000)
	Date	-0.0001 (0.081)
γ SGV	**Intercept**	11.9889 (0.000)
	Date	-0.0001 (0.225)
ε_p SGF	**Intercept**	-2.3275 (0.000)
	Date	0.0001 (0.000)
ε_p SGV	**Intercept**	-2.4775 (0.000)
	Date	0.0001 (0.000)

Lastly, we present the temporal variation in price elasticity for the typical Tucson SFR household in our sample over time. This value demonstrates a much more obvious trend in both models, which is significant at the 99%

confidence level in both cases. Over the course of the study period, mean household price elasticity of demand declines in magnitude and its variability is dampened, implying that household demand is becoming less responsive to price over time. This is probably the result of the decline in per household water consumption shown in Figure 1. As households consume less, they move toward the more inelastic portions of their respective demand curves.

It should also be noted that the trend in mean price elasticity indicates that water consumption is most inelastic in summer. At face value, this may appear to contradict the findings of studies conducted by Howe and Linaweaver (1967) and Mansur and Olmstead (2012), which suggest that water consumption for outdoor use is price elastic while consumption for indoor use is not. However, we caution the reader to remember that the Stone-Geary function does not make a priori distinctions between water consumption for different uses explicitly, but rather accounts for changes in price elasticity at different levels of water consumption. This study is also not the only case in which a pattern of water consumption with more inelastic summer consumption has been identified. Thompson (2012) finds a similar pattern in his analysis of water demand in the Phoenix metro area. Mathematically, this can be explained by the fact that β, mean income, and mean price change very little throughout the year relative to mean quantity consumed. Behaviorally, however, this phenomenon is more difficult to explain. It appears that the proportional change in Tucson households' conditional water use threshold in summer is greater, on average, than the proportional change in mean use. In other words, while Tucson households consume more water overall in summer, they consider a larger percentage of this summer consumption to be necessary than they do in winter. Apparently, for many Tucsonans, irrigation is still a highly-valued use of water.

5.2.2 Models of Aggregate Water Demand

Next, we construct models of water demand for the representative Tucson SFR household using aggregated water consumption data for the 127,644 households in our dataset. Because Census data collected in 2000 and 2010 offer little temporal variation, we do not include demographic characteristics in this model. Neither do we include household-specific characteristics such as parcel size and house square footage, since we attempt to examine trends in Tucson SFR consumption as a whole. Rather, we focus on the control variables that provide the primary source of temporal variation: weather variables. The variables included in our analysis are listed in Table 9 below, along with their descriptive statistics. Because weather data are available from AZMET over the entire study period July 1998 – June 2011, we are able to estimate demand over this entire 156-month period as opposed to the shorter time span considered in the household model.

Table 9: Aggregate Variable Descriptive Statistics

Variable	Min	Mean	Max
StUsage_perHH	7.83	13.01	19.64
Realpcinc	37,465.24	44,338.29	48,037.84
IV_price	4.09	5.59	7.64
IVpcinc_price	5,010.01	8,149.32	11,049.57
N_Rainy_Days	0	4.54	15
ET	2.23	6.50	11.32
IVpcinc_price_NRainyDays	0	36,368.48	157,132.8
IVpcinc_price_ET	14,030.71	52,672.95	110,171.3

StUsage_perHH refers to the total SFR usage divided by the number of SFR households present in our dataset in each period-ending month, standardized to 30-day increments. Since we cannot match aggregated usage to actual billing dates, we cannot control for number of days in each billing cycle as in the household model. As a next-best alternative, we standardize usage to 30-day monthly observations in the following way:

$$StUsage\_perHH_t = \frac{\frac{Sum(Usage_i)_t}{n_t}}{d} \times 30$$

Where:

i : 1,…,n

t : 1,…,156

n : Number of households in a given month

d : Number of days in a given month

This is the dependent variable in our analysis.

Realpcinc and *IV_price* represent the real per capita income of the Tucson MSA and the value of our instrumented lagged average price. Neither of these variables is incorporated directly into our aggregate models, but the ratio of these two variables is used to develop the variable *IVpcinc_price*. We expect that, as the level of per capita income in the Tucson MSA increases relative to price, the water consumption of the representative Tucson SFR household will increase.

N_Rainy_Days corresponds to the number of rainy days per month as measured by AZMET. We expect this variable to be negatively related to the level of water consumption of the representative Tucson household.

ET is total monthly evapotranspiration for the Tucson area as measured by AZMET. We expect this variable to be positively related to representative household water consumption.

IVpcinc_price_nrainydays and *IVpcinc_price_ET* represent interactions between *IVpcinc_price* and the weather control variables *N_Rainy_Days* and *ET*, respectively. They are included in the SGV model formulation to allow β to vary with the values of the control variables, as in the household model.

As in the household analysis, we compare the SGF and SGV model formulations. The aggregate SGF model is specified as:

$$StUsage\_perHH_t = \alpha'_0 + \alpha'_1(N\_Rainy\_Days) + \alpha'_2(ET) + \beta(IVpcinc\_price) + \varepsilon_t$$

Where:

t : 1,…,156

Likewise, the SGV model takes the form:

$$StUsage\_perHH_t = \alpha'_0 + \alpha'_1(N\_Rainy\_Days) + \alpha'_2(ET) + \beta_0(IVpcinc\_price)$$
$$+\beta_1(IVpcinc\_price\_NRainyDays) + \beta_2(IVpcinc\_price\_ET) + \varepsilon_t$$

Where:

t : 1,…,156

We again conduct diagnostic tests to determine the appropriate estimation procedure for each model formulation. The results of these diagnostic tests are presented in Table 10. Because the aggregated data are only time-series and not panel, we do not need to perform a Hausman test. However, we still test for the presence of heteroskedasticity and autocorrelation. In the SGF model, the Breusch-Pagan test suggests that heteroskedasticity is present, but only at the 90% confidence level, whereas we do not find evidence of heteroskedasticity in the SGV case. To test for autocorrelation, we calculate a Durbin-Watson *d* statistic for both models. The resulting *d* value is significantly less than 2 in both cases, indicating that there is positive autocorrelation at 1 lag in both models.

Table 10: Aggregate Model Diagnostics

	SGF		SGV	
Test	Test Statistic	Value (p-value)	Test Statistic	Value (p-value)
Breusch-Pagan	$\chi^2(3)$	6.44 (0.092)	$\chi^2(5)$	7.30 (0.199)

Durbin-Watson	*d*(4, 156)	0.7258 (0.000)	*d*(6, 156)	0.7489 (0.000)

Both the SGF and SGV model formulations are estimated using OLS, and significance is determined using Newey-West standard errors. Newey-West standard errors are an extension of Huber/White/sandwich standard errors that also correct for autocorrelation at a specified lag – in this case, 1 time period (Wooldridge 2013). Since Huber/White/sandwich standard errors are robust to any form of heteroskedasticity, including homoskedasticity, the use of Newey-West standard errors should not present a problem even in the SGV case (Wooldridge 2010). The results of our estimation procedures are summarized in Table 11 below.

Table 11: Aggregate Model Results

		SGF	**SGV**
Variable	Parameter	Estimate (p-value)	Estimate (p-value)
Intercept	α'_0	5.4482 (0.000)	9.6730 (0.000)
N_Rainy_Days	α'_1	0.1751 (0.000)	0.142 (0.401)
ET	α'_2	0.6428 (0.000)	0.0185 (0.950)
IVpcinc_price	β	0.0003 (0.013)	
IVpcinc_price	β_0		-0.0002 (0.390)
IVpcinc_price_NRainyDays	β_1		0.0000 (0.813)
IVpcinc_price_ET	β_2		0.0001 (0.028)
	β	0.0003 (0.013)	0.0003 (0.008)
	γ	10.4154 (0.000)	10.4361 (0.000)

F-test	40.72 (0.000)	26.69 (0.000)

From these results, we can see that the control variable *N_Rainy_Days* does not behave as expected. It is only shown to be significant in the SGF model, but there its coefficient has a positive sign. This implies that the representative Tucson SFR household consumes more water during months with more rainy days, which directly contradicts the result we find in the household analysis. We expect that this result has to do with the fact that weather data for the "representative" Tucson consumer come from a single weather station, while weather data in the household analysis are more spatially disaggregated. Because of this counterintuitive result, we also run three alternative versions of both aggregate model specifications, but none proves superior to the version presented above. In the first, we interact number of rainy days with dummy variables for the months May-June and July-September to differentiate between the effects of rainfall in the dry summer months and the wetter monsoon summer months, respectively, on water consumption. In the second, we drop the number of rainy days variable entirely. In the third, we include the more traditional total monthly precipitation metric in place of number of rainy days per month. The results from these alternative model runs are discussed in Appendix 12.

The *ET* variable does perform as expected. Its sign is positive and significant at the 99% confidence level in the SGF model, implying that consumers use more water (presumably for irrigation) when the evaporative demand of the landscape is higher. In the SGV model, this variable is not significant, but its interaction with *IVpcinc_price* is, suggesting that higher ET levels may lead to more income being allocated to water consumption at the expense of other goods.

After estimation, we calculate the values of the Stone-Geary parameters for the marginal budget share allocated to water and the conditional water use threshold. Both parameter estimates are positive and significant at the 99%

confidence level in each model, as we would expect. Comparing the SGF and SGV model results, we find almost no difference between the levels of β or γ. This is not surprising given the level of aggregation of this dataset. According to these models, the typical Tucson Water SFR consumer will not consume less than about 10.5 CCF per month on average.

The estimated SGF model takes the form:

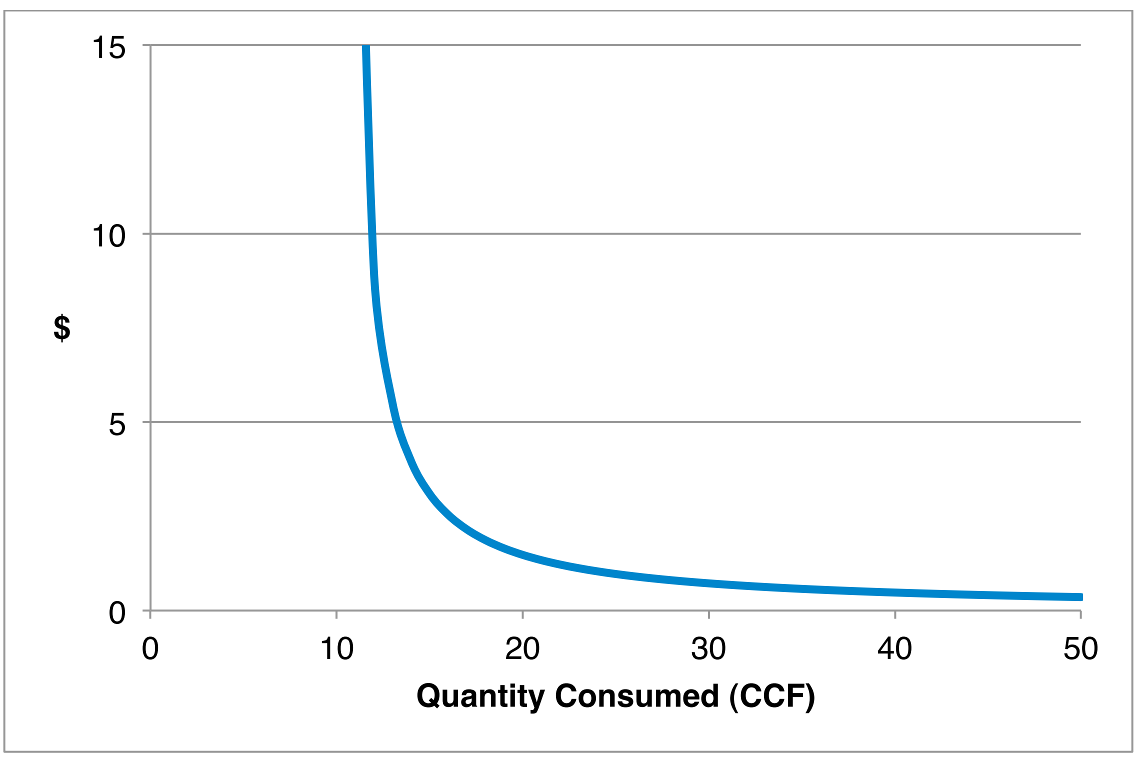
$$Q = 10.4154 + 0.0003\frac{I^*}{P}$$

Similarly, we estimate the SGV model as:

$$Q = 10.4361 + 0.0003\frac{I^*}{P}$$

Because these two models are almost identical, we present only the graph of the SGV model in Figure 11 below.

Figure 11: Aggregate Water Demand at Mean Income (SGV Model)



We also calculate price and income elasticity of demand estimates ex post. Elasticity estimates are again calculated at mean levels for all variables, including weather controls as well as standardized monthly quantity consumed, instrumented lagged average price, and per capita income. Mean elasticity estimates do not differ between the SGF and SGV model specifications. Nonetheless, they are well within the range typically found in the literature as well as the range defined by the two household models.

Table 12: Aggregate Model Price and Income Elasticity of Demand Calculations

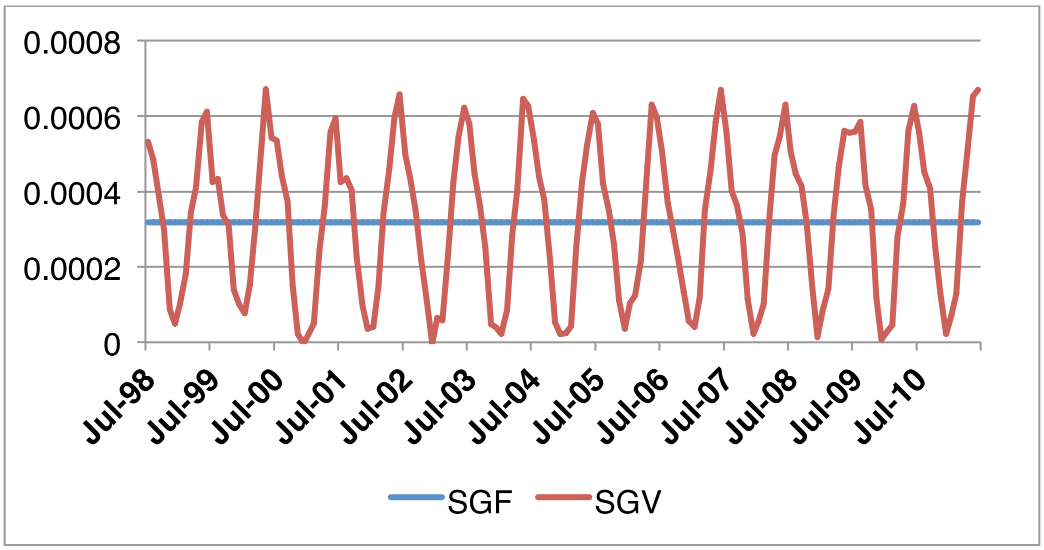
$\varepsilon_p = \frac{-\beta I*}{PQ}$ and $\varepsilon_I = \frac{\beta I*}{PQ}$

	SGF	SGV
ε_p	-0.194	-0.194
ε_I	0.194	0.194

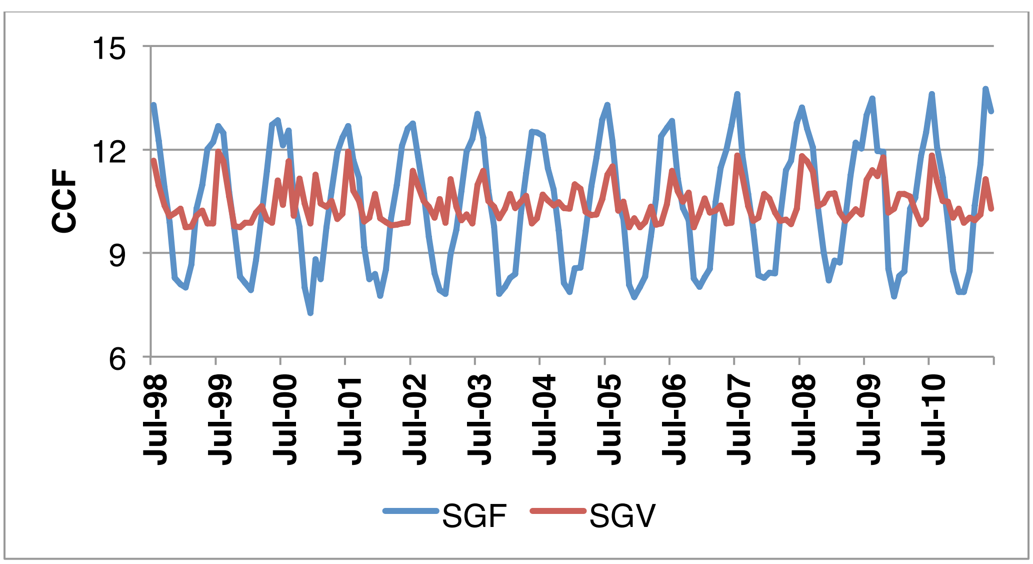
As in the household analysis, we also examine the variation in β , γ , and ε_p over time. For both the SGF and SGV models, we calculate each parameter and elasticity at sample values for all variables in each period-ending month and plot the time series below in Figure 12. Note that allowing β to vary once again results in significantly less seasonality in γ . While γ does still tend to increase during the summer, variation in γ in the SGV model appears to be more volatile throughout the rest of the year, owing to variations in the occurrence of rainfall. Also note also the stability of the range of γ over time. In the household model, there appears to be a slight downward trend in the conditional water use threshold, but here the temporal trend is almost perfectly horizontal. Price elasticity, on the other hand, appears highly volatile and highly seasonal in both models. Notably, like the household models, the SGF model suggests that water consumption is more inelastic in summer. However, the SGV model implies just the opposite – that water consumption is more elastic in summer than during the rest of the year. As in the household analysis, demand appears to become more inelastic over time, though this trend is less obvious here.

