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Three Essays On Understanding Municipal Water Demand In The Western United States

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THREE ESSAYS ON UNDERSTANDING MUNICIPAL WATER DEMAND IN THE WESTERN UNITED STATES

by

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DISSERTATION

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DEDICATION

To Lexi and the boys.

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ABSTRACT

Scarce water resources in the Western United States, in concert with population growth and climate change, constitute a need to better understand factors that impact water demand. In this dissertation, Chapter 1 provides cultural and historical context for water use in the West and argues that understanding water demand is important, especially when managing scarcity is a goal. Chapter 2 uses aggregate city-level data from four municipalities in New Mexico to investigate seasonal trends and breakpoints. Although per premises and aggregate demand tend to decline in all geographies investigated, existence and timing of breakpoints varies by geography. Additionally, drivers of declining trends are difficult to quantify but are likely related to price increases, uptake of water saving technology, the generally soft economic environment, and increased interest in water conservation.

Chapter 3 models water demand for the city of Clovis, New Mexico using administrative premises-level monthly data. Water use declines are associated with

utility-controlled action such as price increases and rebates for landscaping changes and water saving technologies. Water demand was found to be price inelastic and in the neighborhood of -0.50. However, low-volume users were more sensitive to price than the high-volume users. Similarly, low-volume users were more income elastic than high volume users. Additionally, premises receiving water-saving toilet and washing machine rebates were more price inelastic than premises receiving landscaping rebates, perhaps implying that the most effective means of reducing water use for toilet and washing machine rebate-receiving premises is through the installation of new technology rather than price response. Finally, toilet rebates were found to be the most cost effective rebate type per volume of water saved.

Chapter 4 employs an optimal control framework to investigate utility-level fiscal impacts of demand management, such as rebated technology. Given that water-saving technologies reduce water demand, and apparently negatively impact the utility's revenues and costs, it is not immediately clear what benefit this activity provides. Outlined are optimal paths illustrating tradeoffs between infrastructure investment, repair, and advertising. A testable econometric model is also developed.

Chapter 5 concludes the dissertation by summarizing major findings and discussing limitations and future work.

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Chapter 1: Introduction

Stimulated by population pressures and climate change, the fear of water shortage is often at the forefront of our cultural conscience. The prospect that the volume of water supplied may be insufficient to fulfill the quantity demanded, and the associated vulnerability felt by individuals and communities, is frequently highlighted by the media and in popular culture and serves to reinforce this point. For example, recent newspaper and periodical headlines from outlets such as The New York Times, The Wall Street Journal, National Geographic, and others include: *Two-thirds of the World Faces Severe Water Shortage* (St. Fleur, 2016); *Water, Water Everywhere Can't Quell a Western Drought* (Carlton, 2018); *These Are the Forgotten Victims of the West's Drought* (Nobel, 2016); *Drought Planning: Water Shortages Expected in New Mexico* (Montoya Bryan, 2017). Additionally, popular non-fiction books such as *Cadillac Desert* (Reisner, 1987) and *Unquenchable: America's Water Crisis and What to Do About It* (Glennon, 2009) underline the notion that society has a history of sometimes ineffectively managing water resources; and works of literary fiction such as Steinbeck's 1939 novel the *Grapes of Wrath* (Steinbeck, 2006) highlight the social and cultural dislocations that can be caused by extended periods of drought and water shortage. Even films such as the acclaimed *Chinatown* (Polanski, 1974) put water (and shortage) at the forefront, making the resource not only a passive plot device, but rather, a character integral to the narrative.

The fact that water, and in particular water shortage, is so commonly reported on and used as inspiration by media, literature, and the arts is probably unsurprising, as access to high-quality water is critically important; without an adequate water supply, a population will have difficulty flourishing.

While there has always been an interest in cultural aspects of water, management over the past several decades has been further challenged by periods of extended drought,[1] significant inter-jurisdictional challenges,[2] and conflicts between agricultural irrigators and cities,[3] all of which have punctuated a need to better understand and more effectively manage water resources. As a key element to effective management, much effort has been devoted to ensuring that water is reliably supplied (e.g. Colby et al., 2010, 2014). Supply enhancement strategies take forms both large and small, and include everything from infrastructure enhancement, to water reuse and desalination, to transfers from one water user to another, and are based on the argument that if water shortage exists then bolstering supply to meet demand is an effective way to manage shortage.

Understanding the supply side is clearly important when it comes to water shortage – or any type of shortage for that matter. However, the demand side is equally important, because it, like the supply side, also has the ability to "equilibrate" the water market by ensuring that the quantity of water demanded at a given price is equal to the quantity supplied. In other words, rather than focusing simply on increasing supply to match demand, it may be more effective to develop policies that decrease demand to match supply; the benefit of this perspective is particularly true when supply

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[1] For example, see Cook et al. (2004); Diffenbaugh et al. (2015); Gutzler & Robbins (2011); and Woodhouse & Overpeck (1998).

[2] Such as legal challenges between NM and Texas over Rio Grande water (see *Texas v. New Mexico* (1983) and the ongoing litigation in *Texas v. New Mexico and Colorado*, (n.d.)), or potential conflict between Mexico and the US over water via the Convention of May 21, 1906 (Distribution of Waters of Rio Grande, 1906) and the Treaty of February 3, 1944 (Utilization of Waters of Colorado and Tijuana Rivers and the Rio Grande, 1944).

[3] For example, see Garrick (2015); Gleick & Heberger (2014); Molle & Berkoff (2006); and Wines (2014).

enhancement may be constrained by capital budgets, political challenges, and environmental considerations – especially in the near term.[4]

Nevertheless, water demand is often ignored in favor of water supply or even other water-related concepts such as water quality. To put this in perspective, figure 1.1 shows Google Trend index values for worldwide search popularity for the terms "water demand," "water supply," and "water quality" from January 2004 to March 2018.

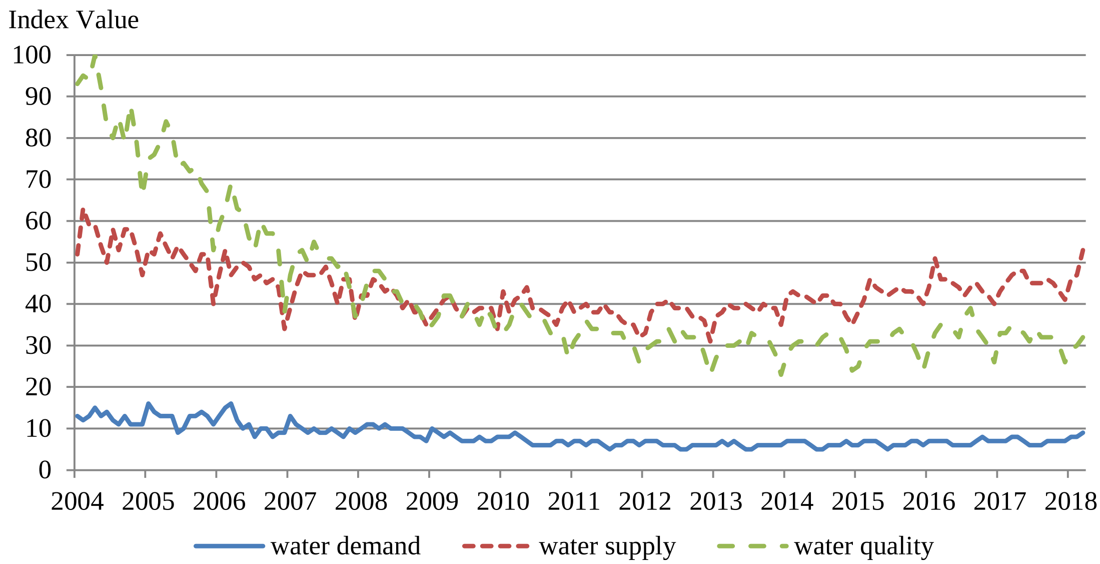


Figure 1.1 Google Trends index values from January 2004 to March 2018

Each line in figure 1.1 shows the relative search popularity for all three terms over the period with an index value of 100 corresponding to the most searched term in any period and all other terms indexed to that term at that point in time. In other words, the most popular search term was "water quality" in early 2004. Since then, the term "water quality" has become relatively less popular. Beginning in 2009, the term "water supply" has become relatively more popular than the term "water quality" as shown by the water

[4] In the language of economics, an increase in supply corresponds to a "rightward" shift of the upward-sloping supply curve and a decrease in demand corresponds to a "leftward" shift of the downward-sloping demand curve. Either, or both, of these movements can clear the market in a situation where the price paid for a good is below the true market price – as is generally the case with municipal water.

supply line overtaking and consistently being above the “water quality” line. Still, the terms “water quality” and “water supply” remained relatively popular throughout the entire period. The search term “water demand,” on the other hand, has always been relatively unpopular as it has consistently been well below the other two lines, perhaps suggesting that our first instincts are to focus on topics other than demand when it comes to water. Given that the demand side is often overlooked compared to other water-related issues, at least with regard to apparent public awareness, this dissertation focuses specifically on the demand side with particular attention on water demand in the arid American West.

Before delving more deeply into understanding demand, it is useful to digress briefly to discuss the genesis of water institutions in the West as those institutions, and in particular legal institutions, undergird the current water regimes and incentive structures. US water law originally stems from English common law under the so-called riparian doctrine (Hobbs, 1997). This doctrine states that water in a river or stream is the property of the public and does not belong to any one individual (Hobbs, 1997; Wilkinson, 1985). Adjoining landowners are typically permitted to use small volumes of water for personal use provided that runoff returns to the stream or river and that they do not alter the waterway (Hobbs, 1997). The Eastern US, which was settled first (i.e. prior to the West), generally had a non-arid climate so was a natural fit for the system developed in England, which also had a generally wet climate (Hobbs, 1997). Further, rivers and streams in the East were typically located in places where the water could be most productively used in situ; these waterways gave rise to the shipping and milling industries that were important in the early Eastern US (Hobbs, 1997).

With expansion to the arid West, however, it became clear that, unlike the East, streams and rivers were not proximal to where the water could be most productively used; rather, water could be more valuable if used outside of the waterway. In particular, settlers discovered that the most valuable uses of water were in irrigation and mining; however, using water in this manner required a break from the tenants of the riparian doctrine as individuals had a desire to divert water from the stream to their respective claims and agricultural plots (Hobbs, 1997; Wilkinson, 1985). As a result, a new rule called the doctrine of prior appropriation was born and essentially provided the user with an entitlement based on seniority (Hobbs, 1997; Wilkinson, 1985).[5] Under this mechanism, the first to divert and (beneficially) use the water had the most senior right. What was once recognized as a custom eventually gave way to codification in several states in the West and this new legal structure bestowed the user with an entitlement that could be secured against more junior users in times of shortage.

Later, The US federal government, which was interested in settling the largely vacant West, took note of the state-sanctioned ability to divert water from the stream. Via large expanses of public, federally-owned, lands, the federal government instituted The Reclamation Act of 1902,[6] which enabled funding for large scale water diversion and infrastructure development (Fahlund et al., 2014; Holland & Moore, 2003; Wilkinson, 1985). So while miners and irrigators on the western frontier were the original beneficiaries of the newly available prior appropriation doctrine, population centers and

[5] There are other requirements under the doctrine of prior of appropriation including the requirement of beneficial use and the no waste requirement. There are also issues regarding management in times of shortage. Those issues are not discussed here; however, for a full treatment, see Hobbs (1997) and Wilkinson (1985).
[6] 43 U.S.C §§ 371-600(e) (1994)

cities also benefited as prior appropriation permitted large volumes of water to be moved to water-poor areas, resulting in more reliable supplies.

Through time, investments in the diversion and supply of freshwater to arid areas led to economic and population growth that would likely not have occurred but for enhanced water supplies (Tarlock, 2001). The removal of a key limiting factor to near term growth, however, also gave rise to a potential feedback loop: surplus water enabled additional population growth via net birth or in-migration, which in turn stimulated demand for goods and services. As a consequence of fulfilling that new demand, actions of enterprising individuals enhanced economic growth and prosperity and aided in improving the standard of living. Given new opportunities and higher standards of living, additional population growth was fostered and the cycle continues.

Provided sufficient water supply to satisfy the demands of the population, including both current and expected future use, increases in water use can continue unabated. In more recent years, however, the adequacy of reliable water supplies to satisfy future demand in arid regions, including in the west, has been questioned (US Bureau of Reclamation, 2012; Zabarenko, 2011). An important driver to this conclusion is the common expectation that water use should rise with population and economic growth (City of Los Angeles, 2010; City of Phoenix, 2011; Griffin, 2006). And at the very least, for a fixed volume of water, additional population or other demands from the economy necessarily reduces the volume available per capita, perhaps leading to tensions among users (Rijsberman, 2006).[7]

[7] Further exacerbating the problem is climate change which may not only impact water supply and demand but also may affect the legal institutions related to water (Gober et al., 2010; Hobbs, 2003; MacDonald, 2010).

However, despite population and economic growth in recent decades (as well as increased climate variability), water use, which once appeared to move in concert with population growth (City of Los Angeles, 2010; City of Phoenix, 2011), has apparently become decoupled with population levels and growth (Fleck, 2016). In other words, even with population and economic growth, per capita use, and in some cases total aggregate use, has declined in many western cities (ABCWUA, 2012; Balling & Gober, 2007; City of Los Angeles, 2010; City of Phoenix, 2011; Donnelly, Kristina & Cooley, 2015; Fleck, 2016).[8]

For example, from 1990 to 2010 water use in Phoenix, Arizona declined from about 250 gallons per capita per day (GPCD) to below 190 GPCD. These figures include both residential and municipal and industrial (M&I) users; however, even stripping out M&I users, residential use declined over the same period from over 140 GPCD to about 110 GPCD. Furthermore, while the population served by the Phoenix water utility increased by 8% from 2002 to 2010, total aggregate water demand declined by more than 16% over that period (City of Phoenix, 2011). Los Angeles, California experienced similar declines over the period as water use was 173 GPCD in 1990 and fell to 117 GPCD by 2010. Like Phoenix, after peaking in aggregate water use in the early-2000's, it has declined since (City of Los Angeles, 2010). Water use in Albuquerque, New Mexico also declined over the last few decades. Even as the number of accounts serviced by the utility increased by 43% from 1995 to 2012, the total aggregate volume demanded fell by

[8] In fact, the pattern of declining demand is not confined only to the American West; rather, declining use has been observed in other parts of the US as well as some other arid and semi-arid countries (Gleick, 2003b; March & Sauri, 2017).

15%; this translates to a decline from 251 GPCD in 1995 to 148 GPCD in 2012 (ABCWUA, 2013).

Several factors have generally been suggested to have contributed to this declining trend, including improved and more efficient plumbing, smaller residential lots, landscaping changes, and increased awareness of drought; however, those, and other, factors may weigh differentially depending on location, climate, preferences, etc. (City of Phoenix, 2011; Fleck, 2016).

Given a need to better understand the drivers of water demand, and to tease apart the various drivers of declining demand, this dissertation investigates the issue of declining water use with particular attention to water use trends in the Western US, and specifically in the arid state of New Mexico. While this research is generally useful in terms of understanding trends in water demand, it is particularly useful for the stakeholders that may be impacted by growth and changing water demand trajectories. One such stakeholder is the community who is interested in ensuring that adequate volumes of water are available to satisfy future populations given expected population levels and growth. Because access to reliable water supply is necessary to provide the community and its constituents the confidence to make costly investments (infrastructure, economic development, etc.) and to thrive, it is critical to understand the drivers of water demand.

Similarly, water utilities that are responsible for ensuring access to a high quality and reliable supply of water are also impacted by the decoupling of growth and water demand. Over time, a utility’s pumping and storage capacity may require expansion in order to accommodate increased demand due to population growth, exogenous factors such as climate variability, and the like. Meanwhile, existing systems degrade and must be maintained or replaced. Given population growth, but consistent per capita water demand and water rate structures, a water utility may recover its high capital investment costs – especially costs related to system expansion, maintenance, and replacement. However, while the decoupling of water demand and growth may help to achieve water conservation goals often imposed by legislators and regulators, reduced water demand, all else equal, puts financial pressure on water utilities and requires a rethinking of rate structures and timing of capital investments.

Therefore, because population and economic growth can apparently no longer be the sole proxy for water use, the following chapters investigate various aspects related to better understanding water demand – and in particular factors contributing to declining demand. To help document and illustrate declining municipal water demand in New Mexico, Chapter 2 begins at an aggregate level by investigating trends in total (aggregate) and premises-level water use in four municipalities in New Mexico. The four municipalities of interest are the cities of Albuquerque, Rio Rancho and Clovis and the town of Edgewood, each of which has vastly different population bases and industrial structures. Although the localities are dissimilar with regard to composition, they share the common feature that significant volumes of water delivered by the water utility come from underground aquifers or wells. Seasonal trend analysis and breakpoint analysis, which are rarely utilized in published literature, are employed to identify general water demand trends and systematic breaks in that trend.

Additionally, although this analysis is atheoretical or descriptive, this chapter highlights institutional and economic factors that help to explain (declining) trends and breaks in water use trends. Results are compared by municipality and factors that are expected to impact trends are discussed. Although per premises and aggregate demand tends to decline in all geographies, existence, timing and apparent reasons for breakpoints varies by geography. For example, the city of Rio Rancho experienced a systematic break in water demand, which changed the slope from increasing to decreasing, near the end of 2013. This is likely due to both the slowdown in manufacturing activity as well as the sharp increase in water price. Clovis experienced two breakpoints which were temporally proximal to extreme drought conditions. Meanwhile, neither Albuquerque nor Edgewood, despite facing similar climate patterns, experienced significant series breaks; however, the trend of declining demand was prominent throughout each series. Reasons for declines are difficult to pinpoint but are likely related to price increases, uptake of water saving technology, the generally soft economic environment, and increased interest by the community for water conservation.