Figure 12: Temporal Variation in β, γ, and ε_p

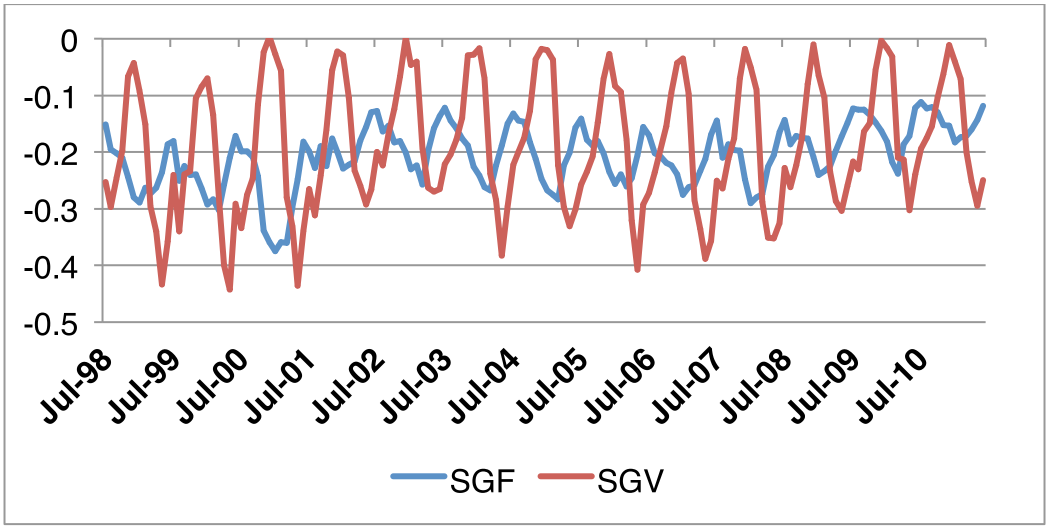
a) Temporal Variation in β



b) Temporal Variation in γ



c) Temporal Variation in Mean ε_p



We regress these parameter and elasticity values on 156-month time trends to assess the significance of any temporal trends that might be present. Unlike in the household analysis, we find significance in only two cases. There appears to be a slight upward trend in γ in the SGV model, significant at the 90% confidence level. Also, the trend toward a more inelastic price elasticity of demand is found to be significant at the 99% confidence level, but only in the SGF model.

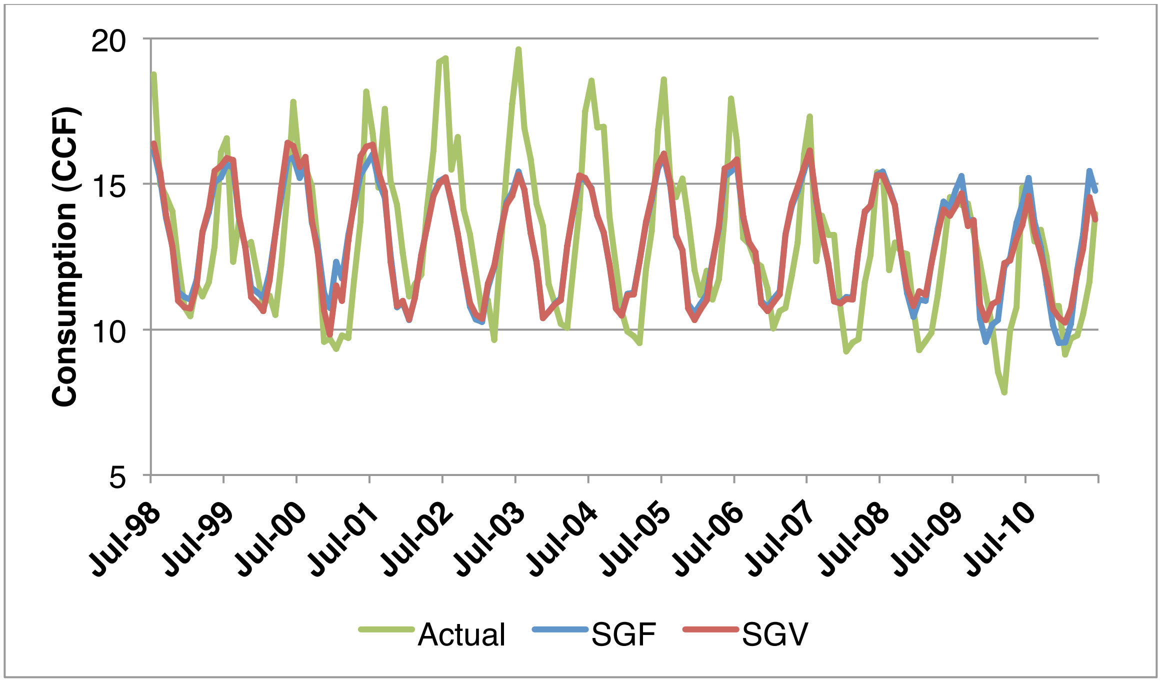
Table 13: Significance of Aggregate Stone-Geary Parameter Trends

Dependent Variable	Explanatory Variable	Coefficient (p-value)
β SGV	Intercept	0.0000 (0.988)
	Date	0.0000 (0.416)
γ SGF	Intercept	5.6958 (0.116)
	Date	0.0001 (0.186)

γ SGV	Intercept	8.2296 (0.000)
	Date	0.0001 (0.060)
ε_p SGF	Intercept	-0.7483 (0.000)
	Date	0.00001 (0.000)
ε_p SGV	Intercept	-0.4237 (0.065)
	Date	0.0000 (0.306)

Finally, in Figure 13, we compare predicted values of per household consumption – representative household consumption – from both model specifications with actual per household consumption over the study period. The two models appear almost identical here, and while they do capture some of the general downward trend in per household usage, they fail to account for high peak summer use in the years 2000 – 2006 as well as unusually low winter use in the years 2008 – 2010. We expect that the reason the model under-predicts so drastically in the summer season from 2000 to 2006 is the counterintuitive positive coefficient on *N_Rainy_Days*. According to Mike Crimmins, a climatologist at the University of Arizona, these years, particularly 2002 and 2003, represent anomalies in the historical record in terms of their somewhat higher temperatures and extremely low levels of precipitation. Indeed, AZMET total precipitation over the study period averages 2.71 inches in July, but from 2000 to 2006, July precipitation levels range from as low as 0.4 inches to a maximum of 1.88 inches. On the other hand, July precipitation levels in the remaining years of the study period total 2.4 inches or more. This translates into a lower number of rainy days in the summer months from 2000 to 2006. Since our estimated coefficient on number of rainy days is positive, the model necessarily predicts lower than actual consumption in low rainfall years. The converse is true in high rainfall years.

Figure 13: Actual vs. Predicted Consumption Per Household



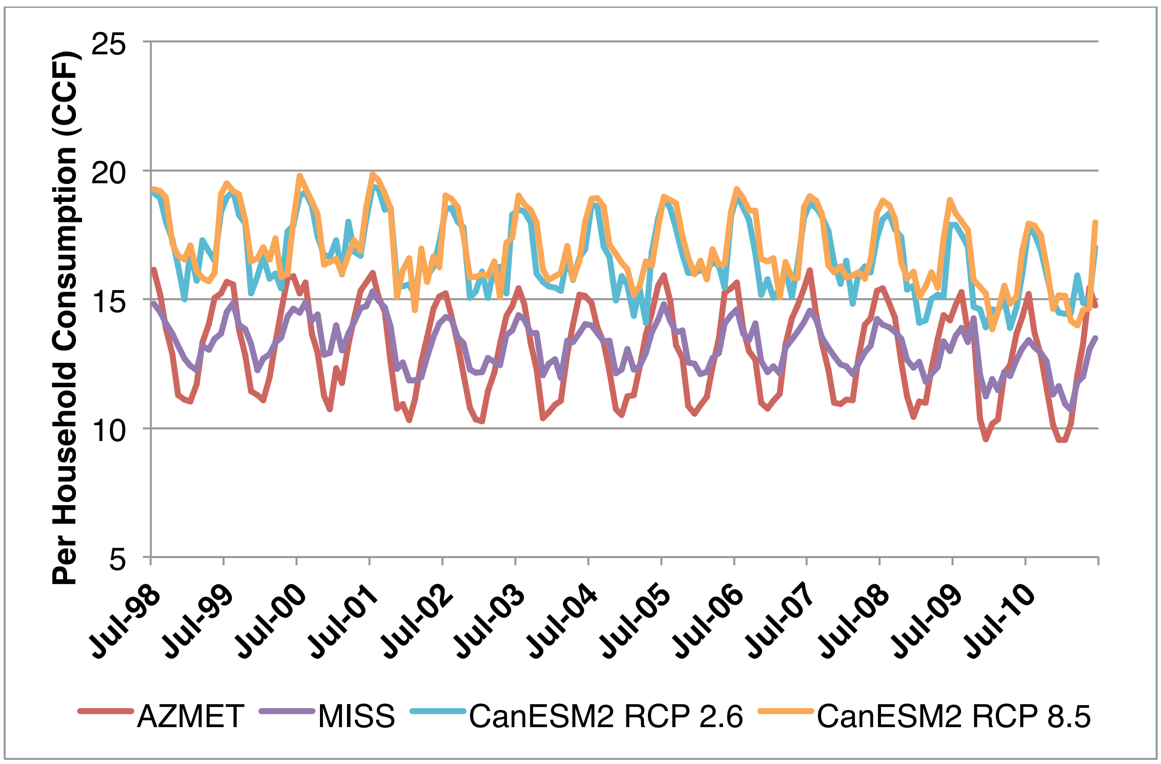
5.3 Counterfactual Climate Scenarios

Finally, we present the results of our analysis of the sensitivity of water consumption to potential climate change. We conduct this sensitivity analysis using our aggregate models, since climate change is a phenomenon that occurs at a large spatial scale. Even the downscaled GCM projections provided by the Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections archive, which allow us to focus on changes in weather patterns for as small a locale as a metropolitan area, should not be expected provide reliable estimates of weather variation on a household scale.

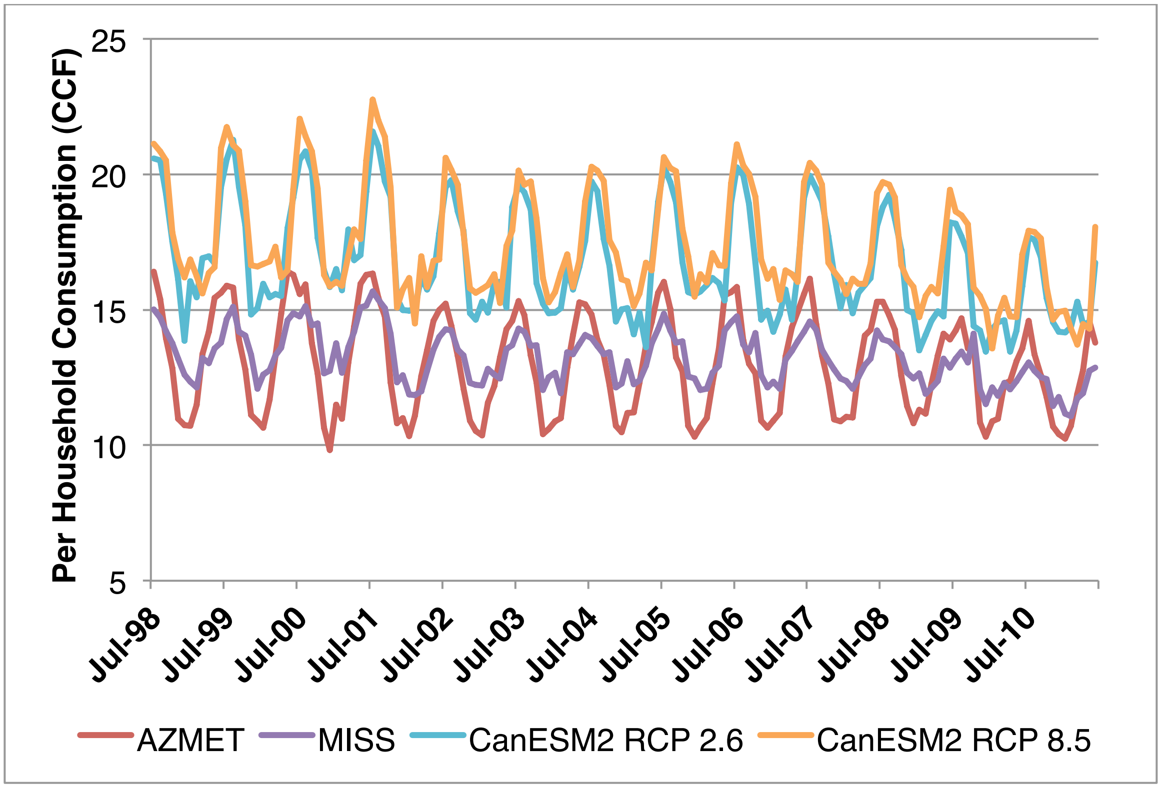
We attempt to assess the impact of alternative weather conditions throughout the study period, or counterfactual climate scenarios, on aggregate water demand. We substitute the projected values of number of rainy days per month and total monthly ET obtained from the MISS scenario and CanESM2 model output under emissions scenarios RCP 2.6 and RCP 8.5 for the current period data and use the estimated coefficients from our aggregate model runs to project average household water use over the study period. These projections, calculated for both the SGF and SGV model formulations, are plotted below in Figure 14. In this case, AZMET refers to the predicted values of per household water consumption obtained from our original aggregate model runs.

Figure 14: Counterfactual Climate Scenario Projected Per Household Consumption Comparison

a) SGF Model



b) SGV Model



Immediately evident is the discrepancy between the CanESM2 scenarios and the results we obtain from our original model runs using AZMET historical data. Per household water consumption projections using CanESM2 data tend to vary between 15 and 20 CCF seasonally over most of the study period, while the model predictions relying on AZMET data tend to vary between 10 and 15 CCF over the study period. This suggests a 4 to 5 CCF increase in average use regardless of the season.

Also notable is the dampened seasonal variation in the MISS scenario. Despite the higher temperatures and decreased rainfall, peak summer use in this scenario is never as high as when the model is run using actual historical data. This result differs from that found by Chandrasekharan and Colby (2013) in their application of the MISS scenario to electricity demand. Under the MISS scenario, they find a general increase in electricity use year-round, with a more pronounced increase in summer electricity – just as we would expect to see in the case of municipal water demand. Our strange result is most likely due to the counterintuitive positive coefficient we estimate for number of rainy days. Since, in the MISS scenario, we reduce the number of rainy days in the months of May-September by 50%, this has the effect of predicting lower, not higher, water consumption when entered into our model. Apparently, the positive effect on water consumption of the higher summer temperatures and ET levels that we assume in the MISS scenario is overwhelmed by this precipitation decrease.

Finally, unlike in our original model runs using historic weather data, we do see much more variation in water use when projecting using the SGV model formulation as opposed to the SGF model. Peak summer use appears to be significantly higher when this model formulation is used. In the CanESM2 scenarios, peak summer use exceeds 20 CCF per household in most years, which does not occur when the SGF model is used. Also, when using the SGV model formulation, differences between RCP 2.6 scenario and the RCP 8.5 scenario are accentuated, particularly in the winter months, since the marginal budget share allocated to water is allowed to vary with the control variables.

While differences in patterns of water consumption throughout the entire study period are substantial and interesting, water utilities' infrastructure investments and capital costs are driven primarily by peak summer demand. Therefore, we drill down to compare monthly means of projected per household water consumption across our original model runs and each of the counterfactual climate scenarios, with particular interest in changes in water consumption in the peak demand months of June and July. Since the SGV model allows us to capture more seasonal variation in demand, we present only results from this model here.

Table 14 displays monthly mean water consumption per household under each of the counterfactual climate scenarios, as well as the predicted values from our original model runs and actual per household consumption during the study period. Below, Table 15 presents the percent difference in monthly mean water use in the representative Tucson household between each of the scenarios and between each of the scenarios and our original model runs. T-tests for differences in means are performed, and significant differences, at the 90% confidence level or higher, are bolded. Only the most relevant comparisons are presented here. More extensive comparisons, including those from the SGF model formulations, and p-values from the t-tests performed, are reported in Appendix 11.

Table 14: Monthly Mean Water Consumption Comparison (SGV)

	Actual	AZMET	MISS	CanESM2 RCP 2.6	CanESM2 RCP 8.5
Jan	10.2	10.8	12.4	15.1	15.8
Feb	10.4	11.2	12.1	14.9	15.6
Mar	10.1	12.6	12.7	15.9	16.2
Apr	11.8	13.7	12.9	15.4	16.0
May	13.5	14.8	13.6	16.0	16.4
Jun	16.6	15.1	13.9	18.3	19.0
Jul	17.1	15.5	14.4	19.8	20.6
Aug	14.4	14.8	14.2	19.7	20.2
Sep	14.8	13.6	13.7	18.7	19.8
Oct	13.6	12.5	13.7	17.0	17.8
Nov	12.6	10.9	12.5	15.2	16.2
Dec	11.2	10.6	12.3	14.8	15.8

Table 15: Percent Difference in Monthly Mean Water Consumption (SGV)

	Percent Difference in Monthly Mean					
	MISS vs. AZMET	RCP 2.6 vs. AZMET	RCP 8.5 vs. AZMET	RCP 2.6 vs. MISS	RCP 8.5 vs. MISS	RCP 8.5 vs. RCP 2.6
Jan	**14.62**	**39.66**	**45.62**	**21.84**	**27.04**	**4.26**
Feb	**8.49**	**33.88**	**39.84**	**23.40**	**28.90**	**4.46**
Mar	0.38	**25.38**	**27.94**	**24.91**	**27.46**	2.04
Apr	**-5.78**	**12.05**	**16.60**	**18.91**	**23.74**	4.06
May	**-8.07**	**7.63**	**10.78**	**17.08**	**20.51**	2.93

Jun	**-7.72**	**21.22**	**25.55**	**31.37**	**36.06**	3.57
Jul	**-7.33**	**27.52**	**32.41**	**37.60**	**42.87**	3.83
Aug	**-3.78**	**33.33**	**36.47**	**38.56**	**41.83**	2.36
Sep	1.19	**37.78**	**46.03**	**36.17**	**44.31**	**5.98**
Oct	**9.13**	**35.71**	**42.20**	**24.36**	**30.31**	4.78
Nov	**14.84**	**40.16**	**49.13**	**22.05**	**29.86**	**6.40**
Dec	**16.31**	**39.96**	**49.14**	**20.33**	**28.23**	**6.56**

According to Table 15, both CanESM2 scenarios project significantly higher per household use on average in the months of June and July than our original model runs (21-26% in June, 27-32% in July). And while RCP 8.5 suggests higher consumption levels in these months than RCP 2.6, these differences are not statistically significant. On the other hand, the MISS scenario suggests on average 7-8% less consumption per household in the months of June and July than do our original model runs. Once again, we expect that this is due to the fact that the number of rainy days in the MISS scenario is reduced and the coefficient we estimate for number of rainy days is positive. Also notable is that, in all 3 counterfactual climate scenarios, water consumption is expected to increase most dramatically in the winter months. This is probably due to the fact that the CanESM2 scenarios predict the most dramatic increase in the number of rainy days in the winter months compared to the historic period. Since our estimated coefficient on number of rainy days is positive, our water consumption projections are most dramatically affected in winter as well.

6. Conclusions and Policy Implications

Despite continual population growth, Southwestern water utilities have recently been experiencing declining levels of water consumption per household, which has had negative impacts on their revenue stream and their ability to cover costs in the short-run. Demand forecasting models need to more accurately reflect household decision-making behavior regarding water consumption, particularly in the face of research that suggests higher regional temperatures and increasing variability in precipitation may be in store.

This analysis leverages the Stone-Geary demand specification to better account for household decision-making behavior with regard to water consumption. In doing so, we attempt to clarify the relationship between household behavior and trends in urban water consumption. We also utilize a substantial suite of control variables, including a novel combination of satellite imagery, weather data, and parcel characteristics, to control for variability in consumption among households and over time. Finally, we examine the degree to which potential climate change may influence consumption behavior.

6.1 Pricing Implications

Our results indicate that price elasticity of demand among SFR households in Tucson is roughly -0.2 at mean values of all variables in our household model and tends to range between 0 and -0.6 over the study period, with a clear trend toward 0 over the study period. This result is consistent with the larger body of literature surrounding municipal water demand; according to Worthington and Hoffman (2008), most studies estimate the price elasticity of demand for water to be between 0 and -0.5 in the short run and between -0.5 and 1 in the long run.

However, an important feature of the Stone-Geary demand function is that it allows the price elasticity of demand to vary with quantity consumed, implying that consumers respond less to price increases if they are not consuming much water to begin with. Related to this, Stone-Geary function assumes a minimum level of consumption below which households will not respond to price – the conditional water use threshold. The notion that households will automatically consume a given amount before taking price into consideration seems to fit the case of residential water consumption well.

In Tucson, we estimate that an average SFR household will consume roughly 10 CCF per billing period before considering price, though this minimum level may vary between 8 and 12 CCF depending on the time of year. The fact that this threshold varies seasonally implies that some portion of household water consumption for outdoor use is inelastic to price. This is important for utility managers to understand, since only at levels above a given household's conditional water use threshold can a marginal price increase be expected to have any influence on water consumption. Over the course of the study period Tucson Water set the first tier of its IBR structure at 15 CCF. Given SFR users' generally low price responsiveness at levels of consumption below 15 CCF, this appears to be a reasonable level at which to impose a price increase if the goal is to restrict consumers from using much more water than 15 CCF. However, we suspect that the imposition of a block price increase at 15 CCF may have had some influence on the average level of the household conditional water use threshold in Tucson in the first place, given our examination of trends in the marginal budget share allocated to water as well as the conditional water use threshold itself.

6.2 Household Decision-Making and Urban Water Consumption

The results of our household analysis suggest that water prices rose relative to income levels throughout the study period, causing households to allocate a larger share of their monthly income to water. In response, we notice a slight decline in the average household conditional water over the study period in the SGF model. While this difference is only a small fraction of a CCF over the entire period, this trend is statistically significant. There is also a slight downward trend in the conditional water use threshold in the SGV model, but this trend is not significant.

Initially, it may seem contradictory that the portion of water use that is supposedly perfectly inelastic to price may actually be responsive to price over time. However, the words “over time” are critically important. While price increases are not expected to influence water consumption below the conditional water use threshold *within the same billing cycle*, it is possible that a rising trend in water prices over time may cause households to revise their assumptions about their baseline monthly water needs. In essence, this reflects a sort of Bayesian process by which consumers may be induced to adopt more conservative water use habits as a result of longer-term price increases.

It is important to note that these trends in the conditional water use threshold and the marginal budget share allocated to water are not evident in the results of our aggregate analyses. For the sake of comparison, we ran our household model using only controls for weather and the number of days in a billing cycle (see Appendix 13). From this, we see that more disaggregated precipitation measurements lead to more reasonable results (a negative and significant coefficient on number of rainy days). We also note that the upward trend in the marginal budget share allocated to water and the downward trend in the conditional water use threshold are not found when household heterogeneity is not accounted for. And while the weak evidence that we find for a decline in the conditional water use threshold in our original household analysis – a small but significant negative trend in the SGF model, and a small, insignificant decline in the SGV model – may not account for much of the declining trend in household water use shown in Figure 1b, it does represent a step forward in our understanding of the way in which household decision-making affects aggregate water consumption trends. Our results appear to point to the value of examining behavior at the household level in order to understand trends in urban water consumption. By controlling for household heterogeneity via a panel model, we can account for more of the variation in aggregate demand trends than we could by treating all Tucson SFR consumers as one.

It is likely that factors such as new appliances or water-saving household technologies – factors for which we do not have data – may contribute to the decline in water consumption over the study period as well. Future research may need to be conducted to incorporate technological change explicitly in the model, with care taken to account for potential endogeneity where water prices may influence appliance choice. Nonetheless, since the conditional water use threshold is a function of the control variables included in the model, the Stone-Geary model should be flexible enough to accommodate such changes.

In short, our analysis suggests that the Stone-Geary functional form is a relatively straightforward yet powerful method that can be used to account for the subtleties of household-level decision-making processes related to municipal water demand.

6.3 Control Variable Impacts

The control variables included in our household analysis are particularly valuable. The number and scope of the control variables in our analysis, including parcel and housing attributes, demographic characteristics, and weather observations, is rivaled by few studies in the water demand literature. And our results indicate that these variables are strong determinants of water demand. In our household model, only the significance of the demographic variables related to household size and age distribution is weak, and we expect that this is more a factor of the available data than the phenomena these variables represent. In most other cases, the scale of data collection corresponds closely to the actual data generating process.

Notably, our triple interaction variable – the product of ET, parcel landscapable area, and instrumented NDVI – and our interaction of pool size and ET have significant positive impacts on household water consumption. Both of these variables, as well as the use of ET in our aggregate model instead of temperature, attempt to represent the relationship between summer weather conditions and outdoor water use in a much more complex manner than has been traditionally undertaken. Each of these variables – ET, NDVI, landscapable area, and even pool size – has received scant attention in the literature thus far in isolation, let alone their interrelationship. Even in our aggregate analysis, ET is shown to have a significant, positive effect on water consumption. Our results suggest that water managers should consider using ET as a more comprehensive measure of weather conditions when attempting to explain consumption behavior related to outdoor water use. On the other hand, our finding that NDVI is endogenous may indicate that, for water managers in Tucson and elsewhere, investing in the time, technological capacity, and expertise necessary to utilize publicly available satellite imagery to inform water demand analysis may not be worthwhile. Instead, it may be more beneficial to rely on more readily available parcel characteristics such as house age and value to indicate parcel vegetative cover.

Additionally, the fact that we find Hispanic ethnicity to have a highly significant effect on water consumption despite the lack of precision in the available data indicates that understanding the relationship between cultural norms and water consumption is an area for future research as well. The notion that a difference in bottled water and tap water dependence exists between foreign-born individuals and American nationals is one potential explanation, but this analysis is not well-suited to address the causal mechanisms behind this relationship.

6.4 Potential Impacts of Climate Change

The results of our counterfactual climate analysis indicate that household water consumption behavior is responsive to changes in weather patterns, all else constant. An important caveat to our counterfactual climate scenario analysis is that we do not make any effort to anticipate changes in the economic or social state of the Tucson region in the future. We simply analyze how water consumption behavior may have differed in the study period under alternative weather regimes. As economic or demographic conditions change, however, the manner in which aggregate water consumption behavior in Tucson is affected by climate may change as well.

Nonetheless, we find significant differences in water consumption behavior under each of our counterfactual climate scenarios. This indicates that, in the absence of substantial technological or socioeconomic change, climate change along the lines of current GCM projections could lead to significant increases in water consumption in Tucson. In the months of June and July, these increases could be as high as 32% in the CanESM2 scenarios, which could have significant ramifications for Tucson Water in terms of their investment in infrastructure to meet peak demand. However, in all three counterfactual climate scenarios, the trend in water consumption is expected to be upward year-round, not just in the months that are hottest and driest. In fact, in the CanESM2 scenarios, per household water consumption is expected to increase by at least 10 percent in every month of the year relative to actual consumption levels over the study period. To satisfy this demand would require obtaining even more water supplies from an already water-stressed environment. Given the pending shortage situation along the Colorado River, this could be a significant challenge for a Southwestern water utility going forward.

Appendices

Appendix 1: Removing Households Prior to Sampling

The original SFR household dataset provided by Tucson Water contains usage data pertaining to 284,993 unique metered connections that can be matched to 259,646 unique Pima GIS parcel identifiers. However, because many households have insufficient or nonsensical data, we are not able to draw our sample for the household analysis from this entire set of households. Households are removed from the dataset as necessary at various stages in the development of the household database.

First, households with insufficient data are removed. To be clear, insufficient data does not refer to all missing data, but rather to missing data for which no reasonable method of approximation exists. In total, 122,633 households (43.0% of our original dataset) on 97,982 parcels are removed from our dataset due to insufficient data. Of these, 112,930 (92.1%) metered connections corresponding to 89,369 parcels are eliminated because the data provided by Tucson Water is insufficient to calculate an approximate water bill for each billing cycle, for a number of reasons. Usage and rate data are complete for the entire dataset; however, as Chapter 4 describes, usage and volumetric rates are far from the only components in a Tucson Water bill. Many households do not have a record of their meter size, which is necessary to calculate meter and groundwater charges in each bill. Likewise, for several households, there is no indication of whether the household has sewer or garbage service, which makes it impossible to determine whether the associated fees for either service should be incorporated in approximations of each household's regular bill. Since price is a key variable in our model, households for which accurate price information could not be obtained are removed from our dataset.

During our calculation of lagged average price, an additional 360 households corresponding to 355 parcels are removed. These households are either so new or billed at such infrequent intervals that a lagged price measure cannot not be calculated for each period-ending month; in fact, the most frequently-billed household in this subset received only 4 bills throughout the study period. Such households would confound our panel analysis. Similarly, 2,092 households on 2,039 parcels are removed when calculating the winter quarter (Dec-Feb) average because no consumption data for December, January, or February of the relevant year are available. These households either started service later in the year or did not have frequent enough meter readings to provide complete usage data. Since we rely on the winter quarter average as an approximation of indoor usage in some of our models, households without sufficient information to calculate this average are eliminated from our dataset.

Finally, 7,251 households were removed from our dataset because records from the Pima County Assessor's Office are not available for their corresponding 6,219 parcel identifiers. Such records are necessary to our calculations of household income and parcel landscapable area. After all households with insufficient data are removed, 162,360 households corresponding to 161,664 unique parcels remain in our dataset.

Once the dataset is pared down to only those households with sufficient data to inform our analysis, remaining households with nonsensical values for parcel size or number of days in a given billing cycle are also eliminated from our dataset. Nonsensical parcel size values include a small number of parcels for which the area measurement provided by Pima GIS is smaller than the minimum house square footage in the Pima County Assessor's database (216 sq. ft.). Additionally, households with billing cycles of less than 7 days or greater than 65 days are removed from the dataset. Billing cycles of roughly 62 days might imply that Tucson Water simply skipped a monthly meter read; however, billing cycles greater than 65 days suggest irregular measurement, which would confound the price signals sent to consumers via the IBR structure. Similarly, billing cycles of less than one week likely do not constitute regular meter reading, but rather some error or change in service. Such anomalies would confound our results regarding the effect of price on consumption and are therefore excluded from our analysis. In total, 34,716 individual metered connections on 34,373 unique parcels are removed from our dataset due to nonsensical values for parcel size or number of days in a billing cycle.

After removing all households listed above, we can be confident that the households remaining in our dataset have complete and reliable information necessary for our analysis. Though our final household analysis is restricted to only a small representative sample of these remaining households, this restriction is imposed due to computational constraints rather than issues of data integrity or incompleteness. The final number of unique metered connections from which our sample is drawn is 127,644, accounting for 127,291 unique parcels.

Appendix 2: Dealing with Period-Ending Months with Multiple Bills

While Tucson Water assigned each bill in our dataset to a “period-ending” month to ensure that each month had only one bill per household, this process was not flawless. Even after data cleaning and sampling, several households in our dataset have multiple usage records assigned to the same month. While an unbalanced panel model could account for missing months or households that were added to the dataset in the middle of our study period, in order to use the period-ending month as the time step of our household analysis, we have to ensure that each month is assigned at maximum one bill.