While it is true that both declining demand and breakpoints were observed in the data, seasonal trend and breakpoint analysis only permit a qualitative understanding of the factors contributing to the observed patterns. Therefore, a model of water demand at the spatial scale of a city is developed in an attempt to better quantify the factors contributing to falling demand. For this purpose, aggregated data for the city of Clovis is used (aggregated at the spatial scale of the entire city). Results confirm that weather and climate conditions impact water use in the city. In addition, econometric estimation suggests that water is inelastic at current prices. Estimation at the city-level is also compared against estimation at the US Census block group spatial scale and the premises-level spatial scales (both discussed in detail in Chapter 3). Results indicate that while signals that generally impact all premises (i.e. climate and price signals) can be picked-up at large spatial scales, other more localized signals, such as premises-level rebates for water saving technology, cannot be accurately identified by city-level aggregation.

Utilizing a large account-level monthly administrative data set over a ten-year period, Chapter 3 models water demand in the city of Clovis, New Mexico. The modeling strategy is informed in part by results obtained in Chapter 2 as well as the relevant water demand literature. Outcomes from this analysis add to the extant water demand literature and also provide the city of Clovis with useful information that may be used in planning and management decisions. Pertinent results include price elasticities, the efficacy of water demand management strategies, effects of climate on water demand, and other results useful for setting policy. In addition to the narrow modeling outcomes, which may be utilized by the local utility, estimation may be compared against the existing water demand literature and results may be applied to other municipalities with similar population and industry characteristics. Finally, since a water utility is interested in ensuring sufficient capacity to satisfy demand on a day-to-day basis, Appendix 3.3.4 examines the issue of peak day estimation.

This Chapter finds that water use declines are associated with utility-controlled actions such as price increases and rebates for landscaping changes and water saving technology in Clovis. Overall water demand was found to be price inelastic and in the neighborhood of -0.50; however, it is relatively more inelastic for premises receiving toilet and washing machine rebates and more elastic (though still inelastic) for premises receiving landscaping rebates. Average premises receiving toilet or washing machine rebates reduced water use by more than 9% while premises receiving landscaping rebates reduced water use by less than 5%. In addition, toilet rebates were determined to be the most cost-effective rebate type (from the perspective of the utility) under a reasonable set of assumptions, with washing machine rebates being the second most cost effective per volume of water saved; landscaping rebates are the least cost effective. This result is likely due to outdoor watering only occurring in part of the year whereas toilets and washing machines are used throughout the year. In addition, the study provides empirical support for climate-related impacts related to water demand. Estimated marginal effects suggest that one inch of precipitation reduced Clovis water use by about 1.2%, while a one degree (Fahrenheit) increase in temperature increases water use by about 1.0%.

It is important to note that different user types had different responses to changes in price and income. While both high and low volume water users were found to be price inelastic, the low volume users were more sensitive to price than the high volume users. Similarly, low volume users were more income elastic than high volume users; in other words, that group changed its water use by a relatively larger amount for a given income change. Given its relatively higher income sensitivity, it stands to reason that the low water-use group, on average, is a relatively lower-income cohort – that in concert with the fact that the group was more price-sensitive, it begs the question about whether water rate increases in pricing are regressive. Therefore, as a policy matter, the utility and regulator should investigate how rate increases affect different user groups to ensure that equity is properly accounted for.

While the municipal water demand literature is generally well-developed, one area that is understudied is the impact of spatial effects on water use. This topic is pursued in Appendix 3.3. After controlling for factors shown to impact demand, this analysis investigates the applicability of spatial econometric methods via application of a spatial weights matrix to a panel municipal water consumption dataset. While diagnostics suggest the presence of spatial lag and spatial error, thus indicating the potential usefulness of spatial empirical methods, several important pitfalls must be acknowledged. First, the application of spatial weights in a panel setting is computationally intensive, especially when the number of time periods or observations is large, and perhaps necessitates aggregation. Second, because most users in a municipality are likely to be subject to similar utility action, climate, etc., a spatial lag signal may be spurious. Third, because premises served by the utility may enter or exit the dataset through time, the requirement of balanced panels requires careful consideration. Fourth, if the option to use premises-level (or similar) data or aggregated data are available it is typically advisable to use premises-level data despite the possible presence of spatial effects.

Because water demand management strategies were shown to effectively reduce demand in Chapter 3 and elsewhere (Kenney et al., 2008; Price et al., 2014). Chapter 4 employs an optimal control framework, which is used to investigate financial impacts of demand management rebates provided by a water utility. Municipal water utilities regularly invest costly resources for the purpose of water demand management programs. One example of this activity is advertisement of water-saving technologies such as low flow toilets, high efficiency washing machines, and the like, and utilities often subsidize the purchase of qualifying products. Given that water-saving technologies reduce water demand, and apparently negatively impact the utility’s revenues and costs, it is not immediately clear what benefit this activity provides.

To investigate this issue, an optimal control model is developed using a capital accumulation framework. Under this model, the utility can use costly resources to replace depreciated capital through direct infrastructure investment and replacement or it can devote costly resources through a demand management advertising program, which reduces stress on existing capital and allows the utility to put off investment and repairs. Outlined are the optimal paths for infrastructure investment and advertising and enumerated are the conditions that must exist for the utility to tradeoff between investment types. In addition, given the results derived from the optimal control model, testable empirical models are developed. Because tradeoffs between infrastructure investment, repairs, and advertising (for rebated technology) have not yet been investigated in the literature, this chapter adds to the literature by providing qualitative outcomes for an optimizing utility, testable empirical hypotheses, and a roadmap for further investigation.

Finally, Chapter 5 concludes the dissertation with a synthesis of results, limitations of the current research, and discusses directions for future research.

Chapter 2: Understanding Declining Municipal Water Demand in the Western USA: A Time-series and Breakpoint Analysis of Water Demand in Four Municipalities

2.1. Introduction

Water demand projections for several western municipalities in the United States call for increasing aggregate water demand over the next several decades (City of Los Angeles, 2010; City of Phoenix, 2011; Olsen & Wilson, 2012; Woodard, 2015). Projections for municipalities and regions in New Mexico are no exception to this general trend (ABCWUA, 2013; Llewellyn & Vaddey, 2013; OSE, 2013, 2016, 2017; Stroud & Kilmer, 2016). However, recent analyses suggest that demand, including aggregate demand, is declining in some western municipalities (Fleck, 2016; Pratt, 2015; Santos, 2013; Wentz & Gober, 2007).

The disconnect between demand projections and the trajectory of recent aggregate water demand is likely due to application of the "requirements approach" to water demand projections (Griffin, 2006). This approach, used in one form or another by municipal water providers as well as state and regional planners, essentially assumes some baseline water use per capita, often dictated by a recent data point, or declining per capita demand with an arbitrary floor, and projects aggregate water demand based on assumed population or economic growth. Critically, the approach may not fully incorporate demand-side effects of increased resource scarcity, efficiency improvements, or temporal preference changes, all of which may invalidate the assumed floor placed on per capita demand. Therefore, demand is essentially taken as given, and as a result of increasing water scarcity, water managers and planners principally focus much of their energy on the supply side of the supply-demand relationship (Davis & Hanke, 1971;

Griffin, 2006). As such, the trajectory of per capita demand is not fully accounted-for in some demand projections, thereby potentially overstating future aggregate demand (Woodard, 2015) and possibly incentivizing unnecessary investment or supply augmentation.

To investigate the demand side of this issue, this study applies time series analysis to aggregate and per premises water demand data from four New Mexico four municipalities: Albuquerque, Rio Rancho, Clovis, and Edgewood. Structural breaks are also estimated using breakpoint analyses; breaks are tied to exogenous events such as policy changes or extreme climate events. Results suggest that per capita and aggregate water demand is declining in nearly all cases over the last decade for both low volume (residential) users and high volume (industrial) users. Breakpoint analysis suggests that series breaks occurred in Clovis and Rio Rancho; however, likely explanations for the breaks are different. The major structural break in Rio Rancho coincides with large water rate increases, which caused a sharp and rapid decline in water demand and is confined to industrial users. Breaks in Clovis were upward in nature and coincided with periods of extreme drought; breaks were observed for both the residential and industrial water users.

While the presence (or absence) of breaks are identifiable and related to exogenous events such as extreme climate or large rate changes, the persistent declining trend in per premises and aggregate water demand for both residential and industrial users in nearly every municipality in this analysis is perhaps the most critical observation. To that end, this study also considers factors that are likely to contribute to changing demand patterns, with special attention to institutional factors, population factors, economic factors and policy interventions, and climate. Using Clovis, New Mexico as an example, an econometric model designed to capture behavioral responses, is developed. Results confirm that water use responded to variation in temperature and precipitation; additionally, water use was found to be price inelastic at current prices. While the thrust in this analysis is at a large spatial scale (i.e. an entire city), estimation results are also compared against two other spatial scales: US Census block groups and premises-level.

2.2. Study Areas

The cities of Albuquerque, Rio Rancho, Clovis, and the town of Edgewood, each in New Mexico, USA are used to investigate temporal trends in municipal water demand. The city of Albuquerque, which is part of the larger Albuquerque Metropolitan Statistical Area (MSA), is located roughly in the center of the state and is its major economic hub; according the US Bureau of Economic Analysis, the MSA's share of New Mexico GDP averaged more than 45% from 2012-15. The city is located at the base of the Sandia Mountain range and is adjacent to the Rio Grande. Critically, two major US highways, Interstate-25 and Interstate-40, intersect in the city, which provide east/west and north/south thoroughfare for goods and services originating from or passing through the state. Its location puts it relatively close to the surrounding states of Arizona, Utah, Colorado, Oklahoma and Texas, as well as the US-Mexico border.

The city of Rio Rancho, which is also located within the Albuquerque MSA and the town of Edgewood are both proximal to Albuquerque and there is significant commuter traffic to and from each municipality. Rio Rancho is about 20 miles north-west of Albuquerque and is its largest suburb. The city, however, provides a broad array of public services through its local tax base; services include public works programs such as streets and water, public schools, police, etc. The town of Edgewood is located about 20 miles east of Albuquerque and is a small commuter town in the Sandia Mountains.

According to its own budget documents, the city's annual budget is in the neighborhood of about $5.7 million dollars (http://www.edgewood-nm.gov/DocumentCenter/View/2221). Much of its expenditures are operational in nature, but also include police and capital projects.

The most geographically distinct municipality is the city of Clovis, which is located near the Texas border in the east-central part of the state on Interstate-60. The city is around 220 miles to the east and slightly south of Albuquerque. Its closest medium-sized cities are Lubbock and Amarillo, Texas, both of which are around 100 miles further east.

2.3. Institutional Frameworks & Demand Projections

To provide greater context for the demand projections discussed in this analysis, this section begins with a brief discussion of the entities charged with tracking or managing water resources in the respective areas or municipalities as well as developing projections.

2.3.1 Institutional frameworks

The institutional frameworks governing water use decisions in New Mexico are overlapping, with the state providing general guidance via the Office of the State Engineer (Verhines, 2013), who under Article 2 of Chapter 72 of the New Mexico State Code (NMSA, 2006, §72-2), is imbued with broad authority over New Mexico's waters. In addition, sixteen regions within the state have some authority over general regional water determinations (OSE, 2013), while individual city or municipal utilities make local water supply decisions.

At the city or municipal level, each water utility operating within the geographies contemplated in this analysis have slightly different organizational structures. EPCOR, which supplies water in Clovis and Edgewood, is a private utility authorized to operate within the respective municipality. In 2011, EPCOR took over operations from the former private sector provider New Mexico American Water. The city of Rio Rancho currently operates its own public water utility whereas the Albuquerque Bernalillo County Water Authority (ABCWUA), which is a public water utility, serves Albuquerque. Historically, groundwater has been the source used by these utilities to fulfill constituent demand; while that is still generally true for the municipalities discussed here, the San Juan-Chama Project, which directs water from the Colorado River to the Rio Grande, began to supplement the city of Albuquerque's supply in 2008. That surface water now accounts for approximately 60% of Albuquerque's total annual supply (Wickert, 2015).

Each bureaucratic layer (state, region, and municipality) develops plans to ensure future water supply reliability. For example, regional water planning in New Mexico began in 1987 for the purpose of demonstrating to other states and the federal government that New Mexico needed its full allotment of water (Buynak et al., 2010). To coordinate and systematize the disparate regional plans, and to ensure that the state was a good steward of it water resources, the state enacted the State Water Plan Act (2003), which requires the State Engineer, in conjunction with the Interstate Stream Commission, to produce updated plans every five years (Buynak et al., 2010). Meanwhile, cities and municipalities develop utility-level water plans dedicated to ensuring adequate supplies and water planning at a local level (ABCWUA, 2013; Rio Rancho, 2014).

In addition, each water utility in conjunction with its local governing body, develops drought management plans, which may be initiated in times of drought.

Drought, according to ABCWUA wastewater ordinance §4-1-3 is defined as: “when there is insufficient precipitation combined with other environmental factors that cause an increase of overall water usage.” Drought management plans may exist at all bureaucratic levels; even at the state level, the State Water Plan requires that the State Engineer develop a drought management plan “designed to address drought emergencies, promote strategies for prevention of drought-related emergencies in the future and coordinate drought planning statewide” (NMSA, n.d., §72-14-3.1(6)). The regional drought plans are consistent with the State Water Plan as that plan lays out the methods for assessing drought conditions generally (OSE, 2013). Likewise, individual water utilities develop plans to manage periods of shortage. For example, contingent on approval from the local Water Authority Board, ABCWUA’s Executive Director is authorized to institute enhanced watering restrictions or temporary rate increases in times of drought (ABCWUA, 2012). Similarly, chapter 52 of the Rio Rancho city ordinances provides analogous tools to the water utility in times of shortage or drought (Rio Rancho, 2016, §52.05(E)).

2.3.2 Demand projections

Water demand projections produced by municipal water utilities as well as relevant state and federal agencies call for increasing aggregate municipal demand in many populated regions in New Mexico (ABCWUA, 2013; Llewellyn & Vaddey, 2013; OSE, 2013, 2016, 2017; Stroud & Kilmer, 2016). For example, the 2017 regional water plan for the 16th region, which includes Bernalillo and Sandoval Counties (containing the cities of Albuquerque and Rio Rancho, respectively), projects increasing aggregate demand over its planning horizon from 2010 to 2060 in both counties (OSE, 2017). Although the projection calls for per capita demand in Bernalillo County to slowly decline from 155 gallons per capita per day (gpcd) in 2010 to 130 gpcd by 2060 (but no lower than 130 gpcd), projected aggregate water demand increases in both the low and high demand scenarios (OSE, 2017). In the near term from 2010 to 2020, projected aggregate demand for premises on public water supplies increase by 7.7% and 5.7% in the respective high and low demand scenarios (OSE, 2017).

ABCWUA, the public utility charged with servicing the Albuquerque-municipal area, also recently published water demand projections. Although aggregate demand generally trended downward since 1990 (ABCWUA, 2013), ABCWUA projects aggregate demand to increase because reductions "cannot reasonably be expected to continue" in the future "without significant mandatory restrictions" (ABCWUA, 2013). The US Bureau of Reclamation similarly projects increasing aggregate municipal demand due to assumed constant per capita indoor demand with population growth (Llewellyn & Vaddey, 2013).

The assumption of increasing demand is not only confined to the Albuquerque Bernalillo County service area or even to this region. The OSE projection for Sandoval County projects that aggregate demand will increase from 2010 to 2020 by 24.5% in its high scenario, and will not decline in its low scenario (OSE, 2017). The city of Rio Rancho's projections also call for increasing demand (Rio Rancho, 2014). Similarly, the state of New Mexico's 1st region, which includes Curry County (and the city of Clovis), also assumes increasing municipal demand (on public water supplies) over the period from 2010 to 2020 to the tune of 14.1% and 8.0% in the respective high and low demand scenarios (OSE, 2016). However, it is unsurprising that projections for this region are similar because the methodology is dictated by the larger state water plan – which, like the 16th region projection, assumes a floor on per capita demand and that population grows more rapidly than per capita demand declines (OSE, 2013).

2.4. Population Size and Population Growth

In 2014, the population within Albuquerque, the state's most populous city, was estimated to total 553,576 persons. This total only includes individuals residing in the city limits and does not include that larger metropolitan area which was estimated to total about 904,587 persons. The city of Rio Rancho, which is included in the Albuquerque metropolitan region, but is its own separate municipality, totaled 90,627 persons in 2014. Illustrating the relatively small population in the state of New Mexico is that, despite the relatively small population of the city of Rio Rancho, it is the third most populous city in the state.

Table 2.1 Population by geography through time

State/City	Population		
	2000*	2010*	2014 Estimate**
New Mexico	1,819,046	2,059,179	2,080,085
Clovis	43,423	45,499	48,702
Edgewood	1,893	3,735	3,763
Rio Rancho	51,765	87,521	90,627
Albuquerque	448,607	545,852	553,576

Notes: * from respective Decennial Census; ** from American Community Survey Estimate

The city of Clovis had an estimated population size of 48,702 persons in 2014, making it the eighth most populous city. Meanwhile, the town of Edgewood, which like Rio Rancho is proximal to Albuquerque, is sparsely populated with an estimated population of 3,763 in 2014. In 2014, the population in the four municipalities accounted for about one-third of total state population. However, note that the percentage is much larger if the Albuquerque MSA, which includes the cities of Albuquerque and Rio Rancho as well as adjacent incorporated and unincorporated areas, is considered.