We examine the 246,049 usage records associated with the 2,000 households in our sample dataset, identifying and removing 4,535 exact duplicate usage records from the dataset. We also find 804 usage records for which the household and billing cycle dates are identical, but usage differs. Upon closer investigation we discovered that these households have multiple connections, one for potable water and another for either reclaimed water or irrigation. Only the 402 records for potable connections are kept.

The remaining usage records “overlapping” on the same month are handled in one of two ways. In 34 of the cases, we use the meter read date to reassign the bill to either the previous or subsequent month, provided that no bill was already assigned to these months. The remaining overlapping usage records are merged together by summing total usage in the period-ending month; 1,771 overlapping usage records are merged to form 883 non-overlapping records in this way.

The final dataset used in our household analysis has 240,224 usage records in unique period-ending months.

Appendix 3: AZMET Weather Data by Month and Year

Table 16: Total Precipitation

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1998	0.19	3.83	1.46	0.49	0.00	0.00	3.37	1.14	0.93	0.11	1.21	0.35
1999	0.00	0.00	0.02	1.10	0.00	0.00	6.80	2.03	1.44	0.00	0.00	0.01
2000	0.17	0.07	1.03	0.01	0.00	2.94	0.40	2.47	0.40	4.07	0.74	0.04
2001	1.96	0.17	0.79	1.43	0.07	0.31	1.44	0.80	0.18	0.01	0.04	0.78
2002	0.21	0.01	0.00	0.00	0.00	0.00	1.88	3.20	2.01	0.48	0.25	0.64
2003	0.01	1.24	0.47	0.04	0.17	0.00	1.72	3.31	1.72	0.55	1.14	0.27
2004	0.99	0.58	1.15	1.22	0.00	0.02	1.18	0.93	1.58	0.79	0.84	0.78
2005	1.60	1.88	0.18	0.44	0.61	0.32	1.40	4.26	0.07	0.17	0.00	0.02
2006	0.00	0.01	0.72	0.00	0.00	0.26	5.08	0.85	1.52	0.59	0.00	0.54
2007	0.68	0.19	0.50	0.55	0.00	0.00	4.33	2.29	0.90	0.23	1.77	1.12
2008	0.82	1.21	0.18	0.02	0.00	0.32	2.75	5.59	1.66	0.06	0.75	0.57
2009	0.74	0.80	0.18	0.47	0.38	0.36	2.42	1.45	0.67	0.45	0.15	0.56
2010	2.53	2.32	0.82	0.09	0.00	0.22	2.97	1.94	0.65	0.98	0.04	0.94
2011	0.20	0.23	0.09	0.30	0.15	0.04	1.90	1.82	2.84	0.14	1.49	2.04
2012	0.35	0.17	0.58	0.16	0.04	0.03	2.98	2.32	0.66	0.03	0.19	1.31
Avg.	**0.70**	**0.85**	**0.54**	**0.42**	**0.09**	**0.32**	**2.71**	**2.29**	**1.15**	**0.58**	**0.57**	**0.66**

Table 17: Number of Rainy Days

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1998	3	11	8	4	0	0	13	8	4	2	3	4
1999	0	0	2	3	0	0	15	13	6	0	0	1
2000	1	3	4	1	0	9	4	13	2	10	5	1
2001	11	5	4	5	1	2	15	7	5	1	2	7
2002	2	1	0	0	0	0	11	8	5	4	2	6
2003	1	10	4	1	2	0	8	11	5	4	2	4
2004	7	4	5	6	0	1	6	5	4	5	4	4
2005	9	8	3	2	2	5	10	12	3	5	0	2
2006	0	1	4	0	0	4	11	7	5	7	0	3
2007	6	3	3	4	0	0	14	10	4	1	2	7
2008	6	3	1	1	0	3	14	13	11	4	5	7
2009	7	3	1	2	3	2	9	11	10	14	3	4
2010	7	7	6	3	0	1	14	9	5	5	2	4
2011	1	2	1	2	9	3	20	22	16	10	8	8
2012	4	5	2	1	1	1	15	11	11	3	4	8
Avg.	**4.3**	**4.4**	**3.2**	**2.3**	**1.2**	**2.1**	**11.9**	**10.7**	**6.4**	**5.0**	**2.8**	**4.7**

Table 18: Mean Temperature

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1998	50	49	56	61	72	81	86	85	82	69	57	49
1999	50	55	60	61	74	83	82	83	80	70	60	48
2000	51	56	58	69	80	84	87	83	82	66	50	49
2001	47	51	59	65	78	84	84	84	83	70	61	46
2002	49	54	57	71	75	87	86	84	80	67	58	47
2003	54	53	59	65	77	86	89	85	82	73	56	49
2004	51	49	65	66	78	85	86	84	80	68	55	50
2005	52	55	58	66	76	84	89	82	81	70	59	50
2006	51	55	58	68	79	87	87	83	77	67	59	48
2007	46	54	62	67	78	86	86	85	82	70	62	46
2008	49	52	59	67	72	85	84	83	81	69	59	50
2009	52	54	61	66	79	82	88	87	81	68	60	48
2010	50	52	57	65	73	85	88	86	83	70	55	52
2011	47	49	62	68	72	85	86	88	81	70	56	46
2012	51	53	58	69	78	87	85	86	80	71	61	50
Avg.	**50.0**	**52.7**	**59.3**	**66.3**	**76.1**	**84.7**	**86.2**	**84.5**	**81.0**	**69.2**	**57.9**	**48.5**

Table 19: Total ET (Modified Penman-Monteith)

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1998	2.91	2.65	5.02	7.18	9.34	10.88	8.68	8.41	7.4	6.39	3.59	3.04
1999	3.98	5.02	6.98	7.78	10.21	10.55	7.18	7.41	6.65	6.65	4.47	3.91
2000	3.59	4.42	6.23	8.96	11.32	9.08	9.31	7.53	7.37	3.98	2.63	2.56
2001	2.25	2.99	5.6	6.96	9.8	10.2	7.17	7.83	7.56	5.52	3.81	2.68
2002	3.06	4.51	7.09	8.6	10.37	11.15	8.38	7.73	6.87	5.19	4.06	2.23
2003	3.43	2.76	5.48	8.07	9.55	10.68	9.62	7.74	6.98	5.65	3.16	2.91
2004	2.5	3.5	6	7.5	11	10.7	9.2	8	7.3	5.2	3.1	2.7
2005	2.4	2.7	5.7	8	9.3	10.2	9.5	7.3	7	5.7	4.1	3
2006	4	4.2	5.2	8	10.8	10.1	8.5	7	6.2	5.1	4.4	3.2
2007	2.8	4	7	8.3	10.2	11.3	8.9	7.2	7.1	6.3	4	2.5
2008	3	3.8	6.9	9	9.7	10.6	8.3	7.6	7.3	6.5	4.2	2.4
2009	3.3	4.3	6.9	8.5	9.7	9.7	9.3	9.5	7.4	6.3	4	2.5
2010	2.6	2.8	5.9	7.2	9.9	10.7	8.9	7.9	7.6	5.6	4.2	2.7
2011	3.5	4.2	7.4	9	10.5	11.1	9.2	8.3	6.9	6	3.4	2.2
2012	3.3	4.4	6.9	8.7	11.2	11.3	8.30	7.80	6.80	6.30	4.10	2.80
Avg.	**3.11**	**3.75**	**6.29**	**8.12**	**10.19**	**10.55**	**8.70**	**7.82**	**7.10**	**5.76**	**3.81**	**2.76**

Appendix 4: Methods of Calculating Evapotranspiration

Our water demand analysis utilizes data on monthly standardized reference crop evapotranspiration (ET) rather than a more traditional temperature metric. According to Brown (2005), ET "provides an estimate of environmental evaporative demand and serves as a critical input for most scientifically-based irrigation scheduling systems." As such, we expect ET to have a substantial influence on SFR irrigation (outdoor water use) behavior.

In practice, ET data are not widely available. In Tucson, the Arizona Meteorological Network (AZMET) represents one of the only publicly available sources of ET, and we use their data in our analysis. Part of the reason for the lack of publicly available sources of ET data is the ongoing debate over appropriate calculation methods. Although the long-used Penman-Monteith equation is widely considered to be the gold standard in ET estimation, its substantial data requirements often make it infeasible in practice. Several methods of approximating the Penman-Monteith equation have evolved in specific regional contexts. The following equation details the process by which the Arizona Meteorological Network (AZMET) estimates standardized reference crop evapotranspiration (ET), which represents only a slight modification of the Penman-Monteith equation.

$$ET_{os} = \frac{0.408\Delta R_n + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34 u_2)}$$

Where:

ET_{os} : Standardized reference crop evapotranspiration for a short crop (mm/day)

Δ : Slope of the saturation vapor pressure-temperature curve (kPA/ºC)

R_n : Calculated net radiation at the crop surface (MJ/(m^2 x day))

γ : Psychrometer constant (kPA/ºC)

T : Mean daily air temperature measured at 1.5 m above ground level (ºC)

u_2 : Mean daily wind speed measured at 2m above ground level (m/s)

e_s : Saturation vapor pressure measured at 1.5 m above ground level (kPA)

e_a : Mean actual vapor pressure measured at 1.5 m above ground level (kPa)

While we use AZMET ET data to estimate water demand during our study period, we cannot obtain such a diverse set of weather measurements for use in our counterfactual climate scenario analysis. In fact, since global climate model output must be regionally downscaled to be useful at a scale as small as a metropolitan area, only daily minimum and maximum temperature and daily precipitation measurements are available in any meaningfully accurate way for the Tucson area, via the Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections archive. Fortunately, recent work by McKellar and Crimmins (2015) has shown that the ET formula developed by Hargreaves (1994) reliably approximates Penman-Monteith ET calculations in southern Arizona. The

Hargreaves (1994) method is advantageous in that it requires only daily minimum and maximum temperature and a latitude-specific measure of solar radiation. To project future ET for our counterfactual climate analysis, we use the Hargreaves (1994) equation, which is presented below.

$$ET_o = 0.0023 \times RA \times (T_{mean} + 17.8) \times (T_{\max} - T_{\min})^{0.5}$$

Where:

ET_o : Potential evapotranspiration

RA : Constant representing water evaporation due to latitude-specific extraterrestrial radiation

$T_{\max}$: Daily maximum temperature (ºC)

$T_{\min}$: Daily minimum temperature (ºC)

T_{mean} : $(T_{\max} + T_{\min})/2$

Appendix 5: Estimating Coefficient to Project ET

In order to obtain reasonable estimates of future ET for our counterfactual climate scenario analysis, we utilize the Hargreaves (1994) ET formula to approximate ET using downscaled daily minimum and maximum temperature data. The Hargreaves formula calls for a latitude-specific solar radiation constant, which we do not have. Instead, we estimate a coefficient for temperature by regressing AZMET daily ET on daily minimum and maximum temperature data during the study period (restricting the intercept to be zero), and use this constant to project future ET. The results of our regression are shown below.

Table 20: Estimating an ET Projection Coefficient for Temperature

Variable	Coefficient (p-value)
Temperature	0.00139 (0.000)
R^2	0.905
F-test	48,639.22 (0.000)

Once daily ET has been projected, we simply calculate by summation total monthly ET for each month over the period July 2085 – June 2099 to include in our water demand model in place of the current period weather data.

Appendix 6: MISS Scenario Weather Data By Month and Year

Table 21: MISS Number of Rainy Days

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1998							6.5	4	2	2	3	4
1999	0	0	2	3	0	0	7.5	6.5	3	0	0	1
2000	1	3	4	1	0	4.5	2	6.5	1	10	5	1
2001	11	5	4	5	0.5	1	7.5	3.5	2.5	1	2	7
2002	2	1	0	0	0	0	5.5	4	2.5	4	2	6
2003	1	10	4	1	1	0	4	5.5	2.5	4	2	4
2004	7	4	5	6	0	0.5	3	2.5	2	5	4	4
2005	9	8	3	2	1	2.5	5	6	1.5	5	0	2
2006	0	1	4	0	0	2	5.5	3.5	2.5	7	0	3
2007	6	3	3	4	0	0	7	5	2	1	2	7
2008	6	3	1	1	0	1.5	7	6.5	5.5	4	5	7
2009	7	3	1	2	1.5	1	4.5	5.5	5	14	3	4
2010	7	7	6	3	0	0.5	7	4.5	2.5	5	2	4
2011	1	2	1	2	4.5	1.5	10	11	8	10	8	8
2012	4	5	2	1	0.5	0.5						
Avg.	**4.4**	**3.9**	**2.9**	**2.2**	**0.6**	**1.1**	**5.9**	**5.3**	**3.0**	**5.1**	**2.7**	**4.4**

Table 22: MISS Temperature

a) Minimum

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1998							80	80	74	56	45	39
1999	37	39	46	49	59	71	76	75	70	55	45	36
2000	38	43	45	54	66	75	80	78	74	59	41	37
2001	39	40	47	52	65	71	79	77	72	58	50	36
2002	38	39	41	56	61	73	80	77	74	56	44	38
2003	41	44	47	51	65	72	81	80	74	62	47	37
2004	42	38	54	55	65	72	79	77	72	57	46	39
2005	44	50	48	52	65	73	80	78	74	59	45	37
2006	38	41	47	53	65	77	82	80	71	56	45	36
2007	37	42	48	54	65	72	81	81	75	58	50	38
2008	40	41	45	50	61	72	80	79	74	55	47	41
2009	41	42	48	52	68	73	83	79	73	55	46	38
2010	41	44	46	52	59	74	84	81	75	60	42	41
2011	35	37	47	55	60	69	79	80	73	56	47	38
2012	39	41	44	53	65	75						
Avg.	**39.3**	**41.5**	**46.7**	**52.7**	**63.4**	**72.8**	**80.1**	**78.8**	**73.2**	**57.4**	**45.7**	**38.0**

b) Mean

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1998							93	93	89	73	63	55
1999	56	59	64	65	77	86	88	88	85	74	66	53
2000	56	60	62	72	84	90	93	91	89	72	55	55
2001	53	56	63	69	83	89	91	91	88	75	65	52
2002	54	58	60	73	80	92	93	92	88	72	62	53
2003	60	58	62	68	82	90	95	93	89	78	62	55
2004	56	54	69	69	82	89	93	91	86	72	59	55
2005	58	60	62	69	81	90	95	90	89	75	64	56
2006	56	59	61	70	83	93	94	91	84	72	64	53
2007	51	58	65	70	82	90	93	93	89	75	68	52
2008	54	57	63	69	78	90	92	91	88	74	64	56
2009	57	59	65	69	84	88	96	93	88	71	65	53
2010	55	57	61	68	78	90	95	93	90	75	59	58
2011	53	54	65	71	77	89	93	94	88	74	61	51
2012	57	57	62	71	83	92						
Avg.	**55.4**	**57.5**	**63.2**	**69.5**	**81.1**	**89.8**	**93.1**	**91.7**	**87.8**	**73.6**	**62.6**	**54.0**

c) Maximum

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1998							106	106	104	91	81	71
1999	75	78	82	81	94	101	99	102	99	94	87	70
2000	75	77	78	90	102	104	107	103	104	84	70	74
2001	66	71	78	85	101	107	104	105	104	92	81	68
2002	70	77	79	91	98	110	106	106	102	87	80	67
2003	78	71	78	85	100	108	110	106	103	94	77	73
2004	70	69	85	84	100	107	107	104	101	87	73	71
2005	72	70	76	86	98	106	109	102	103	90	82	74
2006	74	77	76	88	102	109	107	102	98	89	83	70
2007	66	74	83	87	100	108	106	106	102	91	85	66
2008	68	73	80	88	95	108	104	103	102	92	81	71
2009	73	77	81	85	100	102	109	107	103	87	83	67
2010	70	70	76	83	96	107	106	105	105	90	77	75
2011	71	71	83	88	94	108	107	108	103	92	76	65
2012	74	74	80	89	102	110						
Avg.	**72**	**73**	**80**	**86**	**99**	**107**	**106**	**105**	**102**	**90**	**80**	**70**

Table 23: MISS ET

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1998							8.40	8.47	8.25	7.64	6.54	5.50
1999	6.14	5.85	6.78	6.27	7.75	8.11	7.41	8.08	7.73	8.25	7.32	5.44
2000	6.08	5.81	6.24	7.37	8.99	8.31	8.72	8.09	8.46	6.31	5.11	5.95
2001	4.84	4.93	6.26	6.73	8.89	9.06	8.11	8.56	8.50	7.65	6.22	5.19
2002	5.45	5.67	6.18	7.39	8.69	9.55	8.45	8.62	7.93	7.09	6.38	5.04
2003	6.43	4.76	6.14	6.80	8.63	9.23	9.10	8.33	8.25	7.80	5.73	5.83
2004	5.23	4.87	6.82	6.46	8.69	9.12	8.65	8.34	7.91	7.06	5.26	5.44
2005	5.28	4.24	5.80	6.88	8.39	8.83	9.09	7.74	8.20	7.34	6.69	6.01
2006	5.89	5.71	5.75	7.12	8.98	9.02	8.38	7.70	7.52	7.30	6.88	5.39
2007	4.89	5.26	6.82	7.03	8.62	9.26	8.39	8.26	7.99	7.61	6.81	4.88
2008	4.99	5.38	6.59	7.32	8.04	9.34	7.99	7.93	7.92	7.92	6.40	5.37
2009	5.69	5.60	6.61	6.80	8.51	8.12	8.66	8.83	8.15	7.10	6.67	5.06
2010	5.29	4.59	5.94	6.56	8.32	8.95	8.01	8.23	8.45	7.24	5.99	5.97
2011	5.65	5.02	6.98	7.03	8.03	9.54	8.71	8.70	8.32	7.79	5.65	4.66
2012	5.94	5.49	6.65	7.36	9.02	9.43						
Avg.	**5.56**	**5.23**	**6.40**	**6.94**	**8.54**	**8.99**	**8.43**	**8.28**	**8.11**	**7.44**	**6.26**	**5.41**

Appendix 7: CanESM2 Projections by Month and Year

Table 24: Total Precipitation 2085-2099

a) RCP 2.6

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2085							2.71	1.55	1.16	0.19	0.02	0.07
2086	0.65	1.11	2.68	0.24	0.15	0.55	2.98	1.65	1.14	0.47	0.75	0.38
2087	0.57	1.09	0.11	0.36	0.13	0.55	4.17	1.97	1.03	0.19	1.00	1.07
2088	1.91	0.58	0.88	0.55	0.07	0.43	3.05	3.48	0.92	0.85	1.24	1.66
2089	0.87	0.15	3.47	0.22	0.10	0.34	2.71	2.76	0.62	0.11	0.21	0.41
2090	0.95	3.68	0.99	0.52	0.08	0.72	3.01	5.23	1.73	0.11	0.86	0.60
2091	0.53	0.23	0.89	0.13	0.08	0.55	1.34	2.86	0.25	0.21	0.37	0.17
2092	1.29	0.03	0.15	0.03	0.02	0.27	1.91	3.90	0.67	0.58	0.20	1.54
2093	0.30	2.06	1.32	0.88	0.04	0.20	2.61	3.26	1.41	0.52	0.15	0.90
2094	0.21	2.49	0.67	0.38	0.13	0.16	2.45	4.78	0.33	0.90	2.73	0.38
2095	1.64	0.81	0.51	0.51	0.13	0.24	0.93	2.15	1.10	1.23	0.99	0.83
2096	0.30	0.11	0.57	0.19	0.01	0.33	2.29	2.86	1.93	0.06	0.09	2.31
2097	2.80	2.99	0.20	0.16	0.08	0.51	4.24	4.93	2.44	0.40	0.12	0.54
2098	0.08	2.12	0.19	1.00	0.06	0.16	3.93	3.70	0.95	0.46	1.52	0.47
2099	1.66	0.55	2.08	0.24	0.02	1.02						
Avg.	**0.98**	**1.29**	**1.05**	**0.39**	**0.08**	**0.43**	**2.74**	**3.22**	**1.12**	**0.45**	**0.73**	**0.81**

b) RCP 8.5

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2085							2.57	6.33	4.02	0.38	0.28	2.96
2086	1.52	2.81	0.09	0.19	0.04	0.73	4.39	7.18	2.75	0.53	1.51	1.21
2087	0.50	1.20	0.47	0.53	0.02	0.78	4.31	5.10	3.04	1.01	1.43	1.48
2088	0.36	0.10	0.04	0.13	0.12	0.18	3.05	5.09	4.13	0.42	0.08	1.65
2089	2.22	3.19	0.41	0.28	0.17	0.07	3.68	4.49	3.12	0.21	0.68	1.39
2090	2.89	2.55	0.67	0.12	0.03	0.31	3.86	7.28	1.49	3.45	0.28	0.97

2091	0.68	0.85	1.17	0.29	0.05	0.32	3.26	1.87	1.52	0.65	0.41	1.00
2092	0.57	3.87	1.10	0.26	0.03	0.22	5.70	9.20	1.58	0.63	1.25	0.27
2093	1.04	1.68	0.42	0.19	0.05	0.36	4.22	4.94	1.36	0.50	0.46	0.91
2094	1.47	0.03	0.50	0.13	0.02	1.14	6.99	6.30	4.32	0.32	0.11	0.98
2095	2.79	1.87	0.21	0.10	0.11	1.03	3.93	1.96	2.55	0.06	1.28	2.34
2096	0.23	0.73	1.33	0.10	0.12	0.94	5.73	3.13	0.69	0.10	0.15	0.16
2097	0.25	0.21	0.10	0.11	0.03	0.07	6.21	6.35	1.66	0.46	0.21	1.57
2098	0.59	0.19	0.04	0.11	0.04	1.43	4.90	8.23	4.95	1.29	0.18	4.09
2099	2.51	6.41	0.71	0.14	0.44	1.66						
Avg.	**1.26**	**1.84**	**0.52**	**0.19**	**0.09**	**0.66**	**4.49**	**5.53**	**2.65**	**0.72**	**0.59**	**1.50**

Table 25: Number of Rainy Days 2085-2099

a) RCP 2.6

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2085							31	31	26	25	20	17
2086	29	23	30	24	16	25	31	31	27	26	17	25
2087	25	23	19	12	23	22	30	31	29	23	25	26
2088	28	19	29	23	17	22	31	31	27	29	23	25
2089	24	20	27	19	20	23	31	31	28	28	19	21
2090	26	24	27	23	15	28	31	31	29	20	23	23
2091	25	23	27	19	18	18	31	31	24	22	18	23
2092	25	15	17	9	20	25	31	31	26	22	21	29
2093	27	25	24	22	11	25	31	30	29	21	18	24
2094	19	24	23	14	18	23	31	31	30	27	29	26
2095	29	21	23	22	18	22	29	31	29	28	22	25
2096	16	18	19	18	12	26	31	30	28	15	20	19
2097	23	24	22	13	13	18	31	31	29	23	22	24
2098	22	24	26	20	14	25	31	31	28	27	28	23
2099	28	20	26	18	12	25						

Avg.	24.7	21.6	24.2	18.3	16.2	23.4	30.8	30.9	27.8	24.0	21.8	23.6

b) RCP 8.5

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2085							30	31	30	21	24	27
2086	30	25	16	14	11	27	31	31	30	25	23	25
2087	27	24	26	16	10	20	31	31	29	27	19	24
2088	23	17	16	19	14	22	31	31	30	26	16	26
2089	28	18	27	18	17	14	31	31	30	24	23	28
2090	27	27	25	15	20	20	31	31	30	30	24	23
2091	25	25	26	18	17	22	31	31	30	23	26	29
2092	27	23	18	21	15	21	31	31	30	24	24	23
2093	27	23	23	19	14	23	30	31	28	28	23	26
2094	28	17	21	15	12	25	31	31	30	18	21	26
2095	22	25	19	16	18	24	31	31	30	21	21	27
2096	20	24	23	16	21	28	31	30	28	18	21	22
2097	15	20	22	14	12	21	31	31	30	22	19	25
2098	25	18	13	17	11	28	31	31	30	28	17	26
2099	20	23	20	18	24	27						
Avg.	**24.6**	**22.1**	**21.1**	**16.9**	**15.4**	**23.0**	**30.9**	**30.9**	**29.6**	**23.9**	**21.5**	**25.5**

Table 26: Temperature 2085-2099

a) RCP 2.6 Minimum

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1998							74	74	69	52	47	37
1999	36	40	43	50	61	69	74	75	67	56	42	33
2000	42	40	47	55	59	70	74	72	69	56	43	37
2001	40	43	47	48	57	69	75	71	66	57	43	38

2002	36	43	47	53	57	65	73	74	68	56	43	39
2003	39	41	44	50	55	69	74	74	67	53	43	39
2004	33	38	45	51	60	68	74	73	65	55	42	39
2005	35	41	47	49	58	71	75	72	69	55	47	32
2006	34	44	47	49	58	68	71	74	66	58	42	38
2007	37	38	45	51	57	74	75	72	67	59	42	35
2008	38	41	43	50	56	70	75	73	67	59	43	38
2009	39	40	45	50	59	71	74	72	65	55	40	37
2010	39	41	43	48	59	69	75	72	65	56	44	35
2011	41	40	46	49	62	68	74	72	65	56	44	36
2012	32	40	43	50	61	72						
Avg.	**37.2**	**40.6**	**45.1**	**50.2**	**58.5**	**69.5**	**74.1**	**72.9**	**66.8**	**55.9**	**43.2**	**36.6**

b) RCP 2.6 Mean

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1998							89	87	84	69	65	54
1999	51	55	57	66	78	86	87	89	82	73	58	47
2000	58	55	63	72	76	87	87	86	84	73	59	51
2001	55	60	63	64	74	86	88	85	81	73	59	52
2002	52	60	62	70	73	82	87	87	83	73	60	56
2003	56	54	59	67	71	86	88	87	82	69	58	54
2004	48	54	60	68	78	86	88	87	80	72	59	56
2005	50	58	64	66	76	88	89	85	83	71	64	46
2006	49	59	62	65	76	85	86	87	81	75	60	53
2007	54	53	60	68	74	91	89	86	82	75	56	49
2008	53	55	59	67	73	86	89	87	82	75	60	54
2009	55	56	61	67	77	88	88	85	80	72	58	52
2010	54	55	59	66	76	86	88	86	80	73	61	50
2011	55	55	63	66	80	85	88	86	81	72	59	51
2012	47	56	58	66	78	89						
Avg.	**52.5**	**56.0**	**60.7**	**67.0**	**75.8**	**86.5**	**87.8**	**86.3**	**81.8**	**72.4**	**59.7**	**51.8**

c) RCP 2.6 Maximum

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1998							103	100	99	85	83	71
1999	67	71	72	82	95	103	100	102	97	90	75	62
2000	73	71	78	90	93	103	101	100	98	89	74	66
2001	70	76	78	79	90	102	101	98	96	88	75	66
2002	68	77	77	87	90	98	100	100	99	90	77	73
2003	72	68	73	84	88	103	101	100	97	86	74	69
2004	63	70	75	84	96	104	102	101	96	89	75	73
2005	64	75	81	84	94	105	103	98	98	88	81	59
2006	64	74	78	81	94	103	101	101	96	91	77	69
2007	70	68	76	85	91	109	103	99	97	91	70	63
2008	68	69	75	84	90	103	103	101	97	90	77	70
2009	71	71	78	84	95	105	101	98	95	89	76	67
2010	68	69	75	83	93	103	102	99	94	90	78	65
2011	70	70	80	83	98	102	102	99	97	88	75	66
2012	63	71	72	82	96	105						
Avg.	**67.9**	**71.5**	**76.3**	**83.7**	**93.1**	**103.5**	**101.5**	**99.8**	**96.8**	**88.9**	**76.1**	**67.1**

d) RCP 8.5 Minimum

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1998							83	81	74	63	50	40
1999	41	42	51	59	64	78	84	78	72	63	49	43
2000	42	48	49	55	64	75	84	79	74	64	51	39
2001	42	49	54	59	63	77	85	80	73	60	50	42
2002	45	43	51	56	67	74	84	80	74	61	47	38
2003	41	42	49	57	66	74	83	80	75	62	48	39
2004	40	48	51	52	63	76	83	81	74	63	53	40
2005	40	39	49	57	63	76	83	80	74	60	52	41
2006	41	46	54	55	63	76	84	79	76	67	55	44

2007	42	49	54	60	63	76	83	80	72	62	53	45
2008	46	46	52	58	60	77	84	80	76	61	54	44
2009	44	44	53	60	70	86	85	81	78	66	55	45
2010	46	49	54	61	67	77	82	79	73	63	52	42
2011	40	49	53	55	65	83	84	77	74	65	50	42
2012	45	46	51	56	64	80						
Avg.	**42.5**	**45.8**	**51.7**	**57.2**	**64.4**	**77.4**	**83.5**	**79.7**	**74.3**	**62.9**	**51.4**	**41.7**

e) RCP 8.5 Mean

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1998							96	94	89	79	65	55
1999	56	57	68	75	82	94	97	91	87	79	64	58
2000	57	64	65	71	82	92	97	92	88	79	67	53
2001	57	66	72	77	81	94	98	93	87	77	67	57
2002	60	59	67	72	84	91	97	93	89	78	63	52
2003	55	58	65	73	84	91	96	93	89	77	63	56
2004	55	62	67	69	80	93	96	94	89	79	68	54
2005	55	53	65	73	81	93	95	92	88	77	68	57
2006	56	61	70	72	81	94	97	92	91	83	71	59
2007	57	65	70	77	80	93	96	93	86	78	69	59
2008	61	61	69	76	78	94	97	93	90	78	71	59
2009	60	60	68	77	88	102	98	95	92	82	72	62
2010	62	65	69	78	84	94	95	92	87	80	68	58
2011	56	65	70	71	82	98	97	90	87	81	66	58
2012	60	62	67	74	81	95						
Avg.	**57.5**	**61.2**	**67.9**	**73.9**	**82.2**	**94.1**	**96.6**	**92.6**	**88.6**	**79.0**	**67.3**	**56.8**

f) RCP 8.5 Maximum

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1998							110	106	103	95	81	69
1999	70	72	85	91	100	110	110	103	102	95	79	73

2000	73	80	81	87	100	109	111	105	102	94	84	68
2001	72	82	90	94	99	110	110	105	101	94	84	72
2002	74	74	82	88	102	108	110	106	103	95	80	65
2003	69	73	80	89	102	109	110	105	103	91	79	72
2004	70	77	83	86	97	111	109	108	104	95	83	68
2005	69	67	81	90	99	110	108	105	103	93	83	73
2006	70	76	86	89	99	111	111	105	105	99	86	74
2007	71	82	86	94	98	110	109	106	100	95	85	73
2008	76	76	86	93	96	112	110	106	104	94	87	74
2009	76	76	84	94	106	117	111	108	107	98	88	79
2010	77	80	84	95	102	110	107	105	102	97	84	73
2011	72	82	86	87	100	113	110	103	101	96	83	74
2012	75	78	84	91	99	109						
Avg.	**73**	**77**	**84**	**91**	**100**	**111**	**110**	**106**	**103**	**95**	**83**	**72**

Table 27: Total ET 2085-2099

a) RCP 2.6

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1998							8.4	8.0	7.9	7.1	6.7	5.5
1999	5.1	5.0	5.5	6.5	8.1	8.6	7.9	8.2	7.8	7.5	5.8	4.6
2000	5.7	4.9	6.3	7.4	7.9	8.6	8.1	8.1	7.8	7.5	5.7	4.9
2001	5.4	5.7	6.2	6.1	7.6	8.6	8.0	7.8	7.7	7.2	5.7	4.9
2002	5.2	5.6	6.0	7.1	7.5	8.2	8.0	8.0	7.9	7.6	6.1	5.9
2003	5.7	4.6	5.6	6.7	7.3	8.6	8.1	7.9	7.7	7.0	5.6	5.3
2004	4.7	5.0	5.9	6.7	8.3	8.9	8.3	8.2	7.6	7.5	5.9	5.9
2005	4.8	5.6	6.7	6.8	8.1	8.8	8.4	7.7	7.8	7.3	6.4	4.2
2006	4.8	5.2	6.1	6.4	8.1	8.7	8.3	8.1	7.6	7.7	6.0	5.3
2007	5.5	4.6	6.0	6.9	7.8	9.3	8.3	7.9	7.7	7.6	5.1	4.6
2008	5.1	4.7	6.0	6.8	7.6	8.6	8.4	8.1	7.7	7.5	6.0	5.4