According to the American Community Survey, the population in the MSA totaled nearly 900,000 persons in 2014, or about 44% of total state population.

The population in the city of Clovis experienced relatively slow growth from 2000 to 2010, growing at an average rate of growth of only 0.5% per year; however, from 2010 to 2014, growth accelerated to 1.8% per year on average. The town of Edgewood, on the other hand experienced the opposite, as did the cities of Rio Rancho and Albuquerque. Edgewood population grew an average of 9.7% per year from 2000 to 2010 but then slowed to only 0.2% per year from 2010 to 2014. The population of Rio Rancho grew at an average rate of 6.9% per year from 2000 to 2010 and only 0.9% per year from 2010 to 2014 while the city of Albuquerque grew at average rate of 2.2% per year from 2000 to 2010 and then slowed to 0.4% per year on average from 2010 to 2014.

Table 2.2 Housing units by geography through time

State/City	Housing Units		
	2000*	2010*	2014 Estimate**
New Mexico	780,579	901,388	907,233
Clovis	18,421	19,138	19,623
Edgewood	755	1,563	1,647
Rio Rancho	20,209	33,964	34,800
Albuquerque	198,465	239,166	240,961

Notes: * from respective Decennial Census; ** from American Community Survey Estimate

The number of housing units in each municipality has increased through time, with particularly large increases from 2000 to 2010 in Edgewood and Rio Rancho. Clovis and Albuquerque only experienced modest gains. However, growth from 2010 to 2014 slowed considerably in all four places.

Building permit data, or permits granted by permit-granting jurisdiction for future construction of single- or multi-family homes are available from the University of New Mexico's Bureau of Business and Economic Research from January 2005 through August 2016 for the cities of Albuquerque, Rio Rancho and Clovis. Contractor or builder demand for permits are related to the demand for new construction. Increases in permit demand may also be correlated with population growth and perhaps even increasing incomes. In all cities, but especially in Albuquerque and Rio Rancho, permits granted were especially high in 2005 and 2006; however, building permits fell during the Great Recession and growth has essentially been flat since 2008.

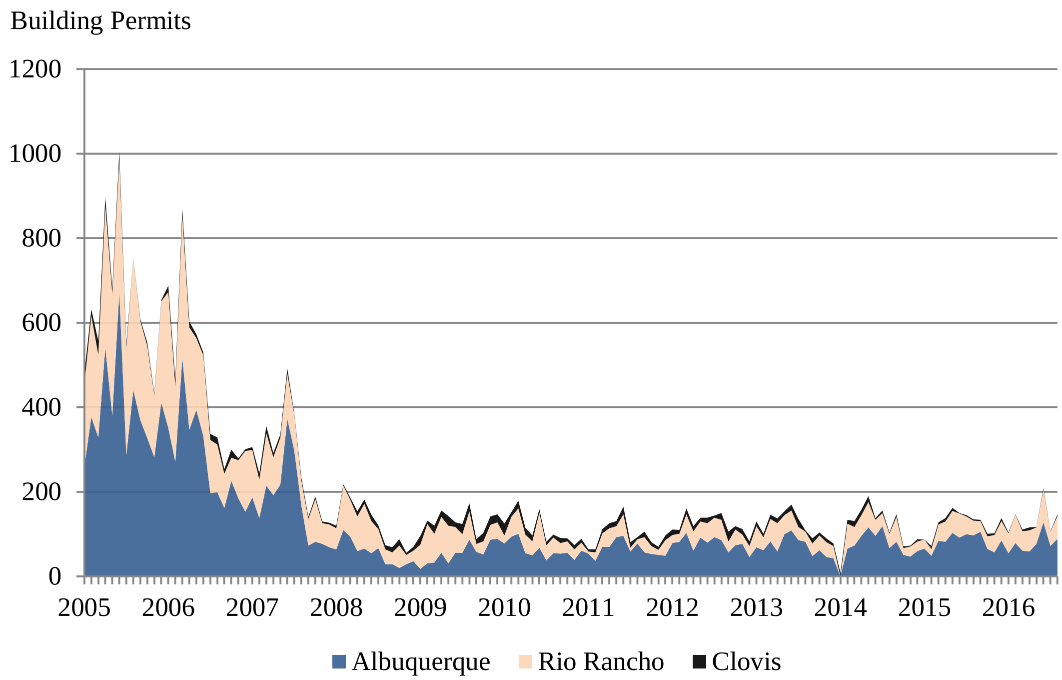


Figure 2.1 Building permits by jurisdiction

2.5. Economy and Economic Transformation

The state of New Mexico has experienced significant shifts in industry composition over the last decade. Movements away from goods producing industries such as manufacturing have given way to rapid increase in service industries such as healthcare and accommodation and food services. Likely exacerbating the shift is the intervening Great Recession from which the state is yet to recover completely.

The city of Albuquerque's economy is relatively diverse. The city supports Sandia National Laboratories, which is privately managed but is funded through the US

Department of Energy; the city also houses Kirtland Air Force Base. Albuquerque also has a relatively large contingent of small high technology manufactures that specialize in a variety of enterprises. However, over time, the economy has moved away from large-scale manufacturing and toward healthcare and hospitality jobs. The city also boasts the University of New Mexico, which is the state's flagship university.

Rio Rancho has grown significantly over the last three decades as it has moved away from being solely a commuter suburb, has developed its industrial base, and expanded the reach of its public services. Principally responsible for the transformation is Intel, which began operations in the area in 1980. As worldwide demand for personal computers expanded in the 1990's, Intel expanded its manufacturing operations. However, as demand has waned, so have the number of jobs at Intel – which now number fewer than 50% of the job-peak (Robinson-Avila, 2016). Meanwhile, the rest of the economy has become more diversified and relatively less reliant on one large employer. As a result, much like Albuquerque, the center of mass has moved away from manufacturing to healthcare services and the hospitality industry.

The city of Clovis is generally reliant on a small number of relatively large employers. Although not within the city limits, Cannon Air Force Base employs Clovis residents. Individuals that provide local services, including local government workers, such as police or public school teachers, are another relatively large bloc. Within the private sector, Clovis has a large number of healthcare and retail workers. Additionally, Burlington Northern Santa Fe Railway has been a mainstay, although it has recently moved some employees out-of-state. Clovis also has a large cheese manufacturing plant, which has seen recent expansion. Edgewood, given its small size and proximity to larger population centers such as Albuquerque and Santa Fe, has little industry and is primarily a commuter town. Therefore, it is unlikely that employment- and industry-dynamics, at least within the town, are major drivers of water demand.

Tables 2.3 and 2.4 show total employment and manufacturing sector employment levels, respectively. In each case, employment levels are shown for the county that each city of interest is located. This is done for two main reasons. First, city-level employment data tend to be relatively unreliable, especially for relatively low-population cities. Second, the highlighted cities, with the exception of Edgewood, are the largest population and industrial centers within each county; so county-level data is likely to reflect the trends in those cities. The table shows that the Great Recession affected Bernalillo County negatively as employment levels in 2010 are well below the 2005 level; as of 2015, the level continued to stay below the 2005 threshold. Curry and Sandoval Counties, on the other hand, saw no similar slowdown as 2010 levels are above 2005 levels. However, although growth was still positive from 2010 to 2015, employment growth slowed in both counties.

Table 2.3 Total employment by county through time (except Santa Fe County)

State/City	County*	Total Employment		
		2005	2010 (growth since 2005)	2015 (growth since 2010)
New Mexico	N/A	778,233	781,694 (0.4%)	822,991 (5.3%)
Clovis	Curry County	16,034	16,764 (4.6%)	17,217 (2.7%)
Edgewood	Santa Fe County	N/A	N/A	N/A
Rio Rancho	Sandoval County	27,114	29,114 (7.4%)	29,156 (0.1%)
Albuquerque	Bernalillo County	319,561	311,725(-2.5%)	318,962 (2.3%)

Notes: * Employment given by county totals from the Bureau of Labor Statistics' Quarterly Census of Employment and Wages

The manufacturing sector is a key water user and employment in this sector can offer insight into the direction of water demand (Hester & Larson, 2016). In the cities of Albuquerque and Rio Rancho, manufacturing employment has fallen. From the period

2005 to 2010, employment fell by nearly 3,000 persons in Albuquerque, and the slide, although slower, continued through 2015. Rio Rancho also lost significant jobs over the period with manufacturing employment levels in 2015 being about half of the 2005 level. Clovis, on the other hand, experienced an uptick in employment over the period. Although the absolute levels are relatively low, numbering fewer than 1,000 persons, employment growth in this sector averaged around 5% per year.

Table 2.4 Manufacturing employment by county (except Santa Fe County) through time

State/City	County*	Manufacturing Employment		
		2005	2010 (growth since 2005)	2015 (growth since 2015)
New Mexico	N/A	36,306	29,026 (-20.1%)	27,778 (-4.3%)
Clovis	Curry County	443	614 (38.6%)	678 (10.4%)
Edgewood	Santa Fe County	N/A	N/A	N/A
Rio Rancho	Sandoval County	6,424	4,123 (-35.8%)	3,277 (-20.5%)
Albuquerque	Bernalillo County	15,588	12,685 (-18.6%)	12,428 (-2.0%)

Notes: * Employment given by county totals from the Bureau of Labor Statistics' Quarterly Census of Employment and Wages

2.6. Climate and Drought

Average annual temperature in all municipalities is generally similar. Over the period from 2006 to 2015, both Clovis and Rio Rancho experienced an average annual temperature of 56.2° Fahrenheit; Albuquerque's average annual temperature was slightly higher at 58.3° Fahrenheit. No data were available for the town of Edgewood. Over the ten- year period, Clovis experienced an average of 16.9 inches of rainfall per year. Rio Rancho and Edgewood experienced similar rainfall volumes at 10.9 inches and 10.4 inches, respectively. The city of Albuquerque only experienced 8.7 inches per year on average.

Table 2.5 Location and climate statistics

City/Town	Lat., Long.	Elevation	Temperature	Precipitation
Clovis	34.5988°, -103.2161°	4,435.04 ft.	56.2° F	16.9 Inches
Edgewood	35.1764°, -106.176°	6,751.97 ft.	N/A	10.4 Inches
Rio Rancho	35.2836°, -106.6194°	5,229.99 ft.	56.2° F	10.9 Inches
Albuquerque	35.0419°, -106.6155°	5,310.04 ft.	58.3° F	8.7 Inches

Notes: Lat.,Long. represents the latitude and longitude of measuring station; elevation is the height above sea level of that station. Temperature is the annual average temperature from 2006 to 2015 and precipitation is the average annual precipitation over that period for Clovis, Rio Rancho and Albuquerque and 2008 to 2015 for Edgewood.

In terms of annual temperature variation, figure 2.2 shows that all geographies experienced similar inter-annual trends from 2006 to 2015 with the Clovis and Rio Rancho trends usually overlapping and with Albuquerque temperature generally surpassing the other two.

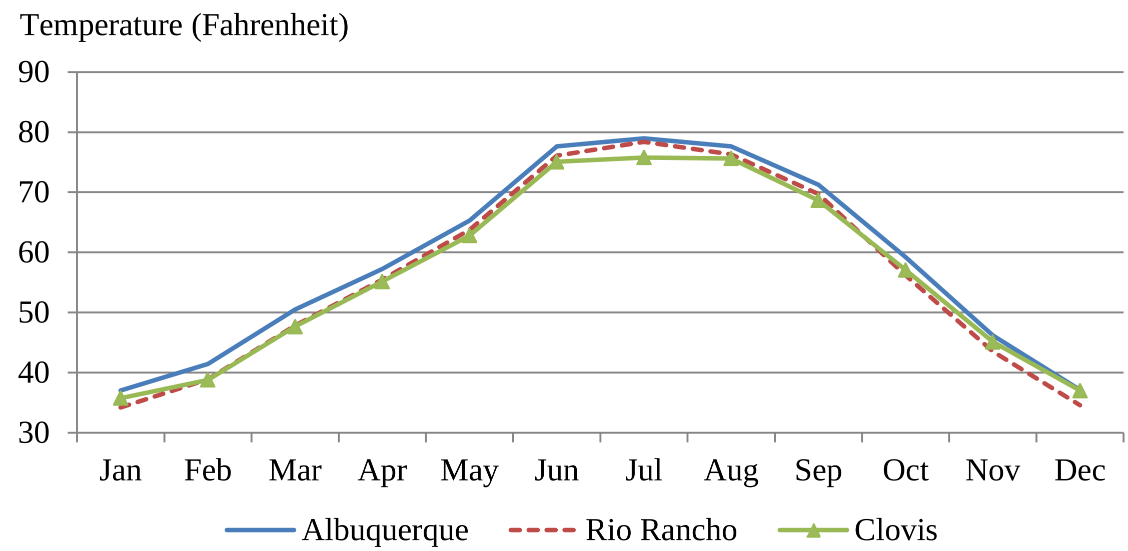


Figure 2.2 Average monthly temperature (Fahrenheit)

Precipitation trends throughout the year, from the period 2006 to 2015, were also generally similar – at least in terms of peaks and valleys. In most cases, the cities of Albuquerque, Rio Rancho and the town of Edgewood overlap especially with regard to summer peaks. Precipitation generally trends downward for the remainder of the year with the possibility of an end-year spike. Clovis precipitation is also similar in that it peaks in the summer; however, it trends upward earlier.

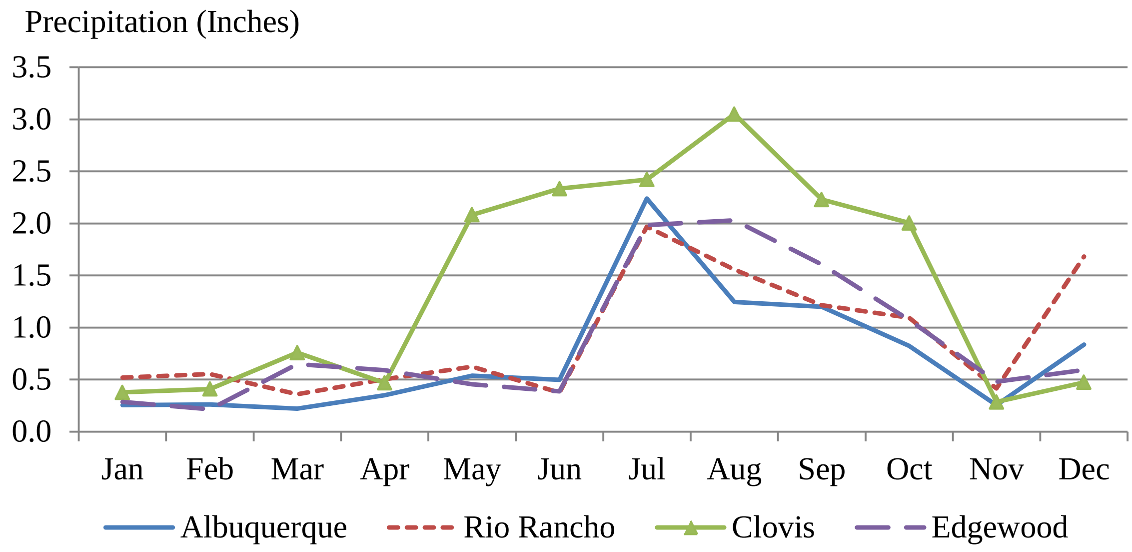


Figure 2.3 Average monthly precipitation (inches)

Both central New Mexico, which includes Albuquerque, Rio Rancho and Edgewood, and the eastern part of the state have experienced several periods of drought since 2000; this is especially true over the last several years where both regions have experienced prolonged, deep, drought. Figure 2.4 shows Palmer Drought Severity Index (PDSI) values for the Albuquerque Area (data collected at the Albuquerque International Airport) and Clovis. Positive values indicate wet conditions while negative values indicate dry conditions; large deviations from the horizontal axis indicate relatively larger anomalies. Unique values are not available for Rio Rancho or Edgewood; however, due to spatial proximity, PDSI behavior is likely similar to Albuquerque.

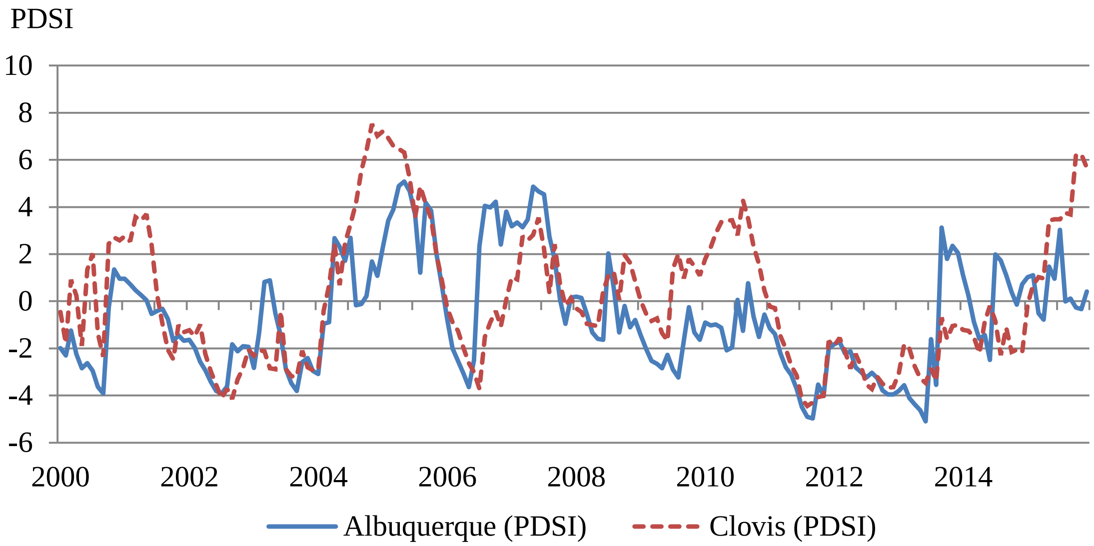


Figure 2.4 Palmer Drought Severity Index (monthly): 2000-2015

Both Albuquerque and Clovis experienced drought-like conditions from 2002 to 2004 and for a short period in 2006. Beginning in 2008 and extending to about the end of 2013, Albuquerque experienced prolonged drought. That trend was broken in 2014 when the area oscillated between wet and dry conditions. Clovis' recent drought, on the other hand, began in earnest in 2011 and finally broke near the end of 2014. For much of 2015, the city experienced conditions that were much wetter than normal.

2.7. Policy Interventions

Policy interventions include any decision made by a governing jurisdiction (such as regulators, the legislature, or local municipality) or water use decisions made by the utility itself. Specific examples of interventions include water rate adjustments or the use of rebates for water-saving technology, both of which have been shown to impact demand (Arbués et al., 2003; Kenney et al., 2008). In fact, recent empirical work on Albuquerque has shown that premises-level water demand falls as price increases and that water rebates reduce water use (Price et al., 2014).

2.7.1 Water rates

In all jurisdictions, marginal water rates are given by an increasing block-rate schedule and rates have been adjusted a number of times in each jurisdiction. Albuquerque experienced water rate increases in 2007 and each year from 2013 to 2015. The most recent increases were done to compensate the utility for reduced water use over the period. The city of Clovis, after adjusting rates in 2005, has increased rates on three separate occasions: in 2007, 2009 and 2012. After purchasing the interest in a private utility servicing the city of Rio Rancho, the city has (recently) increased rates four times: it increased rates twice in 2013 and then once in 2014 and 2015. Rio Rancho rate increases are notable because they were large. In particular, the rate adjustment in February 2013 increased the average bill 8.8% and was subsequently followed by additional increase of 7.8% in July of the same year. The average rate has increased each July since by 7.8% in each year (Lucero, 2016). The town of Edgewood is an outlier. Although the town has increased rates twice, in 2010 and 2015, it actually lowered rates in 2012. Table 2.6 shows the month and year of rate changes in each jurisdiction.

Table 2.6 Summary of water rate change dates (2005-2015)

City/Town	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Clovis	Feb	-	Jun	-	May	-	-	May	-	-	-
Edgewood	-	-	-	-	-	Jul**	-	May*	-	-	Jun
Rio Rancho	-	-	-	-	-	-	-	-	Feb/July	Jul	Jul
Albuquerque	-	-	Jul	-	-	Jul**	-	-	Jul	Jul	Jul

Notes: * Edgewood received a rate decrease in that year; ** Rate hike to a small number of residents taken over by utility

2.7.2 Water rebate programs

The city of Albuquerque has the greatest number and variety of rebate programs and has had rebate programs for a number of years. The city currently provides rebates for the installation of low-flow toilets, showerheads, washing machines, and hot water recirculating systems (Price et al., 2014). The city also provides a rebate for converting outdoor turf to xeriscape. Rio Rancho has three rebates for water-saving technology, including rebates for clothes washing machines, toilets and evaporative cooler thermostats (http://ci.rio-rancho.nm.us/index.aspx?NID=422). The city of Clovis offers toilet rebates, clothes washer rebates, and landscaping rebates (http://www.epcor.com/efficiency-conservation/rebates-clovis/Pages/rebates.aspx). The town of Edgewood does not offer rebates.

2.7.3 Outdoor watering restrictions

The cities of Rio Rancho and Albuquerque each have outdoor water restriction programs; however, the Rio Rancho program is mandatory while the Albuquerque program is voluntary. The city of Rio Rancho restricts outdoor sprinkler/spray irrigation from April 1 through October 31 to hours after 7:00 P.M. to before 11:00 A.M. However, watering by hand, or the use of drippers and low-emitting bubblers are allowed at any time (http://www.rrnm.gov/index.aspx?NID=913). Albuquerque’s current program is voluntary but suggests watering once a week in March, twice a week in April and May, three times a week in June, July and August, twice a week in September and October, and once a week in November (http://www.abcwua.org/Water_by_the_Numbers.aspx). The program does not restrict the day of the week or the timing of watering. Neither the city of Clovis nor the town of Edgewood have restricted watering schedules.

2.8. Methods

Seasonal decomposition and breakpoint analysis are applied to data provided by municipal water authorities. This analysis extends the time series methods utilized by Hester and Larson (Hester & Larson, 2016), who investigated water demand trends in North Carolina, USA municipalities; those municipalities, unlike the municipalities studied here, tend to experience high levels of precipitation, relatively less aridity, and have different institutional and industrial structures. The authors found that declines in per capita demand likely coincided with reduced manufacturing demand in the late 1990's. Additionally, coordinated state-level drought responses in the late 2000's suppressed demand and conservation pricing in 2010 in at least one municipality (Raleigh) caused demand to fall further.

2.8.1 Water data

A variety of sources provided water consumption data for this analysis. The Albuquerque Bernalillo County Water Authority (ABUCWA) provided data for its coverage area; Rio Rancho data from the city water authority; Edgewood and Clovis from private supplier EPCOR.

Water data are reported in terms of aggregate consumption on a monthly time-step. Total water use includes residential and industrial users within each city or town. Analysis is done based on aggregate water consumption as well as on an average water user basis. This analysis is different from Hester and Larson (Hester & Larson, 2016), who used an estimated per capita figure (based on American Community Survey estimates), because the number of accounts in each month is known with certainty but the population is not. Monthly demand was divided by the number of days in each month to produce two statistics: mean daily total daily demand and mean daily demand per premises.

2.8.2 Water data decomposition procedure

Seasonal trend analysis is employed to strip out the seasonal elements (Cleveland et al., 1990). Water demand is assumed to take the following form

$$WU_t = T_t + S_t + u_t \tag{2.1}$$

$$t = 1, \ldots\ldots, n$$

where WU_t is water use in a city in time t (total aggregate demand and per premises water demand are estimated separately); T_t is an unobserved trend component; S_t is the recurring seasonal component – with monthly data there are twelve periods, so $s = 12$; u_t is an unobserved residual.

2.8.3 Breakpoint analysis

Breakpoint analysis elucidates structural breaks in the data. Models are estimated based on total water use in each period and water use per premises and takes the following form

$$WU_t = \alpha_j + \beta_j t + \sum_{i=1}^{s-1} \delta_{i,j} D_{i,t} + u_t \tag{2.2}$$

$$t = t_{j-1}^* + 1, \ldots\ldots, t_,^*$$

α and β are the intercept and slope parameters, respectively, for the j regimes occurring between the m breakpoints (Bai & Perron, 2003; Haywood & Randal, 2014; Hester & Larson, 2016). Seasonal effects are estimated by δ for each season i through a series of monthly indicators, D. Application of the breakpoint analysis to water use data was done using the BFast and strucchange packages in R (Chu et al., 1995; Hester & Larson, 2016; Verbesselt, Hyndman, Newnham, et al., 2010; Verbesselt, Hyndman, Zeileis, et al., 2010; Zeileis et al., 2002). Dependent variables are log transformed in all cases.

2.9. Seasonal Trend and Breakpoint Results

Results are estimated for each municipality using each municipality's entire dataset. Data are then subsetted into low volume (residential) water users and high volume (industrial) users to determine wither there are differences in behavior between broad user classes. In the case of Clovis, low volume users are grouped based on the use of less than 2,000 average gallons used per day. However, unknown is whether the particular account is technically residential or non-residential.

The Central Limit Theorem requires at least 12.5% of the observations before and after the estimated breakpoint (Bai & Perron, 2003; Zeileis et al., 2003). However, given only 120 monthly periods for Clovis, 93 periods for Rio Rancho, 96 period for Albuquerque, and 94 periods for Edgewood, this study imposes a requirement of at least 15% of the data pre- and post-estimated breakpoint. The conservative window is used to better control for drought-like conditions that began early in 2006 (in the case of Clovis) as well as the protracted drought from 2011 to nearly 2014 – both of which may be expected to impact aggregate water demand and on a per premises demand. Forthcoming figures display premises-level data because demand responses are likely to be at that level; however, supplemental material contain aggregate-level results. In addition, results from statistical test of each break identified in the breakpoint analysis are shown in table 2.9 in Appendix 2.1.

Figure 2.5 shows seasonal trends and breakpoints for mean water use in Clovis for all water users and high volume users (left panel and right panel, respectively). The top graphs show monthly mean water use with shaded regions representing drought (sequential PDSI readings of -1.5). The middle graph shows the seasonally decomposed trend with breakpoints given by the vertically hashed loci and 95% confidence intervals shaded. The bottom graph shows estimated breakpoints with confidence intervals and fitted trend lines.

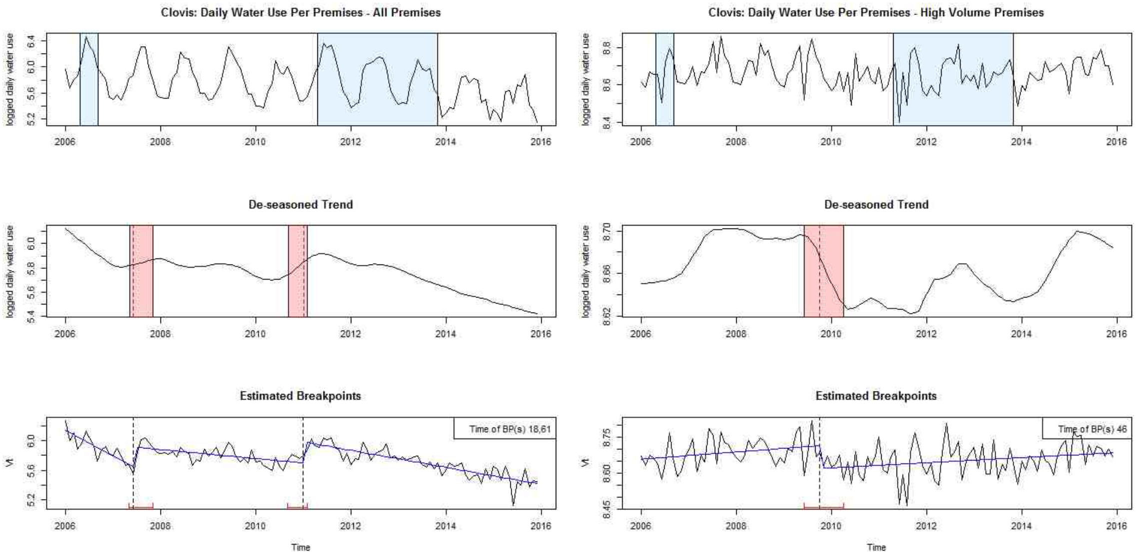


Figure 2.5 Seasonal trends and breakpoints for mean daily water use per premises in Clovis for all premises (left) and for high volume premises (right)

Figure 2.6 shows seasonal trends and breakpoints for mean water use in Rio Rancho for all water users and low volume users (left panel and right panel, respectively).

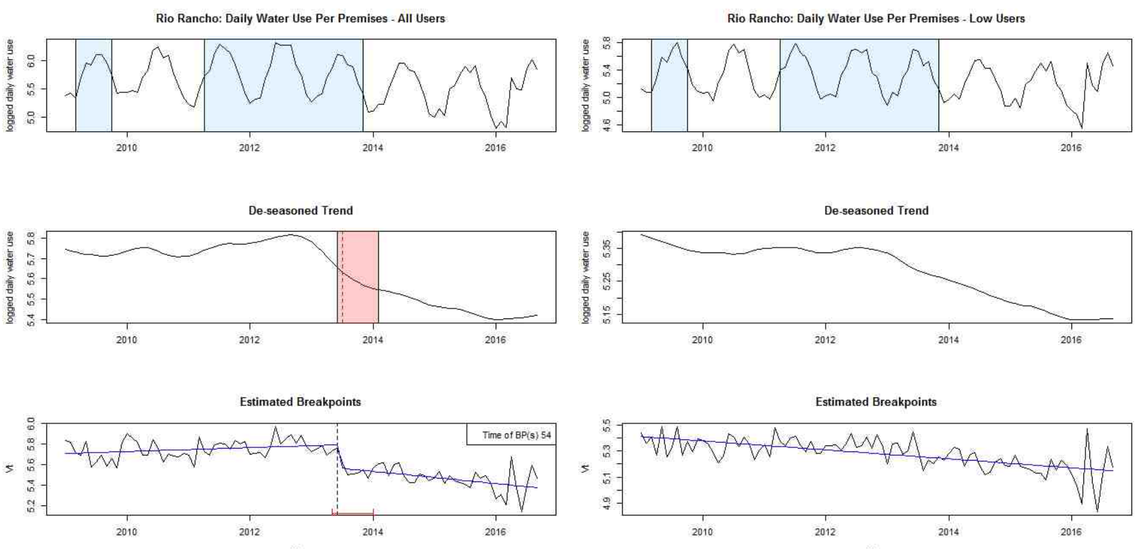


Figure 2.6 Seasonal trends and breakpoints for mean daily water use per premises in Rio Rancho for all premises (left) and for low volume premises (right)

The left panel in figure 2.7 shows seasonal trends and breakpoints (or rather, lack of breakpoints) for water use in Edgewood. The de-seasoned trend clearly indicates declining water use from 2009 through 2015. The trend also indicates a sharp uptick beginning at the end of 2015 through September 2016; however, because a full year of 2016 data are not yet available, it is unclear whether the pattern is truly indicative of a per premises uptick or whether partial year data are causing the sharp increase. Even so, the data exhibit no significant breakpoints. The right panel in figure 2.7 shows seasonal trends and lack of breakpoints for the city of Albuquerque from the period from January 2009 to December 2015. In this case, mean daily water use for all premises is displayed; however, the outcome, with regard to continuously declining demand throughout the period, as well as lack of breakpoints, is consistent across type of user and metric.

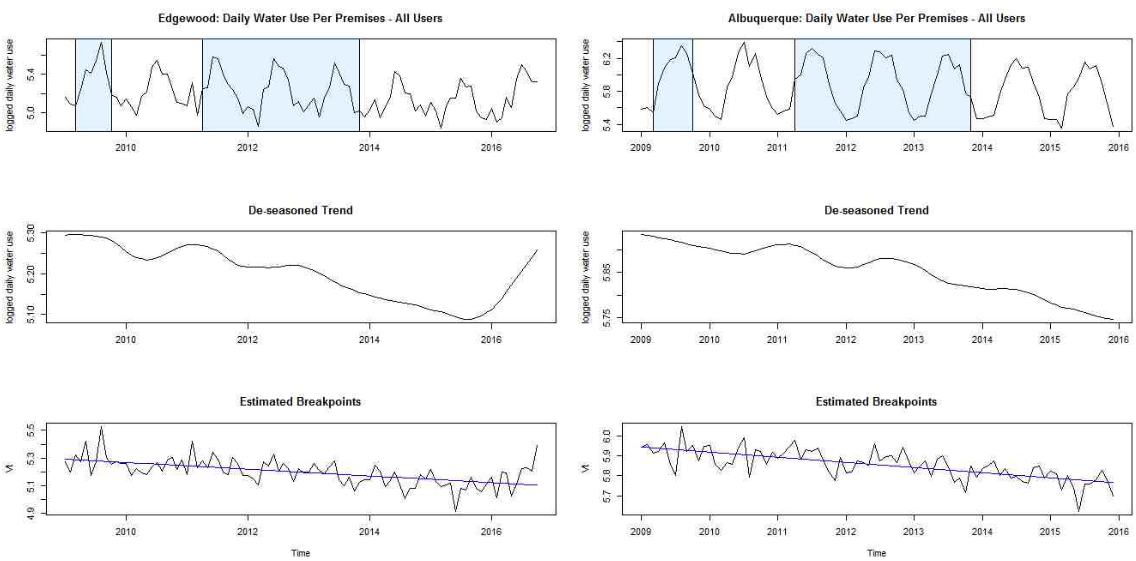


Figure 2.7 Seasonal trends and breakpoints for mean daily water use per premises in Edgewood (left) and Albuquerque (right) for all premises

2.10. Seasonal Trend and Breakpoint Discussion

In most cases, municipalities experienced declining total use and use per premises over the periods investigated. However, existence, timing, and reason for breakpoints appear to be different in each case. Demand trends and breakpoints for each place are discussed in turn.

The city of Clovis generally experienced declines in water use; however, data for all water users (low and high volume users) suggest that the series experienced two breakpoints. The timing of the breakpoints does not appear to relate to significant economic or industrial events, nor do they appear to relate to rate changes; rather, the breakpoints logically occur in relation to the timing of drought. For example, in figure 5, the first breakpoint occurs as the series flattens out after the short-but-severe drought in the first half of 2006. Because drought occurred near the start of the series, the fitted series adjusts upward at the start. Providing additional evidence of these drought effects is the timing of the second breakpoint, which occurs in 2011, and is proximate to the start of the second period of drought.