2009	5.6	5.2	6.2	6.8	8.3	8.9	8.1	7.8	7.6	7.5	6.0	5.1
2010	5.1	4.7	5.9	6.7	8.0	8.6	8.2	7.9	7.4	7.5	6.2	4.9
2011	5.4	4.9	6.6	6.6	8.5	8.6	8.2	8.0	7.8	7.3	5.7	5.1
2012	4.7	5.0	5.6	6.5	8.3	8.8						
Avg.	**5.2**	**5.1**	**6.1**	**6.7**	**8.0**	**8.7**	**8.2**	**8.0**	**7.7**	**7.4**	**5.9**	**5.1**

b) RCP 8.5

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1998							8.9	8.4	8.2	7.9	6.3	5.2
1999	5.2	5.0	7.0	7.4	8.7	9.2	8.8	8.2	8.2	8.0	6.0	5.6
2000	5.7	5.8	6.5	7.0	8.8	9.4	9.1	8.3	8.0	7.7	6.7	5.2
2001	5.6	6.3	7.7	7.9	8.7	9.3	8.8	8.4	7.9	7.9	6.8	5.6
2002	5.7	5.3	6.6	7.0	8.9	9.1	8.9	8.5	8.3	8.1	6.2	4.8
2003	5.2	5.1	6.5	7.1	9.0	9.4	9.0	8.3	8.2	7.4	6.1	5.7
2004	5.4	5.5	6.8	7.0	8.4	9.5	8.7	8.7	8.4	7.9	6.5	5.1
2005	5.2	4.7	6.5	7.2	8.6	9.3	8.5	8.2	8.2	7.9	6.5	5.7
2006	5.4	5.3	7.1	7.3	8.7	9.5	9.0	8.4	8.4	8.4	6.8	5.8
2007	5.4	6.0	7.1	7.8	8.6	9.4	8.7	8.4	7.8	8.0	6.7	5.6
2008	6.0	5.3	7.2	7.7	8.3	9.7	8.9	8.6	8.1	7.9	7.0	5.7
2009	6.1	5.6	6.8	7.8	9.4	9.9	8.8	8.6	8.6	8.3	7.1	6.4
2010	6.1	5.8	6.8	7.9	8.9	9.3	8.5	8.4	8.1	8.3	6.6	5.7
2011	5.7	6.0	7.1	7.0	8.7	9.3	8.7	8.2	7.9	7.9	6.5	5.8
2012	5.8	5.6	6.9	7.5	8.5	8.8						
Avg.	**5.6**	**5.5**	**6.9**	**7.4**	**8.7**	**9.4**	**8.8**	**8.4**	**8.2**	**8.0**	**6.6**	**5.6**

Appendix 8: Weather Variable Comparison: Current Period vs. Counterfactual Climate Scenarios

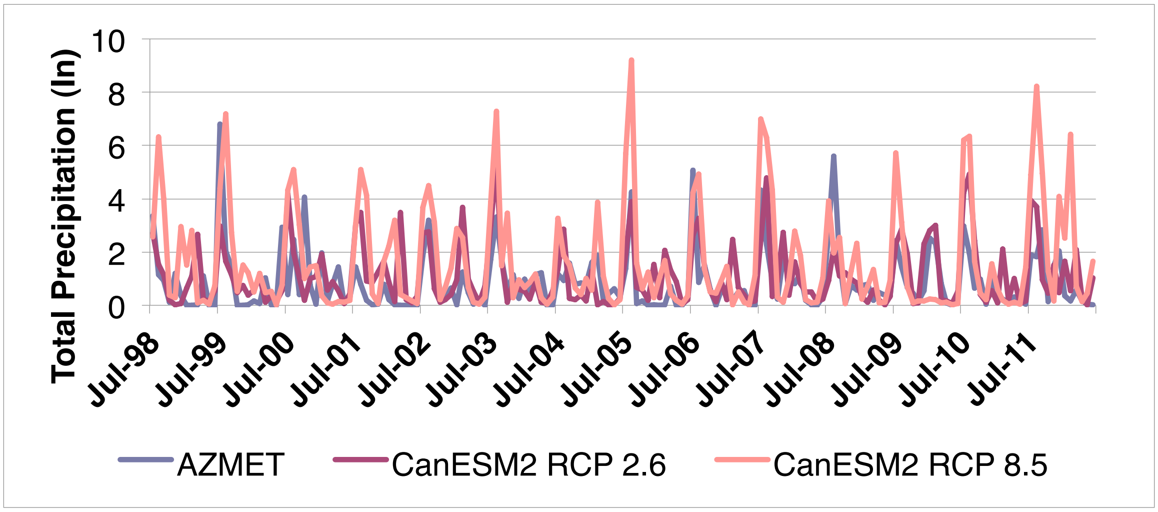
To provide a visual sense of how different weather projections from the MISS scenario or the CanESM2 model under RCP 2.6 and RCP 8.5 are from the current period weather data, we present graphs comparing total monthly precipitation, number of rainy days, mean monthly temperature, and total monthly ET from the current period and each of the 3 scenarios. Note that we do not include the MISS scenario in the total precipitation comparison because in the MISS scenario we simply cut the number of rainy days in the historic period in half without considering actual precipitation levels.

Because MISS data are an artificial transformation of the AZMET data, we have already described how number of rainy days and temperature vary between the two. However, we do see that ET estimates using the Hargreaves method appear to vary much less seasonally than do historic ET levels.

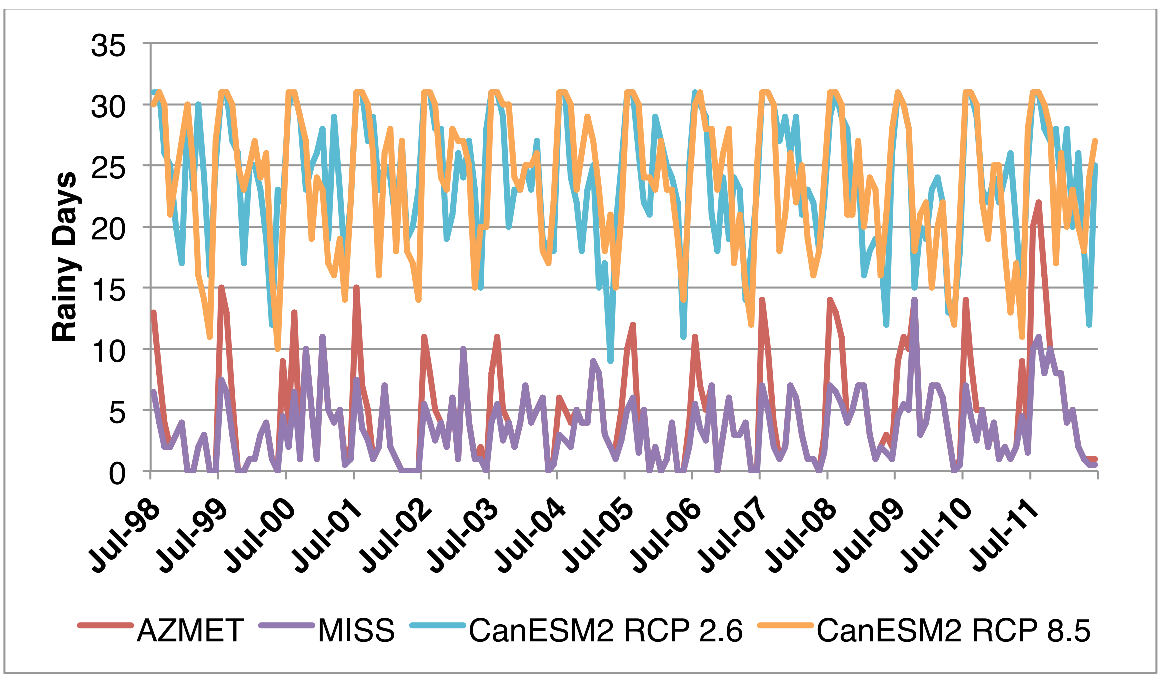
Examining the differences between CanESM2 projections and the historic AZMET data, we see that precipitation appears more volatile in the CanESM2 projections, particularly the RCP 8.5 scenario. CanESM2 projections data also suggest a substantially higher number of rainy days than in the current period. Temperatures appear higher throughout the year, particularly in the summer months and most noticeably in the RCP 8.5 scenario. Our ET projections using the Hargreaves method tend to be slightly higher on average than current period monthly ET, but these projections are not nearly as volatile as the current period data.

Figure 15: Weather Variable Comparison

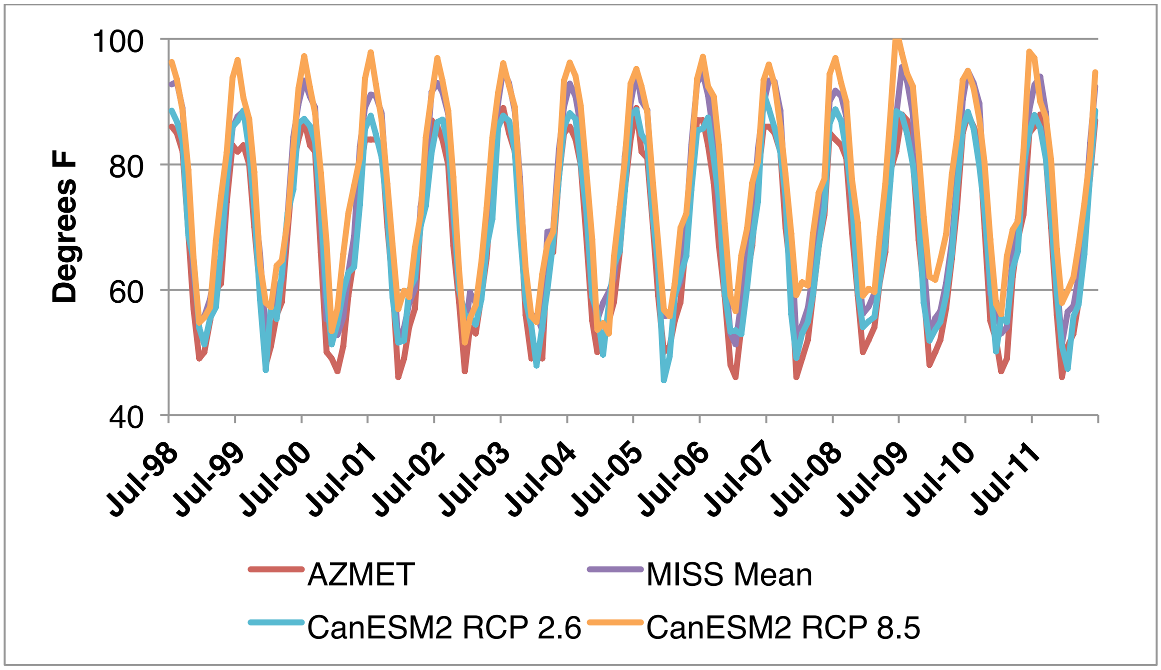
a) Total Monthly Precipitation



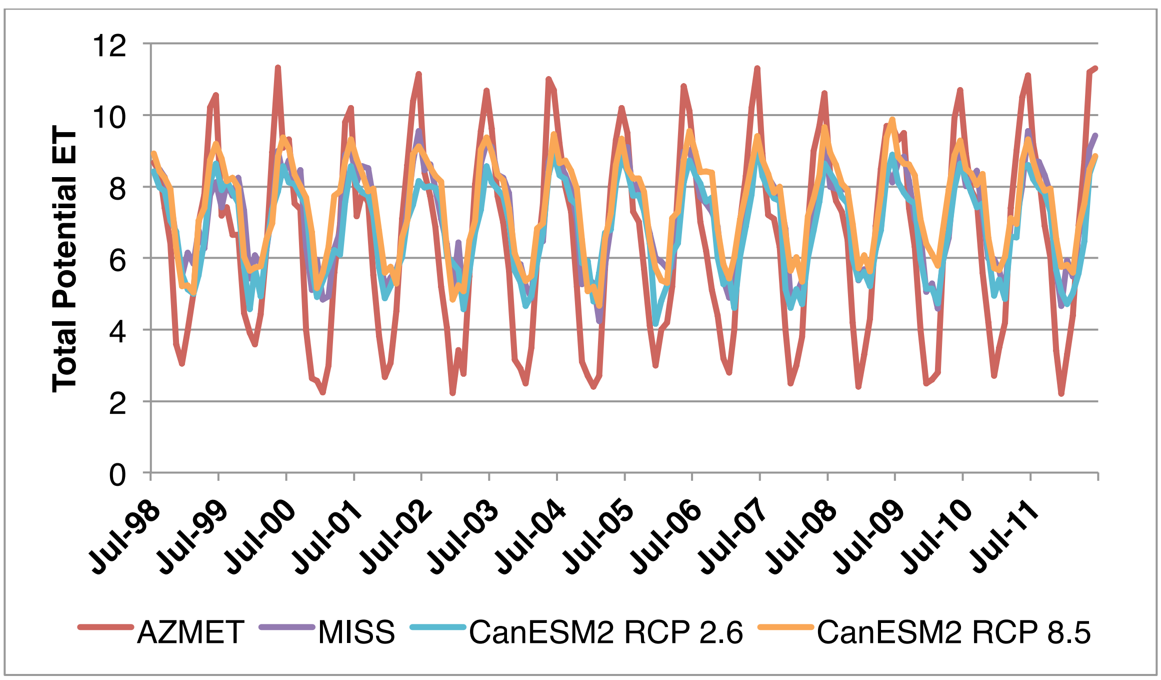
b) Number of Rainy Days Per Month



c) Mean Monthly Temperature



d) Total Monthly ET



Appendix 9: Method to Determine the Significance of Stone-Geary Parameters

Here we present a general framework of the delta method to calculate the standard errors and determine the significance of the Stone-Geary parameters.

First, we present the method used to calculate standard errors of γ in the SGF model formulation. The parameter γ is a function of the estimated parameters:

$$\gamma = f(\hat{\beta}) = \alpha_0 + \sum_{i=1}^{k} \alpha_i \bar{C}_i$$

Where:

$$\alpha_i = \alpha'_i(1-\beta)$$

The variance of the parameter γ is approximated as:

$$Var(\gamma) \approx Var\left[f(\hat{\beta})\right] = \left[\frac{\partial f(\hat{\beta})}{\partial \hat{\beta}}\right]' Var(\hat{\beta}) \left[\frac{\partial f(\hat{\beta})}{\partial \hat{\beta}}\right]$$

Where:

$$\frac{\partial f(\hat{\beta})}{\partial \hat{\beta}} = \begin{bmatrix} (1-\beta) \\ \bar{C}_i(1-\beta) \\ \vdots \\ \bar{C}_k(1-\beta) \\ -(\alpha'_0 + \sum_{i=1}^{k} \alpha'_i \bar{C}_i) \end{bmatrix}$$

The covariance matrix $Var(\hat{\beta})$ is the robust covariance matrix calculated via Huber/White/sandwich standard errors in the case of the household models, or via Newey-West standard errors in the case of the aggregate models. The standard error of γ is calculated as the square root of $Var(\gamma)$. To determine the significance of γ, the test statistic below is calculated and compared to critical values of a standard normal distribution.

$$\frac{\gamma}{S.E(\gamma)} \sim z(0,1)$$

The standard normal distribution is used because $f(\hat{\beta})$ is nonlinear in the estimated parameters.

Next, we describe the process of calculating the standard errors of both β and γ in the SGV model formulation. In this case, both parameters are functions of the estimated parameters:

$$\beta = f(\hat{\beta}) = \beta_0 + \sum_{i=1}^{k} \beta_i \bar{C}_i$$

$$\gamma = g(\hat{\beta}) = \alpha_0 + \sum_{i=1}^{k} \alpha_i \bar{C}_i$$

Where:

$$\alpha_i = \alpha'_i (1-\beta)$$

The variance of these parameters is estimated as follows:

$$Var(\beta) \approx Var\left[f(\hat{\beta})\right] = \left[\frac{\partial f(\hat{\beta})}{\partial \hat{\beta}}\right]' Var(\hat{\beta}) \left[\frac{\partial f(\hat{\beta})}{\partial \hat{\beta}}\right]$$

$$Var(\gamma) \approx Var\left[g(\hat{\beta})\right] = \left[\frac{\partial g(\hat{\beta})}{\partial \hat{\beta}}\right]' Var(\hat{\beta}) \left[\frac{\partial g(\hat{\beta})}{\partial \hat{\beta}}\right]$$

Where:

$$\frac{\partial f(\hat{\beta})}{\partial \hat{\beta}} = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ 1 \\ \bar{C}_i \\ \vdots \\ \bar{C}_k \end{bmatrix}$$

$$\frac{\partial g(\hat{\beta})}{\partial \hat{\beta}} = \begin{bmatrix} \\ \\ \\ \\ (1-\beta) \\ \overline{C}_i(1-\beta) \\ \vdots \\ \overline{C}_k(1-\beta) \\ -(\alpha'_0 + \sum_{i=1}^{k} \alpha'_i \overline{C}_i) \\ -\overline{C}_i(\alpha'_0 + \sum_{i=1}^{k} \alpha'_i \overline{C}_i) \\ \vdots \\ -\overline{C}_k(\alpha'_0 + \sum_{i=1}^{k} \alpha'_i \overline{C}_i) \end{bmatrix}$$

Once again, the covariance matrix $Var(\hat{\beta})$ is the robust covariance matrix calculated via Huber/White/sandwich standard errors in the case of the household models, or via Newey-West standard errors in the case of the aggregate models. The standard error of β or γ can be calculated as the square root of $Var(\beta)$ or $Var(\gamma)$, respectively. To determine the significance of these parameters, the test statistics below can be calculated and compared to critical values of a standard normal distribution.

$$\frac{\beta}{S.E(\beta)} \sim z(0,1)$$

$$\frac{\gamma}{S.E(\gamma)} \sim z(0,1)$$

Once again, the standard normal distribution is used because β and γ are nonlinear in the estimated parameters.