However, this does not explain the water use patterns (per premises) for high volume users, which is generally increasing, although the series experiences a downward break in 2011. However, the reason for the upward sloping trend is that the number of premises classified high volume (i.e. 2,000 gpd) declined through time, thereby leaving only the largest users in the dataset. In particular, premises that are relatively close to the 2,000 gpd threshold began to reduce water use through time and fell into the low-user category. For example, in 2006, the average number of premises that qualified as a high volume user totaled 257 premises; by 2016, the average number fell to 123 premises. The very high users, on the other hand, who are likely to be larger business and manufacturing interests, continued to use high water volumes, thus increasing use per premises for the high volume group. Supporting this position is that when total aggregate water use for high volume users (instead of per premises use) is examined, the series and breakpoints appear similar to the analogous series for low volume users.

Although water use has generally declined through time in Rio Rancho – especially residential use – high volume use dipped significantly in 2013 and continued to fall. A likely culprit for the decline is the change in the manufacturing sector, and specifically the change in the water demand from Intel. The company, which uses a combination of water supplied from the city water utility as well as its own wells and reuse programs, began to reduce its reliance on city wells in 2013 (Intel, 2014). In particular, from June 2012 to December 2013, the monthly volume of water purchase by Intel fell from 118.4 million gallons to 968,000 gallons (Intel, 2014). Additionally, to the extent that employment and production are correlated, reduced manufacturing employment levels may help to explain reduced demand. However, production efficiencies also likely contribute to the decline. Nevertheless, because Intel is a large water consumer, changes in its water use patterns is the leading candidate to explain the breakpoint.

Left unexplained, however, is the generally declining water use trend through time. While it is unclear exactly why this seemingly sharp decline exists for these groups, it may be related to the series of relatively large rate adjustments beginning in February 2013. These rate adjustments likely play a role in recent water use reductions for residential consumers and likely also explain why Intel traded off city water use with its own well use. However, without premises-level data and an ability to estimate price elasticity of demand, this effect cannot be quantified accurately.

Data from the town of Edgewood also suggest declining water demand at both the aggregate and premises level. Output from seasonal trend analysis suggests that per premises use declined almost uninterrupted from 2009 to near the end of 2015. The analysis also suggests an uptick in demand near the start of 2016. However, despite the apparent change in direction, the uptick is not accompanied by an identifiable breakpoint.

The lack of a breakpoint in this case may be due to not having enough data near the end of the series to characterize the break.

Similar patterns of generally declining demand but a recent uptick are shown at the premises level when all data are examined as well as for low- and high-volume users. This is also generally true for aggregate demand except for high volume users, who experienced large variation and directional change several times over the period. For the period, three breakpoints, as shown in table 2.9, were detected: March 2010, November 2011 and May 2015 (although statistical significance was rejected), which broke the series into four distinct regions: declining from January 2009 to March 2010, increasing from March 2010 to November 2011, flat from November 2011 to May 2015 and then increasing after May 2015.

However, volatile aggregate water use for high volume users in Edgewood is probably unsurprising given that it is primarily a commuter town (so little industry) and because there are relatively few users (an average of 75 per month) in this category. In addition, the average user in this group uses only 571 gallons per day, which is much different from the nearly 5,800 gallons per day and 2,650 gallons per day used by high volume users in Clovis and Rio Rancho, respectively. This suggests a categorical difference between the types of operations undertaken by high volume Edgewood users and likely makes their water use trends and patterns not directly comparable to high volume users elsewhere.[9]

[9] Because Edgewood is primarily a commuter town (and almost entirely residential) it probably makes sense to compare all of its users to low volume water users in the other municipalities. When examining all users in Edgewood, no statistically significant breakpoint is observed and the series generally declines (see left panel of figure 2.7).

The city of Albuquerque, like the other municipalities, experienced declining water demand over the period of study. This is true of both demand per premises and aggregate demand, even though the number of premises increased over the period – from an average of 194,758 premises in 2009 to 201,742 premises in 2015. Although not discussed specifically in this context, prior analysis investigated some of the factors that are likely related to declining demand, including price increases, rebates for water saving technology, and rebates for conversion of turf to xeriscape (Price et al., 2014).

However, Price et al. (2014) did not assess or estimate all of the potential factors that are likely linked to reduced demand in Albuquerque. One possible factor is that the Albuquerque economy has fared poorly since the Great Recession.[10] Some of this is captured by the decline in total and manufacturing employment shown in tables 2.3 and 2.4, respectively. To give greater context, the Albuquerque Metropolitan Statistical Area, which is comprised of a four county region (including Sandoval County, where Rio Rancho resides), was only the 387th fastest growing region in terms of employment growth (0.2% over the period) out of 436 metro regions as defined by the Bureau of Labor Statistics from 2009 to 2015 (http://www.bls.gov/ces/). Furthermore, the Albuquerque MSA experienced the slowest rate of growth of any metro region with at least 200,000 jobs. Given the relative lack of business growth and the likely dearth of investment, it is perhaps not surprising that water use is declining.

[10] Price et al. (2014) included a time trend in a secondary analysis which may have captured at least some of the effect of the poorly performing economy. However, to the extent that other factors influencing demand, such as uptake of rebated technology (or other factors potentially impacting demand), are temporally correlated with Albuquerque's poorly performing economy, the time trend will be unable to pull apart the impact of both effects.

Additionally, increasing preference for water conservation is not estimated by Price et al. (2014) but may be driven by myriad factors. These include the public information campaigns pursued by ABCWUA regarding relative water vulnerability – which, among other things, required water supply investment via the San Juan-Chama water project; the large number of news stories by local media outlets; and perhaps a greater awareness of the potential impacts on the water supply due to climate change.

An additional avenue of potential investigation in all municipalities is the rate of housing stock turnover and the extent to which new or improved building materials or different landscaping standards have reduced water demand per-premises, which has not been fully investigated in the literature (Woodard, 2015). Relatedly, improvements may have been made to existing businesses, households and city infrastructure – all of which may have reduced system leakage. Further investigation is needed to uncover and quantify these and additional drivers of declining demand in Albuquerque and elsewhere.

2.11. Econometric Estimation: Case of Clovis, New Mexico

Given the results from the previous section, it appears as though either extreme drought conditions (in the case of Clovis) or severe utility action (in the case of Rio Rancho) may create a series break at least in some instances. In effort to quantify a more precise behavioral response, this section estimates an economic model of water demand for the city of Clovis. Output from this model is compared against known output from models at the US Census block group level and premises-level. Of particular interest is the degree to which water users respond to utility action, such as rate changes and rebate programs, and climate conditions. For a thorough discussion of the empirical challenges involved in estimating water demand, including managing endogenieity and fixed effects, please see Chapter 3.4.

2.11.1 Data

Monthly data on water use (January 2006 to December 2015) in Clovis was converted to average daily water use. Average water price (per gallon) was calculated by taking the bill amount (i.e. amount paid by water users) and dividing by the volume used. Because the time period is relatively long (10 years), price is adjusted for inflation on an annual basis using the consumer price index (CPI) using 2015 as the base year. Data on rebates for water saving technology and landscaping changes were provided by EPCOR. Data are known at the premises-level; at larger geographic scales (i.e. US Census block group or city levels), the relevant variables are defined as the fraction of premises that received a rebate by rebate type.

Daily temperature data was used to construct average temperature for each month while daily precipitation data was summed to arrive at a monthly precipitation total. Over the study period from January 2006 to December 2015, Clovis experienced several periods of extreme drought: from a short period of drought in 2006 to extended and deep drought from 2011 to 2014. Monthly Palmer Drought Severity Index (PDSI) data were also employed in an effort to better account for the effects of drought.

In an attempt to control for socioeconomic and demographic shifts, county-level (Curry County) estimates for household size and income were employed. Also used were permits granted for single family construction in the city of Clovis; this was done to proxy for the age of the housing stock. Table 2.7 shows descriptive statistics and data sources for the key variables used in this analysis.

Table 2.7 Variable definitions and descriptive statistics

Variable	Description	Period	Unit	Mean	Std. dev.	Source
WU	Average daily household water use	Month	Gallons	323.6	653.51	EPCOR
AvgPrice	Average water price	Month	$/Gallon	0.003	0.002	EPCOR
ToiletPrem	Premises toilet rebate indicator	Month	1/0	0.03	0.18	EPCOR
Washer	Washing machine rebate indicator	Month	1/0	0.02	0.13	EPCOR
Landscape	Landscape rebate indicator	Month	1/0	0.01	0.08	EPCOR
Income	Average household income in county	Ann.	Dollars	40,945	1.02	US Census (ACS)
HHSize	Average household size in county	Ann.	Persons	2.61	0.08	US Census (ACS)
Permits	Number of single family building permits	Month	Permits	10.37	5.47	BBER & Clovis
Temp	Average monthly temperature	Month	Fahrenheit	56.80	14.86	NOAA
Precip	Average total monthly precipitation	Month	Inches	1.28	1.44	NOAA
PDSI	Palmer Drought Severity Index	Month	Unitless	-0.28	2.45	NOAA

2.11.2 Model and estimation

Econometric estimation is undertaken according to the following model:

$$\begin{aligned}\mathrm{lnWU}_{it} = {} & B_0 + B_1\mathrm{lnAvgPrice}_{i(t-1)} + B_2\mathrm{Temp}_{it} + B_3\mathrm{Precip}_{it} \\ & + B_4\mathrm{lnIncome}_{it} + B_5\mathrm{HHsize}_{it} + B_7\mathrm{BldPermit}_{it} + B_8\mathrm{PDSI}_{it} \\ & + \sum_{j=1}^{3}\delta_j\mathrm{Rebate}_{jit} + \sum_{k=1}^{11}\psi_k\mathrm{Month}_k + \sum_{l=1}^{3}\gamma_l\mathrm{MeterSize}_{li} + \nu_i \\ & + \varepsilon_{it}\end{aligned} \tag{2.3}$$

B_0 is the intercept and terms from B_1 to B_8 correspond to estimated coefficients on continuous variables. $\mathrm{lnAvgPrice}_{i(t-1)}$, is water price lagged one month. Due to endogenous price, this variable is constructed based on a first stage estimates using marginal price as instruments (Arbués & Villanúa, 2006; Kenney et al., 2008; Price et al., 2014). δ_j, at the premises-level, corresponds to the receipt of a rebate and at the more aggregated spatial scales to the proportion of premise that had received a toilet rebate, washing machine rebate and/or landscaping rebate at the respective spatial scale. ψ_k is the coefficient on month; December is the base month. γ_l controls for the size of the water deliver pipe attached to the premises. ν_i controls for premises or block group fixed effects (at the city spatial scale, fixed effects are not employed), while ε_{it} is the error term. i and t are indices that correspond to premises (or census block) and time period, respectively.

Table 2.8 Modeling results

	Model 2.1	Model 2.2	Model 2.3	Model 2.4	Model 2.5
	FEIV	FEIV	2SLS	2SLS	2SLS
Variable Name	Premises-Level	Block Group	City-Level	City-Level	City-Level
lnAvgPrice	-0.534***	-0.406***	0.021	-0.440***	-0.508***
	(0.008)	(0.039)	(0.670)	(0.147)	(0.125)
ToiletPrem	-0.083***	-0.123	-12.194**		
	(0.004)	(0.106)	(4.483)		
Washer	-0.060***	-0.613***	21.890*		
	(0.006)	(0.157)	(10.165)		
Landscape	-0.100***	-0.937***	-11.207***		
	(0.007)	(0.170)	(1.894)		
lnIncome	0.568***	0.829***	0.044	0.590	0.232
	(0.027)	(0.142)	(0.481)	(0.507)	(0.437)
Temp	0.010***	0.011***	0.013***	0.013***	0.011***
	(0.000)	(0.001)	(0.996)	(0.004)	(0.003)
Precip	-0.012***	-0.012***	-0.007	-0.019***	
	(0.000)	(0.003)	(0.992)	(0.008)	
PDSI					-0.021***
					(0.003)
N	1,575,980	3,960	119	119	119
R^2	0.280	0.581	0.865	0.856	0.892

Notes: Standard errors reported in parentheses. The following variables and controls suppressed: month, BldPermit, HHsize, suppressed. MeterSize control used in premises-level estimation but not block group or city-level estimation. No fixed effects are employed in the city-level estimation.
*Significant at 10%; **significant at 5%; *** significant at 1%

Models 2.1 and 2.2 correspond to estimations undertaken at the premises level and US Census block group level, respectively. Models 2.3-2.5 correspond to estimates at the city-wide spatial scale. In other words, the data are aggregated to the spatial level of the entire city. It is clear that the larger spatial scales improve the overall model fit; at the premises-level (model 2.1), R^2 is only 0.28, at the block group level (model 2.2), R^2 is 0.58 and the fit nearly reaches 0.9 in the city-wide estimations (models 2.3-2.5). However, despite the improved model fits, compressing the data into a single spatial scale comes at a cost. For example, at the larger spatial scales, the estimated coefficients on the rebate variables, in terms of magnitude and significance, are affected (when compared against the results from the premises-level analysis). Additionally, the rebate variables appear to impact the magnitude and significance of the price variable (lnAvgPrice). It turned out that at the most aggregated level (city level), the price variable was found to correlate at a 1% level with the toilet, washing machine, and landscaping rebates ($\rho = 0.82, 0.83,$ and 0.74, respectively). The justification for including the rebate variables at the spatial scale of an entire city is somewhat dubious (because it effectively applying a premises-level concept to an entire city), so it may make sense to exclude those variables when investigating water demand at large spatial scales. Results are shown in models 2.4 and 2.5.

In models 2.4 and 2.5, several salient points are illuminated. First, demand is price inelastic, and depending on the particular model, falls near to the elasticity estimates in models 2.1 and 2.2. Therefore, although the breakpoint analysis did not appear to identify a significant break in trend due to rate increases, the regularity of the increases appeared to operate to reduce demand and likely helped contribute to the declining trend. Second, the temperature coefficient is negative and significant at the 1% level across models, indicating that increased temperatures give way to increased demand. In models 2.1, 2.2, and 2.4, the precipitation variables are negative and significant at the 1% level, indicating that water use increases in times of low precipitation. Overall, the temperature and precipitation variables are particularly interesting because they are similar across models and imply that in times of low precipitation or high temperature, water use increases. In model 2.5, precipitation is replaced with PDSI. Precipitation is removed in this model because it is correlated at a 1% level with PDSI ($\rho = 0.40$). The estimates of the climate variables provide some support for the notion that weather-related events, including drought, may not only impact water use, but might also contribute to the systematic breaks seen in the breakpoint analysis. Overall, at the city-wide level, the estimates suggest that much of the variation can be understood in terms of price change and weather/climate conditions. Therefore, if adequate projections for price and climate are known, that information may be used to produce projections of water demand at large spatial scales, especially in the near term. This issue is briefly considered Appendix 2.2.

2.12. Conclusion

This analysis utilized seasonal trend decomposition and breakpoint analysis to investigate trends in temporal water demand in four arid municipalities in New Mexico. These methods can help inform water demand analysis by stripping away seasonal noise to uncover trends in demand and systematic series breaks. Seasonal trend and breakpoint analysis have been relatively underutilized in a water demand estimation context (Hester & Larson, 2016); however, given the relatively light data requirements, these analyses can be useful in quickly identifying patterns or trends that can be qualitatively compared against known events.

This study found that water demand has been declining in the investigated municipalities. This pattern is generally true for both high and low volume users and terms of aggregate water use or per premises water use. However, there are a few of exceptions to this general rule. For instance, water use per premises for high volume users appeared to be increasing in the city of Clovis and water use per premises for high volume users increased (slightly) from about 2009 to 2014 in Rio Rancho. However, those are exceptional cases. In the case of Clovis, the pattern is explained by the decline in the number of high volume users through time, leaving only highest water demanders in the high volume cohort. Rio Rancho's explanation is different not only because of the large increase in the number of water users over the period, but also because the city's population and industrial growth likely contributed to increased water use from high volume users. However, it is important to note that although the trend was only slightly increasing until about 2014 but has been falling since.

Likewise, significant breakpoints were uncovered in the trends for the cities of Clovis for all users, and Rio Rancho for high volume users. Despite the generally declining trend in water demand in the city of Clovis, upward breaks appear to be related to severe drought conditions. This is interesting because, despite the fact that all municipalities experienced drought over their respective series, no other municipality exhibited that degree of apparent climate sensitivity. Nevertheless, given the timing of the Clovis breaks drought is the most likely culprit. The explanation for the break in the Rio Rancho series, however, is likely associated with the large rate increases experienced in the municipality and the associated reduction in demand from industrial users, and in particular, reduced demand from Intel.

No significant breakpoints were detected for Albuquerque or Edgewood. While there is no definitive reason for the lack of breaks in these two municipalities, one plausible explanation is the relative size of each municipality (in terms of the number of water-user accounts in each place). For example, the large number and type of varied users in Albuquerque could operate to put a floor or ceiling on rapid declines or spikes in demand. Edgewood, on the other hand, experiences high statistical variability due to having relatively few users. This statistical noise can operate to muffle the effect of spikes.

Exceptional cases aside, this leads back to a primary theme in this analysis: that aggregate and per premises water demand is generally declining in the municipalities investigated in this study. However, although it appears that premises-level demand is likely to continue to fall in the near future, left unanswered is how long aggregate demand declines will persist. And although some projections assume that aggregate demand declines "cannot reasonably be expected to continue" (ABCWUA, 2013), given the recent trend, it makes demand projections, especially in the near term, somewhat puzzling and it perhaps calls into question the use of the requirements approach, at least in its current form (Griffin, 2006). Nevertheless, the application of the requirements approach, or placing a seemingly reasonable but arbitrary floor on assumed per capita demand, is understandable in terms of risk aversion as the risk of being wrong is likely more palatable in cases of oversupply as compared to undersupply (Woodard, 2015). However, if the errors always fall on the side of oversupply, costly overinvestment in infrastructure or potentially unnecessary supply augmentation strategies may be incentivized.

As such, agencies engaged in water demand projections should seek to minimize, or at least limit, the oversupply buffer. Seasonal trend and breakpoint analysis provides a preliminary approach to understanding premises-level and aggregate water demand trends in the four municipalities. This knowledge may be leveraged in the development of economic models and further econometric estimation strategies such as those suggested in section 2.11. This type of analysis can allow for a deeper investigation and important insights into some of the elements and key variables that impact demand even relatively large spatial scales. However, the utility of large scale estimation is clearly limited; while it is possible to make some useful inferences regarding general water use, it is nearly impossible to develop more fine-tuned inferences of individual or premises level action using only city-level or aggregate data.

With the goal of developing a better understanding of the factors that are likely contributing to declining demand at smaller spatial scales in mind, Chapter 3 develops models at the premises-level.

Appendix 2.1 Statistical breakpoint analysis

Table 2.9 Breakpoint statistics

Municipality	User Type	Mean Number of Premises	Mean Usage	Water-use Statistic	Breakpoint Date	95% Confidence Interval	F-statistic	Prob > F
Clovis	All Users	14,986	333 gal/day	Total water use	June 2007	May 2007 - January 2008	11.67	0.0000
					February 2011	August 2010 - March 2011	29.45	0.0000
				Use per premises	June 2007	May 2007 - November 2007	15.81	0.0000
					January 2011	September 2010 - February 2011	39.34	0.0000
	Low Volume	14,786	259 gal/day	Total water use	June 2007	May 2007 - January 2008	12.71	0.0000
					February 2011	July 2010 - March 2011	23.07	0.0000
				Use per premises	June 2007	May 2007 - November 2007	18.56	0.0000
					January 2011	August 2010 - February 2011	33.74	0.0000
	High Volume	199	5,795 gal/day	Total water use	June 2007	May 2007 - April 2008	6.89	0.0015
					January 2011	September 2009 - February 2011	33.48	0.0000
				Use per premises	October 2009	June 2009 - April 2010	3.82	0.0251

Table 2.9 (cont.)

Municipality	User Type	Mean Number of Premises	Mean Usage	Water-use Statistic	Breakpoint Date	95% Confidence Interval	F-statistic	Prob > F
Rio Rancho	All Users	32,082	301 gal/day	Total water use	June 2013	May 2013 - February 2014	22.07	0.0000
				Use per premises	June 2013	May 2013 - January 2014	28.87	0.0000
	Low Volume	30,779	205 gal/day	Total water use	None			
				Use per premises	None			
	High Volume	1,303	2,650 gal/day	Total water use	May 2013	April 2013 - April 2014	19.60	0.0000
				Use per premises	May 2013	March 2013 - December 2013	19.44	0.0000
Edgewood	All Users	1,929	185 gal/day	Total water use	None			
				Use per premises	None			
	Low Volume	1,854	169 gal/day	Total water use	None			
				Use per premises	None			
	High Volume	75	571 gal/day	Total water use	March 2010	February 2010 - June 2010	1.03	0.3617
					November 2011	October 2011 - July 2012	3.92	0.0238
					May 2015	January 2015 - June 2015	7.62	0.0009
				Use per premises	None			

Table 2.9 (cont.)

Municipality	User Type	Mean Number of Premises	Mean Usage	Water-use Statistic	Breakpoint Date	95% Confidence Interval	F-statistic	Prob > F
Albuquerque	All Users	198,238	365 gal/day	Total water use	None			
				Use per premises	None			
	Low Volume	184,105	296 gal/day	Total water use	None			
				Use per premises	None			
	High Volume	14,133	1,264 gal/day	Total water use	None			
				Use per premises	None			

Notes: Low volume water users in Clovis defined as using less than 2,000 gpd and high volume water users defined as using at least 2,000 gpd. High water users in Rio Rancho, Edgewood and Albuquerque defined as commercial users. Low volume users in Albuquerque defined as residential and multifamily users. Breakpoints and confidence intervals estimated using the bfast procedure in R; Manual (Chow, 1960) test used to determine breakpoint significance.

Appendix 2.2 City-level sample prediction

Using the estimates given in models 2.4 and 2.5, near-term projections can be developed by water managers. Specifically, figure 2.8. shows in-sample projections using temperature and precipitation is explanatory variables (model 2.4) and temperature and PDSI as explanatory variables (model 2.5). Also shown is a series that only includes a monthly time trend as well as the actual data series.

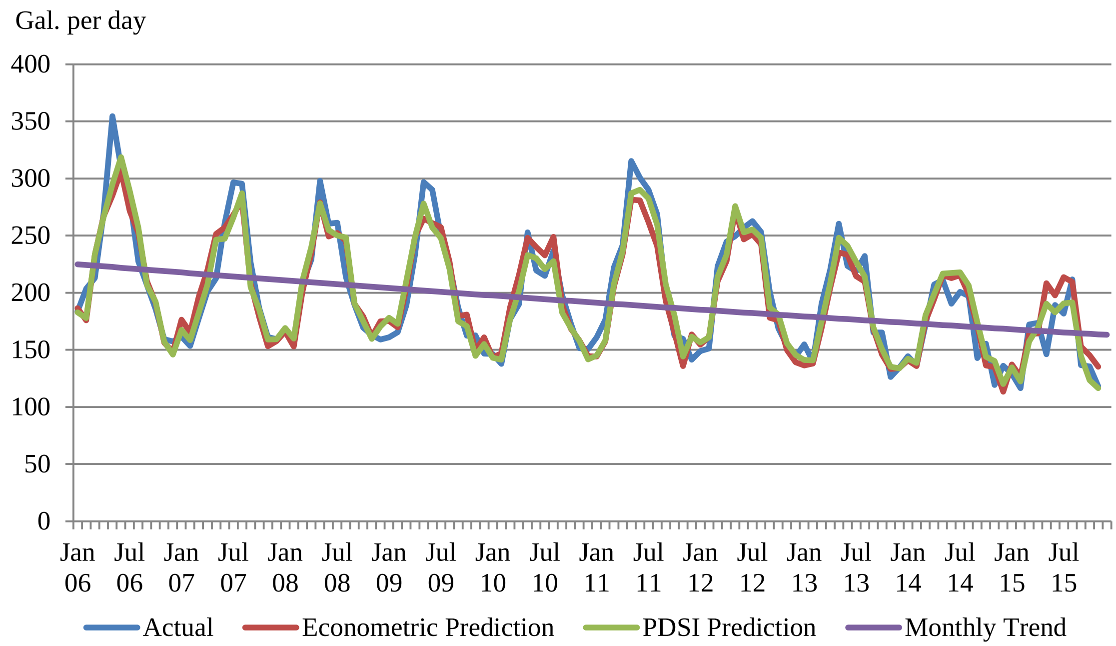


Figure 2.8 Trends actual and predicted series (gallons per day per premises)

It is clear that all estimated series account for the generally declining trend over the period. However, time trended series does not account for the peaks and valleys of the series. The predictions that use temperature and precipitation (or PDSI) follow the peaks and valleys of the actual series and have a much stronger model fit – although the PDSI has the strongest model fit over the series. In order to visually inspect to model fit, figure 2.9. shows predicted versus actual values for the three estimated series already described as well as a series using an annual (rather than monthly) time trend.

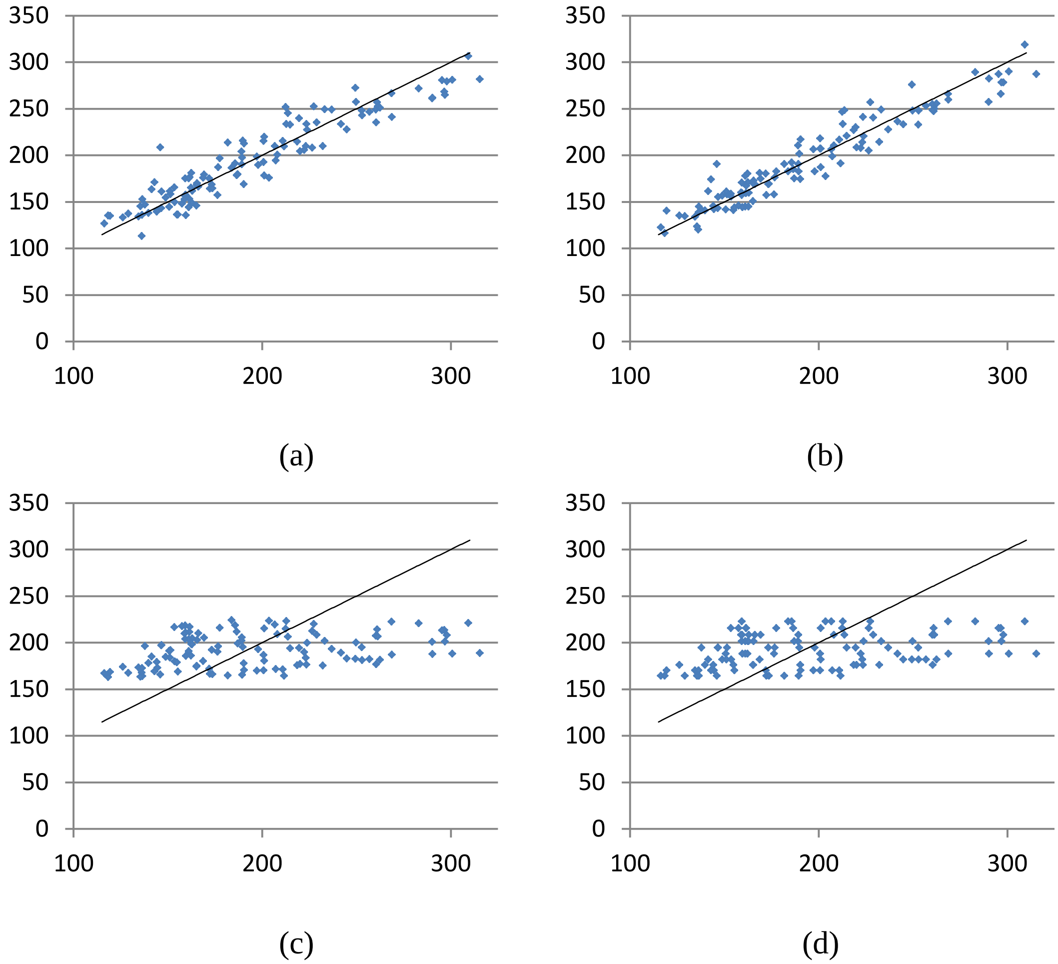


Figure 2.9 Scatter plot, predicted versus actual with 45-degree line: (a) From model 3.4; (b) From model 3.5; (c) monthly time trend; (d) annual time trend (horizontal axis are actual vertical axis are predicted)

Panels (a) and (b) provide similar results with panel (b) fitting slightly more tightly with the 45-degree line. Panels (c) and (d) show the results from a monthly and yearly time trend, respectively; both models fit poorly. With regard to the models that fit well, panels (a) and (b), although the PDSI model appears to be slightly more accurate, in terms of the development of actual projections, and the requirement of input series to produce out-of-sample estimates, it may be more realistic to use precipitation projections. In any event, the utility of using this method to project demand ultimately turns on the quality of the price and climate projections; the more accurate those projections, the more accurate the demand projections are likely to be. In addition, the underlying equations should be periodically re-estimated to ensure that the statistical relationships hold. If those relationship change through time then the updated estimates should be employed.

Given that the econometric model (that includes precipitation in inches) and the PDSI model (which uses PDSI but excludes precipitation) generally produce the strongest fit, models 2.4 and 2.5 were re-estimated in an effort to perform out-of-sample prediction. In particular the estimation range was restricted from the full 120 months to the 60 month period from January 2006 to December 2010. Based on these estimation results, an out-of-sample predictions beginning January 2011 were produced. A comparison of the two out-of-sample predictions and the actual series is shown in figure 2.10.

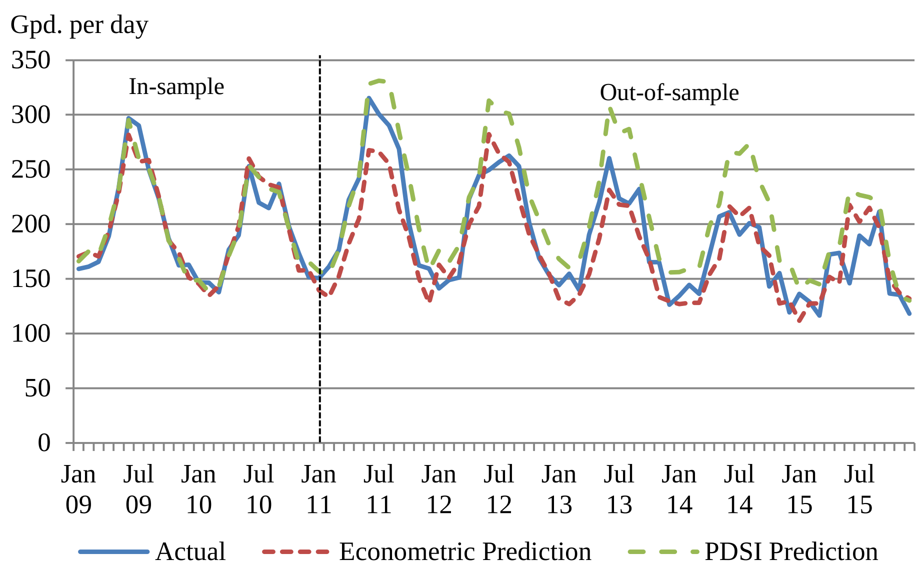
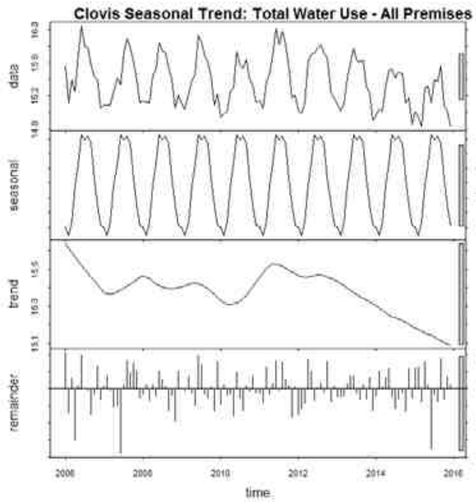


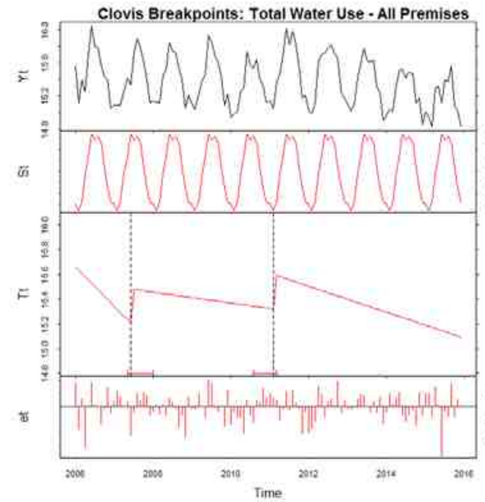
Figure 2.10 Out-of-sample prediction (gallons per day per premises)

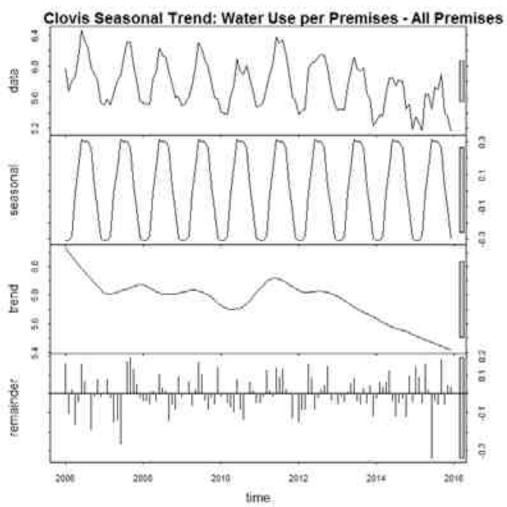
Interesting is that although the model fit for the PDSI model (model 2.5) was slightly stronger than the model fit in the econometric model (model 2.4), with an R^2 of 0.89 versus 0.86, the out-of-sample prediction for the econometric prediction (precipitation model) is generally tighter to the actual series than the PDSI prediction.

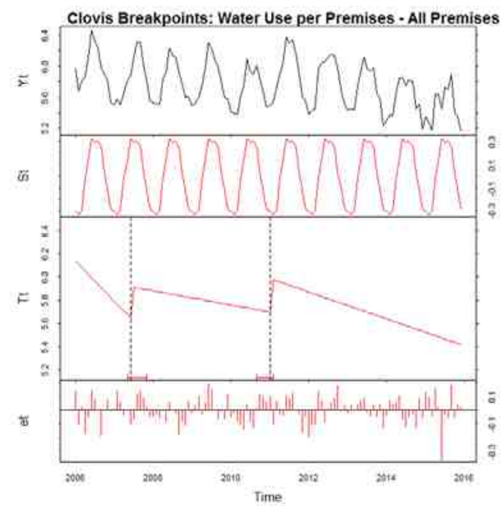
This result provides some evidence of the benefit of using a more straight-forward measurement (precipitation) as opposed to a measurement that may be more attractive at first glance (PDSI). Chapter 3 in this manuscripts toils with the same issue in choosing the appropriate model variables and also settles on the use of precipitation over PDSI. In that case, the justification is similar: precipitation data are nearly instantaneous and is easy to understand whereas PDSI data are required to be computed from other underlying data, are complex, and may not be instantaneously available.