Appendix 10: IV Estimation of NDVI

Having received feedback that the relationships between parcel greenness, water price, and quantity of water consumed are likely to be endogenous, we conduct a Durbin-Wu-Hausman test to determine whether our NDVI measure is truly exogenous to quantity consumed. We reject the null hypothesis of exogeneity with 99% confidence, and therefore we must instrument NDVI using other variables in order to include it in our household water demand model. This is a difficult task, since few available variables not already included explicitly in our demand model can be expected to provide reliable indicators of parcel greenness. We select three instrumental variables: the construction year of each house (*BuildYear*), the assessed value of each house in a given year (*HomeValue*), and the area of each parcel (*ParcelArea*). While these variables may be correlated with quantity consumed, we can be confident that they are exogenously determined. We expect that older homes will tend to have greener yards, since they are often more centrally located and tend to have more non-native landscaping. We also expect that, in general, the higher the assessed home value, the greener that household's yard will be, since they can presumably afford to irrigate more. We also expect parcel size to be related to parcel greenness, although its expected sign is unclear. It may be that smaller lots in the center of town have greener, non-native landscaping, or it may be that households with more land have more vegetation.

The results of our regression of *NDVI* on these three variables are presented below. We see that, although the model has a low R^2, the overall F-statistic is significant at the 99% confidence level, as are each of the variables. Both *BuildYear* and *HomeValue* have the expected signs, and their large t-statistics (-85.7 and 163.95, respectively) indicate that they have strong explanatory power in the model. The predicted values from this regression are used in place of actual NDVI values in our final demand model.

Table 28: IV Estimation of NDVI

Variable	Coefficient (p-value)
Intercept	1.0573 (0.000)
BuildYear	-0.0005 (0.000)
HomeValue	0.00000014 (0.000)
ParcelArea	-0.00000001 (0.000)
R^2	0.128
F-test	11,760.73 (0.000)

Appendix 11: Counterfactual Climate Scenario Per Household Consumption Monthly Mean Comparison

Table 29: Per Household Consumption Monthly Means by Weather Data

a) SGF

	Actual	AZMET	MISS	CanESM2 RCP 2.6	CanESM2 RCP 8.5
Jan	10.2	10.8	12.4	15.7	16.0
Feb	10.4	11.2	12.1	15.1	15.5
Mar	10.1	12.7	12.7	16.2	16.2
Apr	11.8	13.7	12.9	15.6	15.7
May	13.5	14.8	13.6	16.0	16.3
Jun	16.6	15.1	14.0	17.7	18.0
Jul	17.1	15.5	14.4	18.6	19.1
Aug	14.4	14.7	14.2	18.6	18.8
Sep	14.8	13.6	13.7	17.9	18.5
Oct	13.6	12.6	13.7	17.0	17.3
Nov	12.6	10.9	12.5	15.5	16.0
Dec	11.2	10.6	12.3	15.5	16.1

b) SGV

	Actual	AZMET	MISS	CanESM2 RCP 2.6	CanESM2 RCP 8.5
Jan	10.2	10.8	12.4	15.1	15.8
Feb	10.4	11.2	12.1	14.9	15.6
Mar	10.1	12.6	12.7	15.9	16.2
Apr	11.8	13.7	12.9	15.4	16.0
May	13.5	14.8	13.6	16.0	16.4
Jun	16.6	15.1	13.9	18.3	19.0
Jul	17.1	15.5	14.4	19.8	20.6
Aug	14.4	14.8	14.2	19.7	20.2
Sep	14.8	13.6	13.7	18.7	19.8
Oct	13.6	12.5	13.7	17.0	17.8
Nov	12.6	10.9	12.5	15.2	16.2
Dec	11.2	10.6	12.3	14.8	15.8

Table 30: Per Household Consumption Monthly Mean Percent Difference

a) SGF

	Percent Difference (p-value)					
	MISS vs. AZMET	**RCP 2.6 vs. AZMET**	**RCP 8.5 vs. AZMET**	**RCP 2.6 vs. MISS**	**RCP 8.5 vs. MISS**	**RCP 8.5 vs. RCP 2.6**
Jan	14.34 (0.000)	44.89 (0.000)	47.79 (0.000)	26.73 (0.000)	29.26 (0.000)	2.00 (0.405)
Feb	8.17 (0.000)	35.38 (0.000)	38.38 (0.000)	25.15 (0.000)	27.92 (0.000)	2.22 (0.220)
Mar	0.20 (0.907)	27.98 (0.000)	28.09 (0.000)	27.72 (0.000)	27.84 (0.000)	0.09 (0.967)
Apr	-5.81 (0.002)	13.74 (0.000)	14.88 (0.000)	20.76 (0.000)	21.96 (0.000)	1.00 (0.642)
May	-8.06 (0.000)	8.20 (0.000)	9.73 (0.000)	17.68 (0.000)	19.34 (0.000)	1.41 (0.486)
Jun	-7.75 (0.000)	16.66 (0.000)	19.06 (0.000)	26.47 (0.000)	29.07 (0.000)	2.06 (0.233)
Jul	-7.39 (0.000)	20.20 (0.000)	22.79 (0.000)	29.79 (0.000)	32.59 (0.000)	2.16 (0.056)

Aug	-3.77 (0.025)	25.89 (0.000)	27.90 (0.000)	30.82 (0.000)	32.92 (0.000)	1.60 (0.158)
Sep	1.15 (0.410)	31.77 (0.000)	36.43 (0.000)	30.28 (0.000)	34.88 (0.000)	3.54 (0.005)
Oct	8.75 (0.000)	35.31 (0.000)	37.96 (0.000)	24.42 (0.000)	26.86 (0.000)	1.96 (0.387)
Nov	14.69 (0.000)	43.08 (0.000)	47.64 (0.000)	24.76 (0.000)	28.73 (0.000)	3.19 (0.065)
Dec	16.26 (0.000)	46.37 (0.000)	52.11 (0.000)	25.90 (0.000)	30.84 (0.000)	3.92 (0.017)

Percent Difference
(p-value)

	AZMET vs. Actual	**MISS vs. Actual**	**RCP 2.6 vs. Actual**	**RCP 8.5 vs. Actual**	**MISS vs. AZMET**
Jan	6.71 (0.021)	22.01 (0.000)	54.61 (0.000)	57.70 (0.000)	14.34 (0.000)
Feb	7.67 (0.021)	16.47 (0.000)	45.76 (0.000)	48.99 (0.000)	8.17 (0.000)
Mar	25.30 (0.000)	25.55 (0.000)	60.35 (0.000)	60.50 (0.000)	0.20 (0.907)
Apr	16.36 (0.000)	9.60 (0.002)	32.35 (0.000)	33.67 (0.000)	-5.81 (0.002)
May	10.12 (0.007)	1.25 (0.704)	19.15 (0.000)	20.84 (0.000)	-8.06 (0.000)
Jun	-9.01 (0.006)	-16.06 (0.000)	6.15 (0.051)	8.34 (0.012)	-7.75 (0.000)
Jul	-9.02 (0.011)	-15.74 (0.000)	9.36 (0.009)	11.72 (0.002)	-7.39 (0.000)
Aug	2.38 (0.505)	-1.49 (0.669)	28.88 (0.000)	30.95 (0.000)	-3.77 (0.025)
Sep	-8.45 (0.013)	-7.40 (0.026)	20.64 (0.000)	24.90 (0.000)	1.15 (0.410)
Oct	-7.58 (0.003)	0.51 (0.816)	25.06 (0.000)	27.51 (0.000)	8.75 (0.000)
Nov	-13.42 (0.000)	-0.70 (0.818)	23.88 (0.000)	27.83 (0.000)	14.69 (0.000)
Dec	-5.95 (0.019)	9.34 (0.001)	37.67 (0.000)	43.06 (0.000)	16.26 (0.000)

b) SGV

	Percent Difference (p-value)					
	MISS vs. AZMET	RCP 2.6 vs. AZMET	RCP 8.5 vs. AZMET	RCP 2.6 vs. MISS	RCP 8.5 vs. MISS	RCP 8.5 vs. RCP 2.6
Jan	14.62 (0.000)	39.66 (0.000)	45.62 (0.000)	21.84 (0.000)	27.04 (0.000)	4.26 (0.080)
Feb	8.49 (0.000)	33.88 (0.000)	39.84 (0.000)	23.40 (0.000)	28.90 (0.000)	4.46 (0.020)
Mar	0.38 (0.827)	25.38 (0.000)	27.94 (0.000)	24.91 (0.000)	27.46 (0.000)	2.04 (0.402)
Apr	-5.78 (0.006)	12.05 (0.000)	16.60 (0.000)	18.91 (0.000)	23.74 (0.000)	4.06 (0.125)
May	-8.07 (0.001)	7.63 (0.008)	10.78 (0.000)	17.08 (0.000)	20.51 (0.000)	2.93 (0.261)
Jun	-7.72 (0.002)	21.22 (0.000)	25.55 (0.000)	31.37 (0.000)	36.06 (0.000)	3.57 (0.166)
Jul	-7.33 (0.000)	27.52 (0.000)	32.41 (0.000)	37.60 (0.000)	42.87 (0.000)	3.83 (0.120)
Aug	-3.78 (0.072)	33.33 (0.000)	36.47 (0.000)	38.56 (0.000)	41.83 (0.000)	2.36 (0.301)
Sep	1.19 (0.502)	37.78 (0.000)	46.03 (0.000)	36.17 (0.000)	44.31 (0.000)	5.98 (0.010)
Oct	9.13 (0.000)	35.71 (0.000)	42.20 (0.000)	24.36 (0.000)	30.31 (0.000)	4.78 (0.114)
Nov	14.84 (0.000)	40.16 (0.000)	49.13 (0.000)	22.05 (0.000)	29.86 (0.000)	6.40 (0.003)
Dec	16.31 (0.000)	39.96 (0.000)	49.14 (0.000)	20.33 (0.000)	28.23 (0.000)	6.56 (0.000)

	Percent Difference (p-value)			
	AZMET vs. Actual	MISS vs. Actual	RCP 2.6 vs. Actual	RCP 8.5 vs. Actual
Jan	6.52 (0.011)	22.10 (0.000)	48.77 (0.000)	55.11 (0.000)
Feb	7.46 (0.019)	16.58 (0.000)	43.86 (0.000)	50.28 (0.000)
Mar	25.13 (0.000)	25.60 (0.000)	56.89 (0.000)	60.09 (0.000)
Apr	16.48	9.75	30.51	35.81

	(0.000)	(0.002)	(0.000)	(0.000)
May	10.36	1.46	18.78	22.26
	(0.008)	(0.673)	(0.000)	(0.000)
Jun	-9.13	-16.15	10.15	14.09
	(0.008)	(0.000)	(0.005)	(0.000)
Jul	-8.98	-15.65	16.06	20.51
	(0.012)	(0.000)	(0.000)	(0.000)
Aug	2.57	-1.31	36.75	39.98
	(0.482)	(0.718)	(0.000)	(0.000)
Sep	-8.36	-7.27	26.26	33.82
	(0.015)	(0.032)	(0.000)	(0.000)
Oct	-7.70	0.73	25.27	31.25
	(0.002)	(0.747)	(0.000)	(0.000)
Nov	-13.46	-0.62	21.29	29.05
	(0.000)	(0.839)	(0.000)	(0.000)
Dec	-5.87	9.48	31.74	40.39
	(0.013)	(0.000)	(0.000)	(0.000)

Appendix 12: Alternative Aggregate Model Runs

Since our original aggregate model runs including control variables for number of rainy days per month and total monthly ET produce a counterintuitive positive sign on the coefficient for number of rainy days, we experiment with alternative combinations of control variables. We run the aggregate model (for both Stone-Geary specifications) in three different ways. First, we attempt to distinguish between the impacts of rainfall on water consumption at different times of year. Second, we run the model excluding any precipitation variable. Third, we consider the more traditional total monthly precipitation metric instead of number of rainy days per month.

Our first alternative model attempts to account for seasonality in the effect of rainfall on water consumption. Since rainfall is expected to influence only the portion of water consumption related to outdoor use, we focus our efforts on highlighting the effect of rainfall events on water consumption in summer. However, in Tucson, summer weather patterns are not uniform. The months of

May and June tend to be hot, with little to no rainfall, whereas the months of June through September remain hot but see substantial rainfall due to the occurrence of the North American monsoon. We expect that rainfall events will have a much more substantial influence on water consumption if they occur during the portion of the summer that does not typically experience precipitation (May-June). Therefore, we construct a dummy variable for the months of May and June (*DSummer*) and a dummy variable for the months of July, August, and September (*DMonsoon*), and interact each of these dummies with number of rainy days. Thus, two separate interaction terms, *N_Rainy_Days_DSummer*, and *N_Rainy_Days_DMonsoon*, are included in the model in addition to the original variable *N_Rainy_Days*. Results from these model runs are summarized below in Table 31.

Table 31: Aggregate Model Results Including Seasonal Dummies

		SGF	**SGV**
Variable	Parameter	Estimate (p-value)	Estimate (p-value)
Intercept	α'_0	7.3341 (0.000)	8.3660 (0.001)
N_Rainy_Days	α'_1	-0.0706 (0.288)	0.2389 (0.403)
N_Rainy_Days_DSummer	α'_2	0.2879 (0.154)	-1.1561 (0.014)
N_Rainy_Days_DMonsoon	α'_3	0.2853 (0.000)	-0.1089 (0.738)
ET	α'_4	0.4557 (0.000)	0.2954 (0.429)
IVpcinc_price	β	0.0003 (0.014)	
IVpcinc_price	β_0		0.0002 (0.572)
IVpcinc_price_NRainyDays	β_1		0.0000 (0.258)

IVpcinc_price_N_Rainy_Days_DSummer	β_2		0.0002 (0.001)
IVpcinc_price_N_Rainy_Days_DMonsoon	β_3		0.0000 (0.207)
IVpcinc_price_ET	β_4		0.0000 (0.648)
	β	0.0003 (0.014)	0.0003 (0.010)
	γ	10.6788 (0.000)	10.7819 (0.000)
	F-test	28.79 (0.000)	22.57 (0.000)

Precipitation aside, these results qualitatively similar to those of our original model runs, with one exception. In the SGV model, the interaction term between *IVpcinc_price* and *ET* was not found to be significant, whereas our original model runs showed this variable to be positive with 95% confidence. The precipitation variables also prove less than satisfactory. In the SGF model, only the coefficient on *N_Rainy_Days_DMonsoon* is significant, and this coefficient is positive. The SGV model appears more promising on first glance. Only the coefficients on *N_Rainy_Days_DSummer* and the interaction between *IVpcinc_price* and *N_Rainy_Days_DSummer* are significant. However, the two coefficients have opposite signs, which makes their interpretation unclear. Given that the inclusion of seasonal dummies 1) appears to offer little additional information in terms of the effects of precipitation on water consumption and 2) eliminates the significance of the ET variable, which has been much more robust than the precipitation variables across household and aggregate model runs, we prefer our original model formulation.

In our second alternative model, we drop the precipitation variable completely, regressing consumption on simply ET and the ratio of per capita income to instrumented lagged average price. However, the significance of β in both models is adversely affected by the elimination of the precipitation variable, as are the significance levels of the SGV model coefficients related to ET. In fact, neither of the variables related to ET appear significant in the SGV model. We conclude that, despite the counterintuitive sign on our precipitation variable, precipitation does influence water consumption substantially enough to warrant inclusion in the model.

Our third alternative model substitutes total monthly precipitation, the conventional metric used to approximate rainfall in water demand models, for number of rainy days per month. However, as we would expect, this variable performs more poorly than number of rainy days in both model specifications. The sign of the precipitation variable remains positive, but the significance level is less than that of number of rainy days. Additionally, the significance of all other variables in the model is adversely affected. We conclude that number of rainy days is the superior precipitation metric.