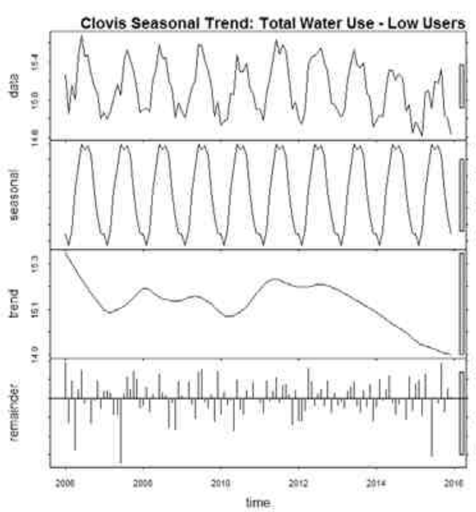
Appendix 2.3 Full Seasonal Trend and Breakpoint Output

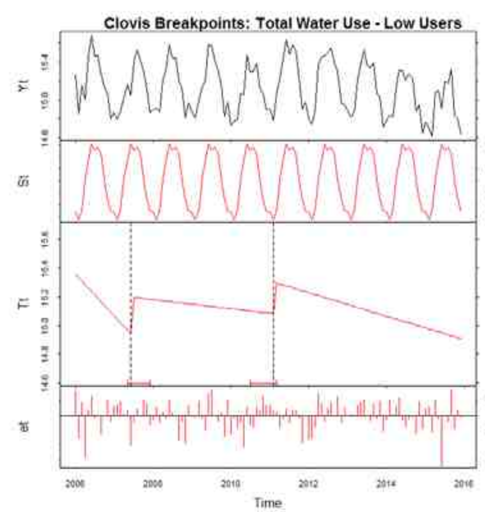


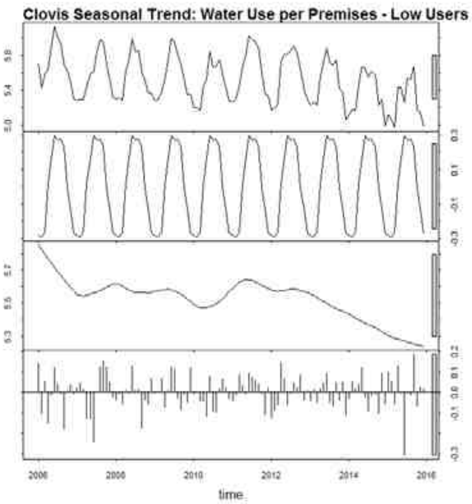











Clovis Seasonal Trend: Water Use per Premises - Low Users
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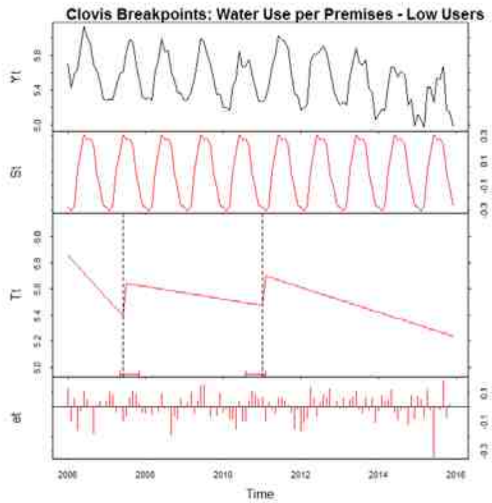
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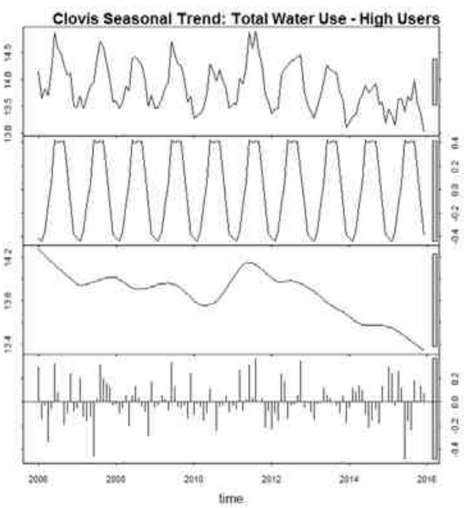
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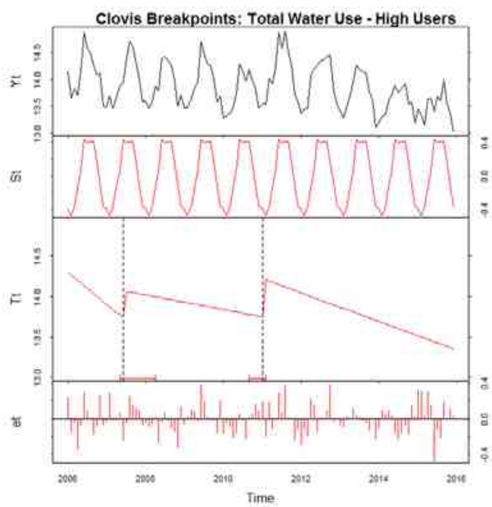
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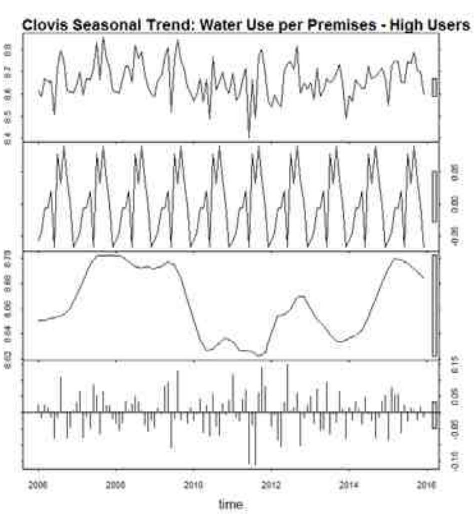
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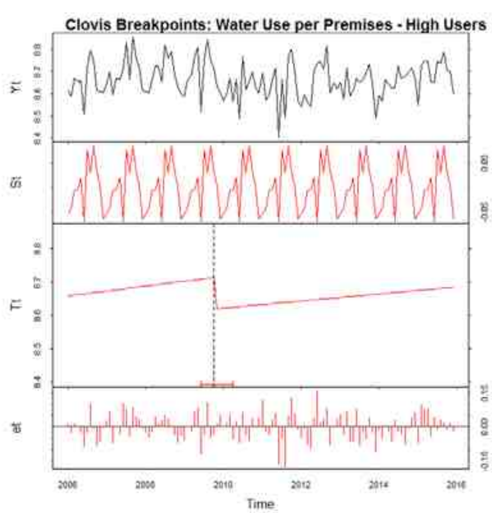
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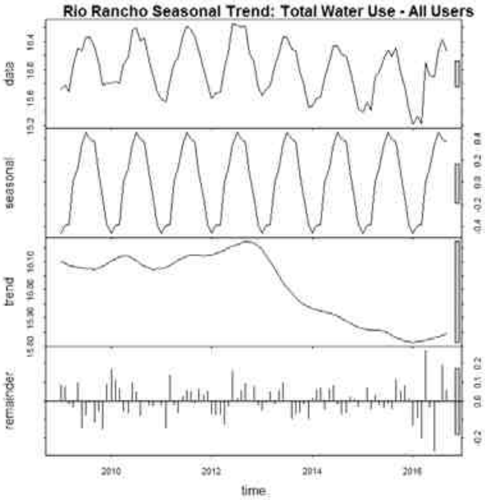
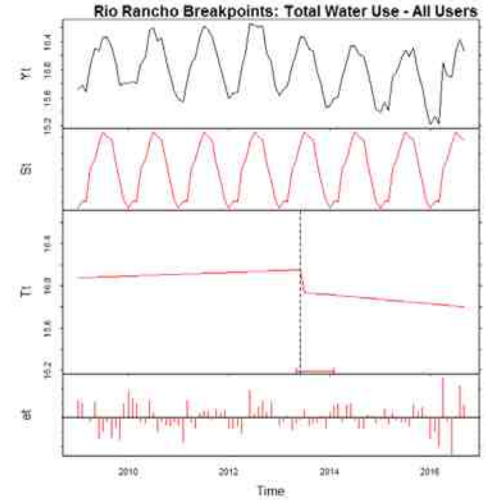
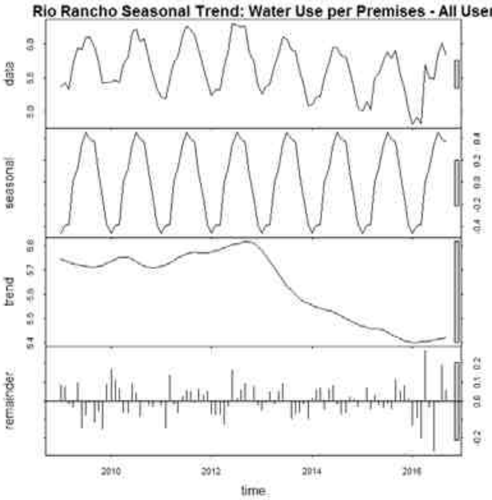
Rio Rancho Seasonal Trend: Total Water Use - All Users



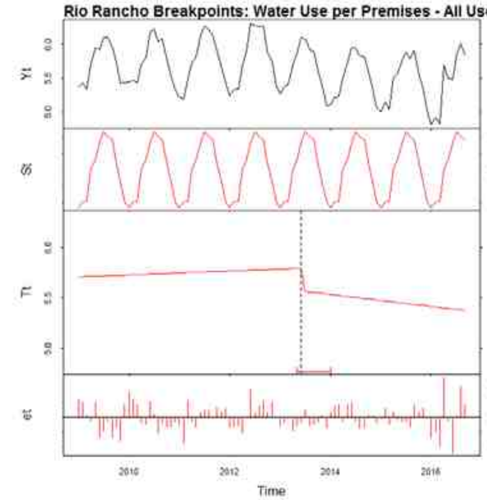
Rio Rancho Breakpoints: Total Water Use - All Users



Rio Rancho Seasonal Trend: Water Use per Premises - All Users



Rio Rancho Breakpoints: Water Use per Premises - All Users



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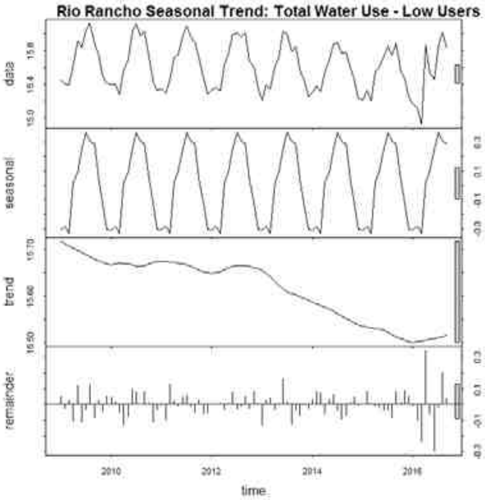
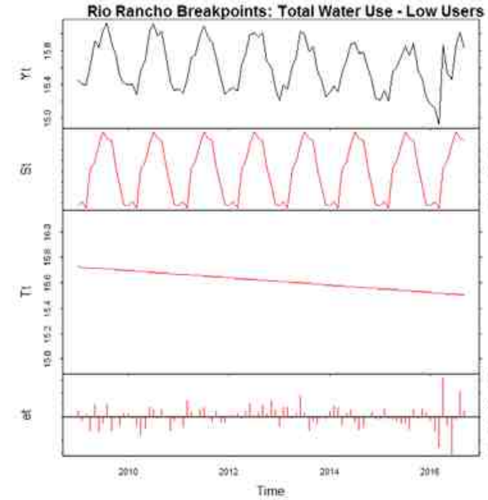
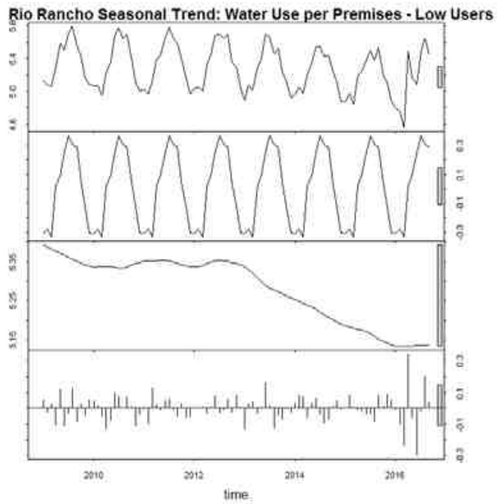