Because none of these alternative model specifications appear superior to our original specification, we maintain our original model specification for use in assessing the sensitivity of water consumption to potential climate change.

Appendix 13: Household Analysis with Only Time-Varying Controls

To determine whether performing a water demand analysis at the household level, which requires much more data and more sophisticated econometric methods than an analysis at the aggregate level, provides substantial marginal benefit, we develop a household model including only time-varying control variables. This provides a more balanced comparison of our aggregate and household models, and allows us to see what additional information we glean from controlling for household heterogeneity.

A few key differences between the two models remain, aside from the fact that one is a panel model and the other is a time-series model. One is the way in which we control for asynchronous billing cycles. In the household analysis, we control for the number of days in a billing cycle explicitly in the model, and match weather variables exactly to each billing cycle. In the aggregate analysis, we had to match weather variables to period-ending months and standardize billing cycles to 30-day increments. Lastly, in our household analysis, we utilize precipitation data from 11 spatially-dispersed Pima County RFCD rain gauges, whereas our aggregate analysis relies on precipitation data from a single gauge maintained by AZMET.

We specify the simplified household model in the SGF case as:

$$Usage_{i,t} = \alpha'_0 + \alpha'_1(ET)_{i,t} + \alpha'_2(N\_Rainy\_Days)_{i,t} + \alpha'_3(DaysinRead)_{i,t}$$
$$+\beta(IVinc\_price)_{i,t} + u_i + \varepsilon_{i,t}$$

In the SGV case, the simplified model is as follows:

$$Usage_{i,t} = \alpha'_0 + \alpha'_1(ET)_{i,t} + \alpha'_2(N\_Rainy\_Days)_{i,t} + \alpha'_3(DaysinRead)_{i,t}$$
$$+\beta_0(IVinc\_price)_{i,t} + \beta_1(IVinc\_price\_ET)_{i,t} + \beta_2(IVinc\_price\_NRainyDays)_{i,t}$$
$$+\beta_3(IVinc\_price\_Days)_{i,t} + u_i + \varepsilon_{i,t}$$

For the simplified model, diagnostic test results are similar, so we estimate the model using feasible GLS with fixed effects and Huber/White/sandwich standard errors, as before. The results from these simplified models are presented below in Table 32.

Table 32: Simplified Household Model Results

		SGF	SGV
Variable	Parameter	Estimate (p-value)	Estimate (p-value)
Intercept	α'_0	-6.1381 (0.000)	-0.3917 (0.416)
N_Rainy_Days	α'_1	-0.0128 (0.046)	-0.0410 (0.002)
ET	α'_2	0.8171 (0.000)	0.4767 (0.000)
DaysinRead	α'_3	0.3507 (0.000)	0.2373 (0.000)
IVpcinc_price	β	0.0024 (0.000)	
IVpcinc_price	β_0		-0.0037

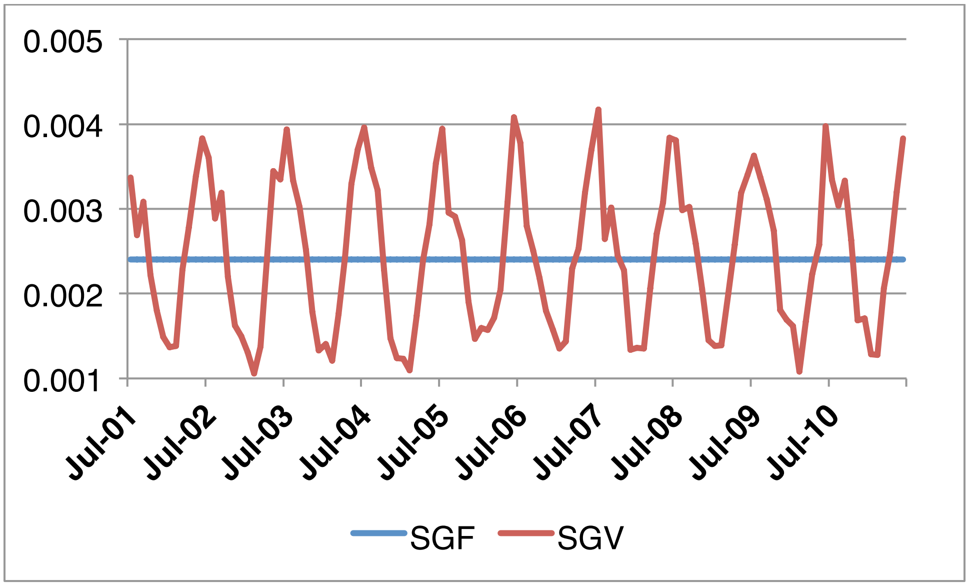
			(0.000)
IVpcinc_price_NRainyDays	β_1		0.00002 (0.052)
IVpcinc_price_ET	β_2		0.0004 (0.000)
IVpcinc_price_Days	β_3		0.0001 (0.000)
	β	0.0024 (0.000)	0.0025 (0.000)
	γ	9.8956 (0.000)	9.8473 (0.000)
	F-test	718.96 (0.000)	532.74 (0.000)

Immediately evident is the significant, negative sign on number of rainy days. This is much more reasonable than the positive and significant coefficient we estimate for number of rainy days in the aggregate model. Thus, we can see the benefit of using disaggregated precipitation measurements to estimate water demand. The other parameter estimates here resemble results from our original household model runs as well as our aggregate model in terms of both sign and significance. The magnitudes of β and γ appear to be somewhat smaller in the household models than in the aggregate model, but this is consistent between our original household model runs and these simplified models.

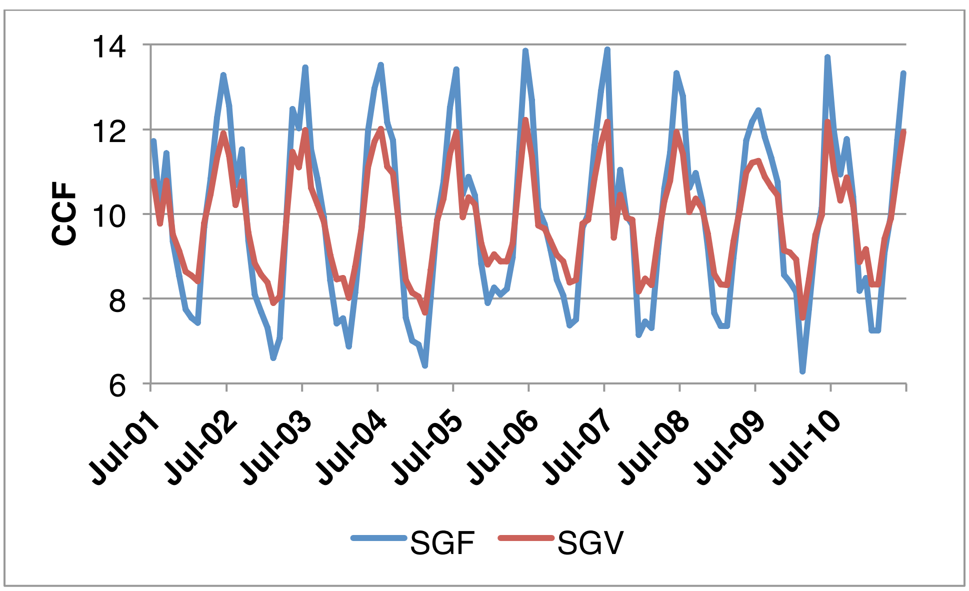
The other comparison of interest using these simplified household models is an examination of the trends in the average marginal budget share allocated to water, the average conditional water use threshold, and price elasticity of demand over time. These trends are plotted below in Figure 16, and their significance is tested using a regression on a time trend. These results are tabulated in Table 33.

Figure 16: Simplified Household Model Stone-Geary Parameter Trends

a) Temporal Variation in Mean β



b) Temporal Variation in Mean γ



c) Temporal Variation in Mean ε_p

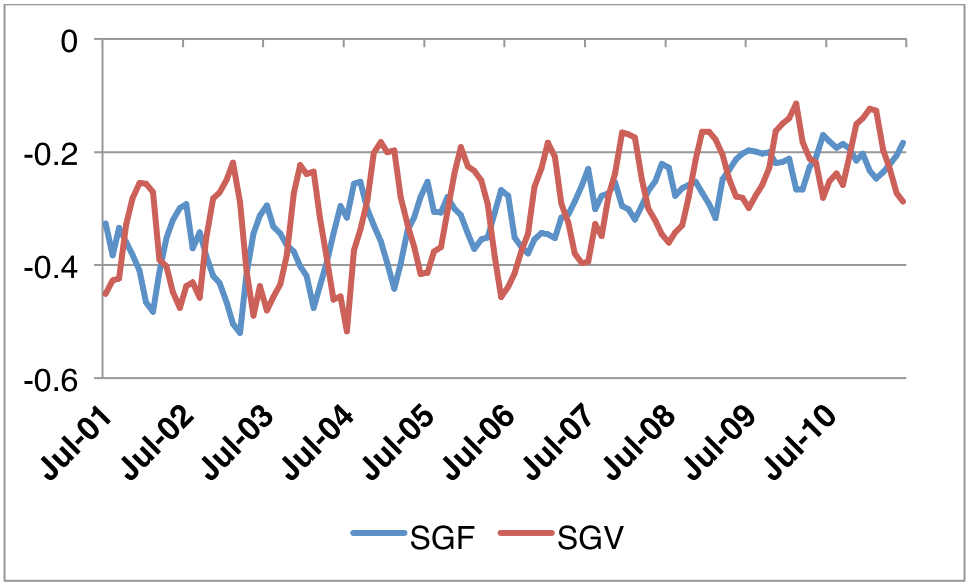


Table 33: Significance of Simplified Household Model Stone-Geary Parameter Trends

Dependent Variable	Explanatory Variable	Coefficient (p-value)
β SGV	**Intercept**	0.0019 (0.442)
	Date	0.0000 (0.828)
γ SGF	**Intercept**	8.3928 (0.149)
	Date	0.0000 (0.795)
γ SGV	**Intercept**	8.8932 (0.010)
	Date	0.0000 (0.780)
ε_p SGF	**Intercept**	-2.4555 (0.000)
	Date	0.0001 (0.000)
ε_p SGV	**Intercept**	-2.2518 (0.000)

	Date	0.0001 (0.000)

From these results, we can see that, while the trend toward zero in elasticity remains, we no longer see any distinct trend in either the marginal budget share allocated to water or the conditional water use threshold. This is probably because results from our original household model runs imply that Hispanic ethnicity has a significant, positive effect on the marginal budget share allocated to water and a significant, negative effect on the conditional water use threshold. It appears that trends in the proportion of Hispanic residents in Tucson's various Census tracts have influenced trends in water consumption over the study period. When we eliminate this variable from our model, we fail to account for changing demographic conditions that affect water demand. In other words, failing to account for household heterogeneity masks household-level trends that are affecting aggregate water consumption, and thus we do gain valuable information by conducting our water demand analysis at the household level.

Appendix 14: Preliminary Counterfactual Climate Scenario ET Projection

Prior to our discovery of the Hargreaves (1994) ET formula, we used a somewhat simpler method of estimating total monthly ET from CanESM2 temperature projections. Originally, we obtained downscaled mean monthly temperature projections for the CanESM2 model. We used a simple regression model to estimate the historical relationship between ET and temperature, and then, assuming the same relationship between mean monthly temperature and total monthly ET in the future, we projected future ET using the estimated coefficients. This process is recorded below.

To project ET for the period July 2085 to June 2099 from CanESM2 mean monthly temperature projections over this period, we first quantify the historical relationship between ET and mean monthly temperature. We collect total monthly ET and mean monthly temperature measurements from AZMET over the 25-year period July 1987 to June 2012, since AZMET has only published weather data for Tucson going back to 1987. We assess the sensitivity of the ET/temperature relationship by estimating OLS regression models of total monthly ET on mean monthly temperature over five 5-year increments and comparing the estimated coefficients for temperature. We also estimate coefficients for the 14-year study period (July 1998 – June 2012) and treat the remaining 12 years of available data (July 1987 – June 1998) as the prior period for comparison. The results of these regressions are summarized in Table 34 below. In every case, the parameter estimates were found to be significant at the 99% confidence level, so p-values are not reported.

Table 34: OLS Regression Results, Dependent Variable: Total Monthly ET

a) 5-Year Incremental Estimates

Variable	7/87-6/92	7/92-6/97	7/97-6/02	7/02-6/07	7/07-6/12
Intercept	-5.777	-6.194	-4.360	-5.403	-4.463
Mean Temp.	0.181	0.186	0.160	0.172	0.163

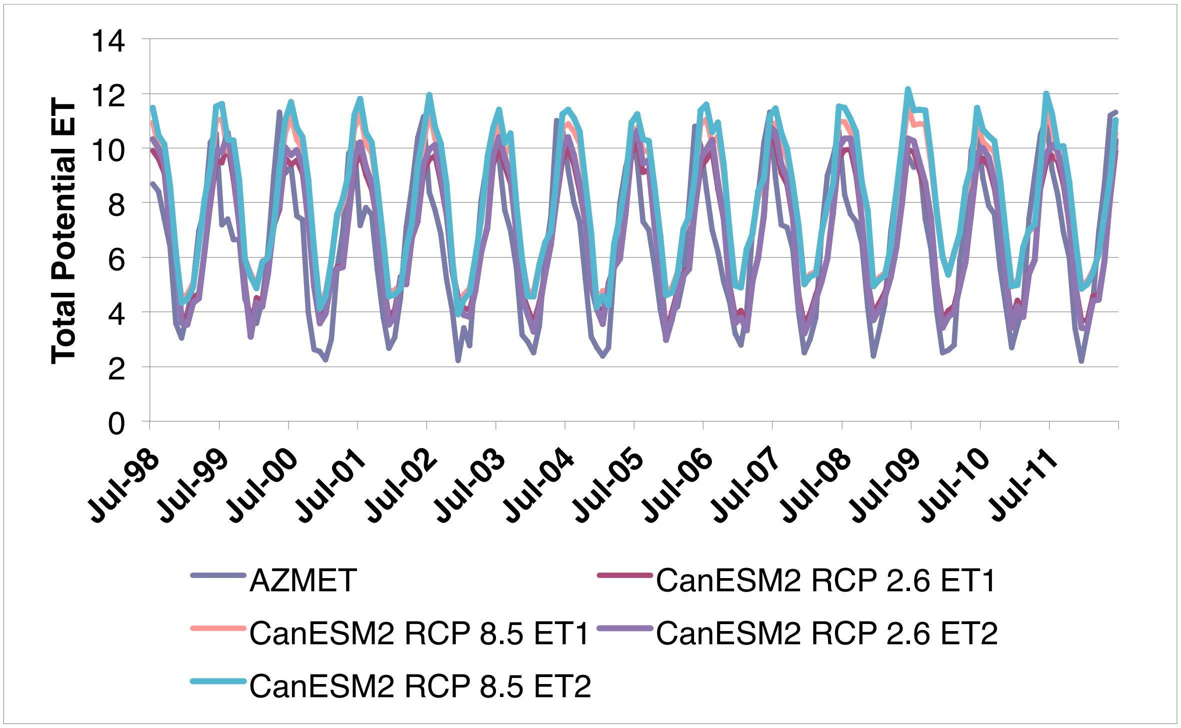
b) Study Period vs. Prior Period Estimates

Variable	7/87-6/98	7/98-6/12
Intercept	-5.923	-4.671
Mean Temp.	0.183	0.164

From these results, it is evident that the relationship between ET and mean temperature tends to vary somewhat over time, though its sign and significance remains stable. It can also be seen that the coefficient on temperature, when estimated over the study period, has a lower value than the same estimate during the prior period. In fact, the study period coefficient (0.164) is very close to the minimum coefficient out of the 5-year estimates (0.160), while the prior period coefficient (0.183) is very close to the maximum value out of the 5-year estimates. Since the two longer period estimates appear to accurately represent the extremes of temperature coefficients estimated from the available data, we use these two sets of coefficients to project ET from CanESM2 mean temperature projections.

We graphically illustrate the differences between ET projected using these two sets of coefficients below in Figure 17, comparing them to current period weather data as well. “ET1” refers to ET projections using temperature coefficients estimated in the study period July 1998 – June 2012, while “ET2” refers to ET projections using temperature coefficients estimated over the prior period July 1987 – June 1998. Note that the RCP 8.5 scenario has generally higher ET estimates than either the RCP 2.6 scenario or the study period data. And while ET2 levels are higher than ET1 values due to the larger temperature coefficient used to estimate them, these differences are not very pronounced.

Figure 17: Preliminary Monthly ET Projection Comparison



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