Rio Rancho Breakpoints: Total Water Use - Low Users

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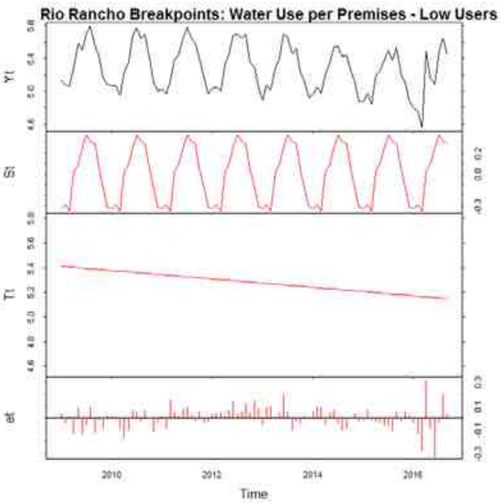
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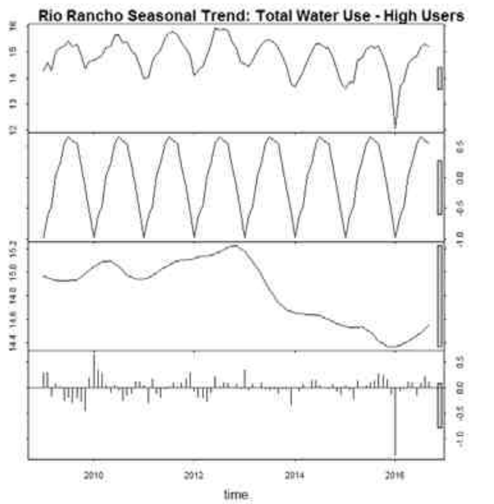
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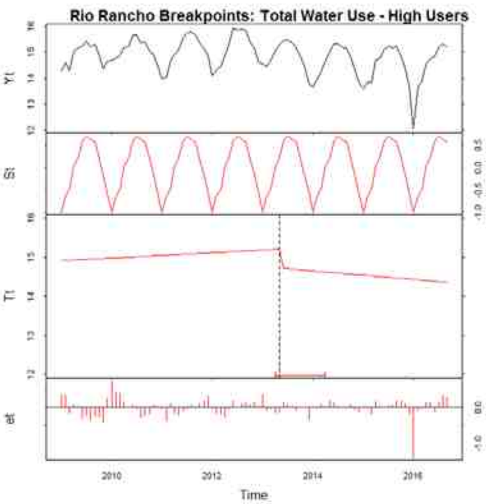
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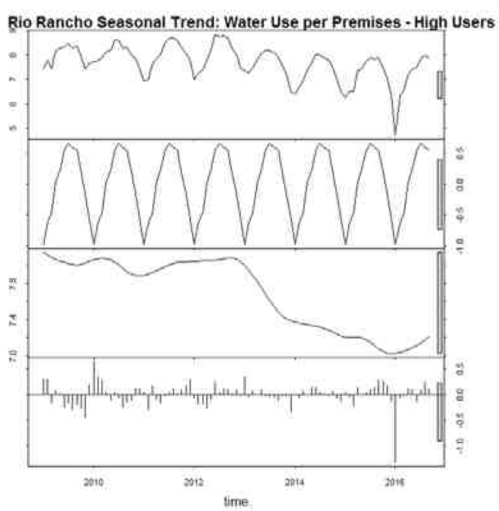
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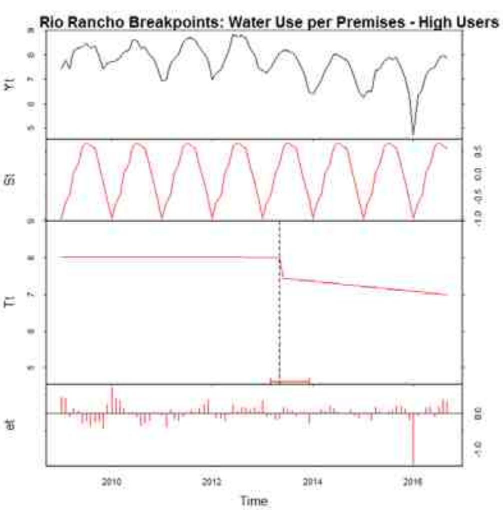
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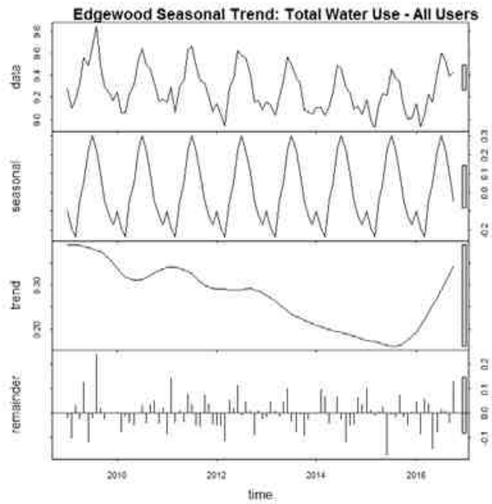
Edgewood Seasonal Trend: Total Water Use - All Users
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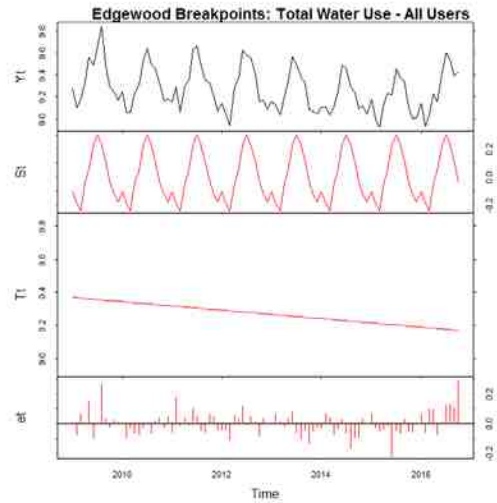
Edgewood Breakpoints: Total Water Use - All Users
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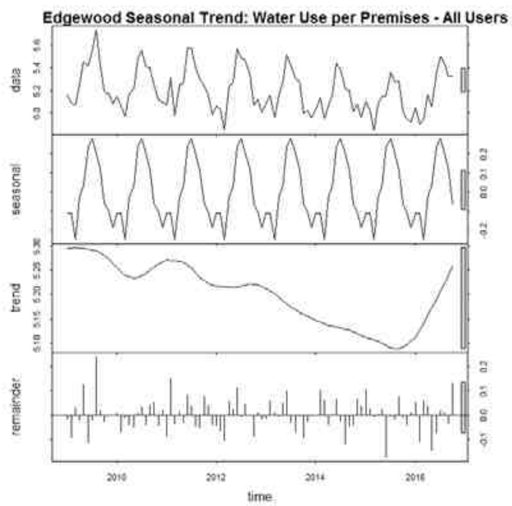
Edgewood Seasonal Trend: Water Use per Premises - All Users
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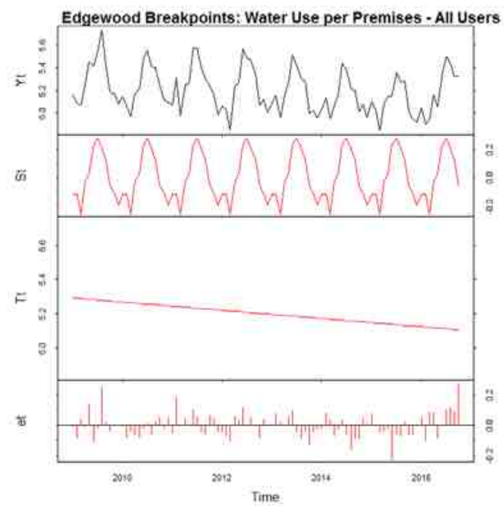
Edgewood Breakpoints: Water Use per Premises - All Users
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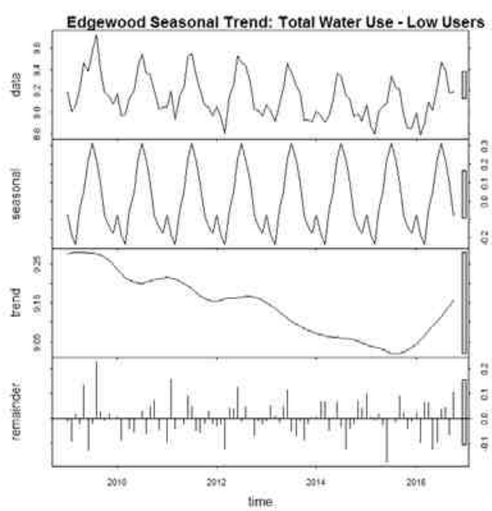
Edgewood Seasonal Trend: Total Water Use - Low Users
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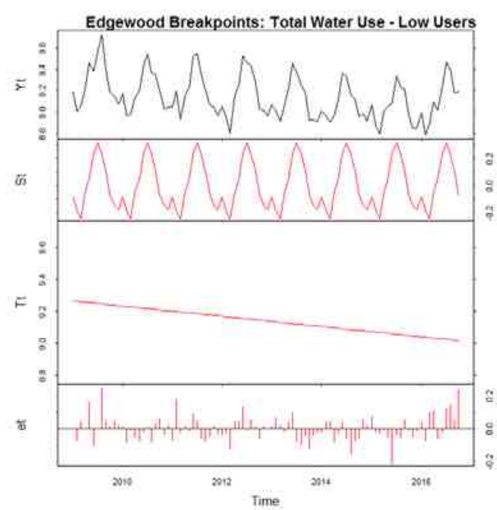
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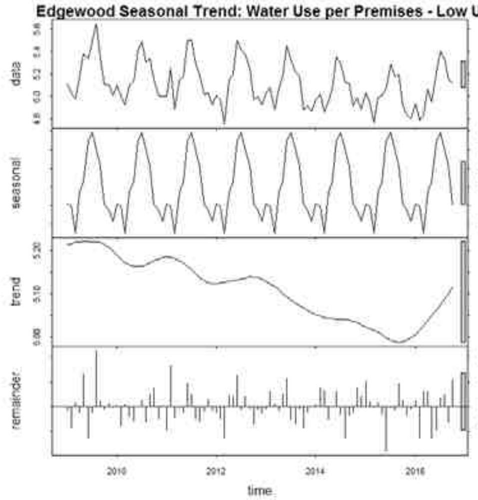
Edgewood Seasonal Trend: Water Use per Premises - Low Users



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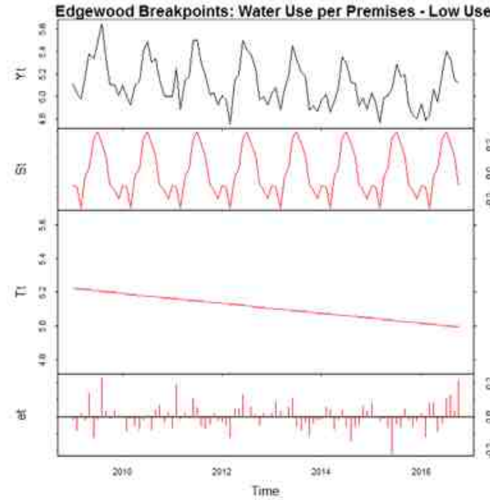
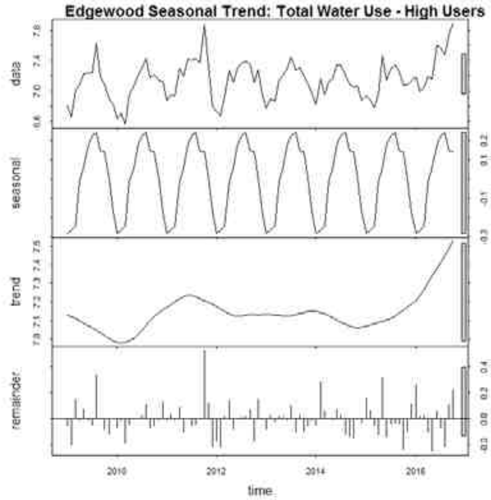
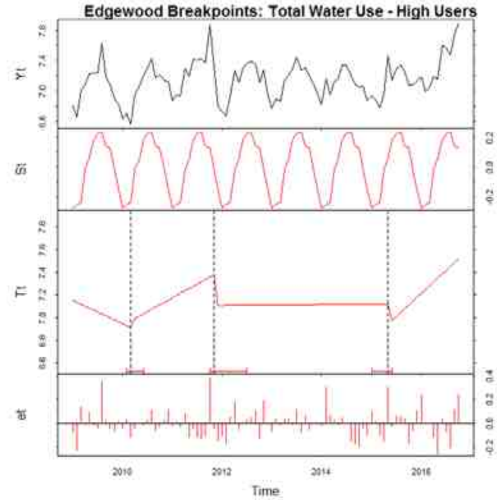


Edgewood Seasonal Trend: Total Water Use - High Users



Edgewood Breakpoints: Total Water Use - High Users



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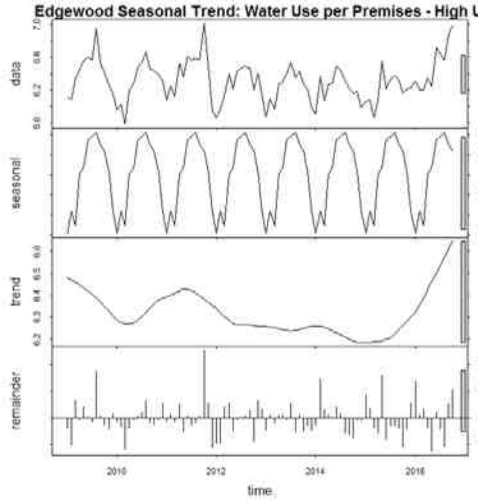

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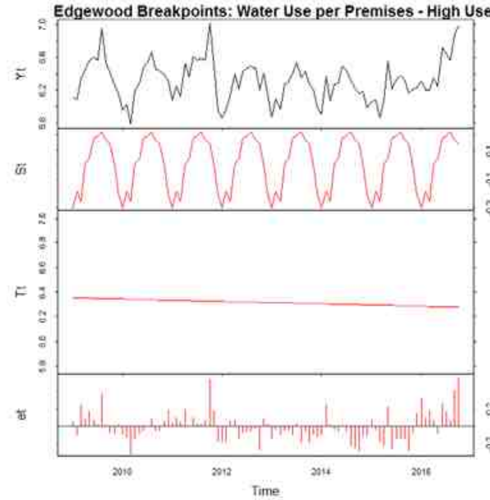
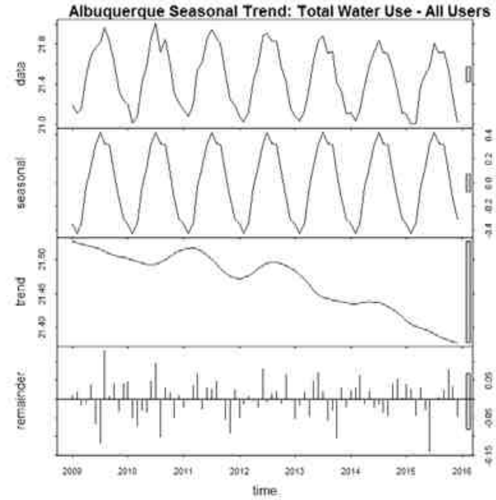
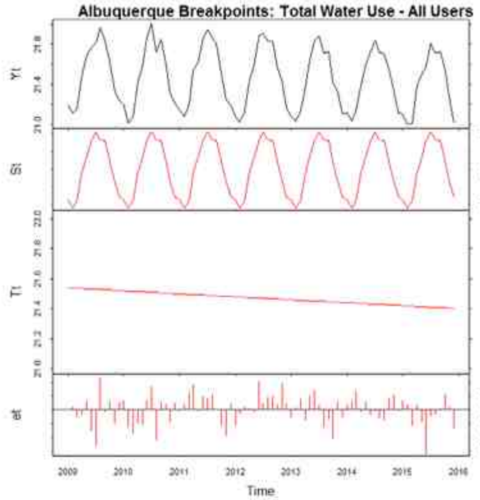


Albuquerque Seasonal Trend: Total Water Use - All Users



Albuquerque Breakpoints: Total Water Use - All Users



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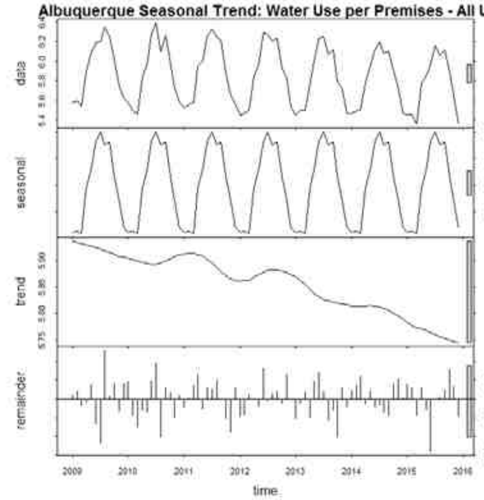
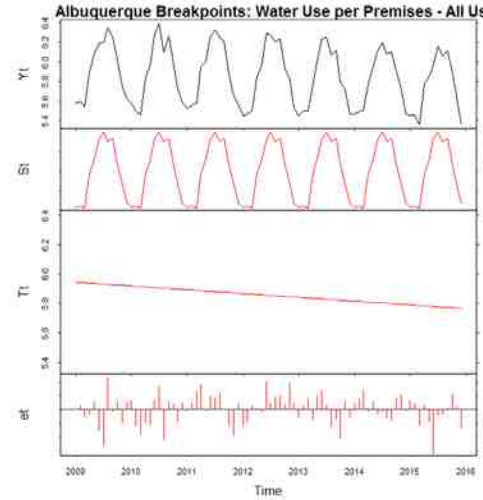


Albuquerque Breakpoints: Water Use per Premises - All Users



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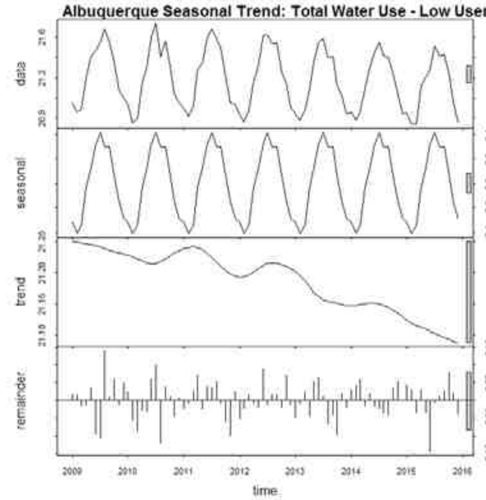
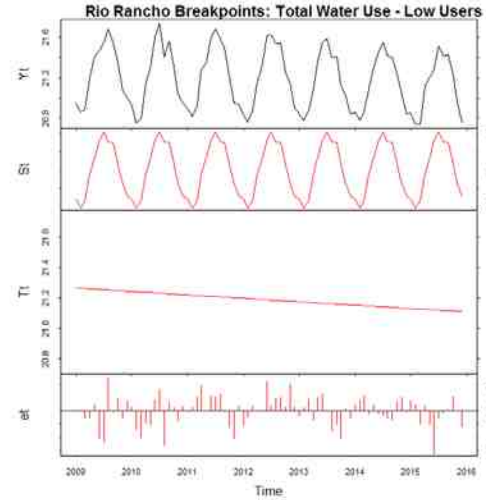
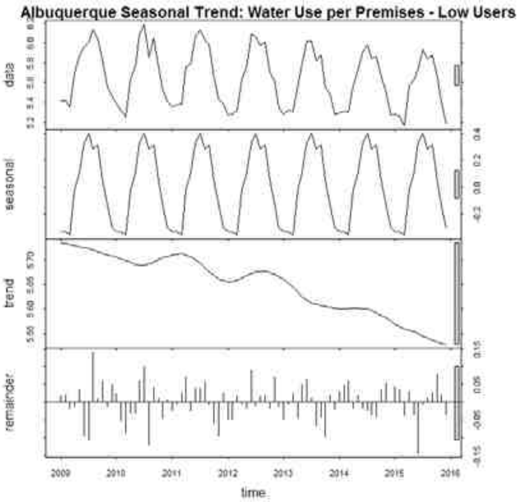


Rio Rancho Breakpoints: Total Water Use - Low Users

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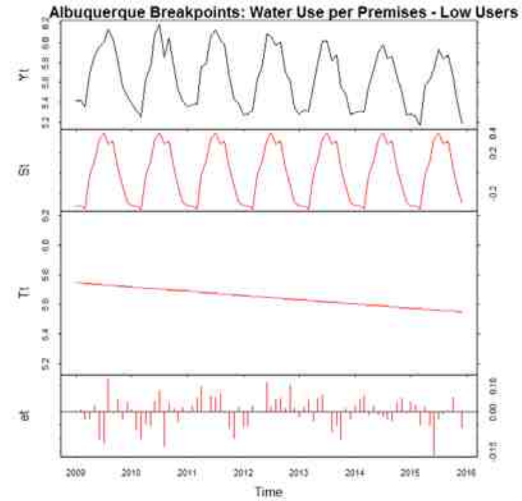
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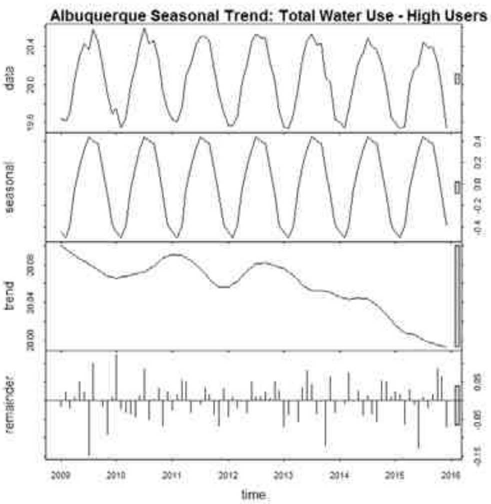
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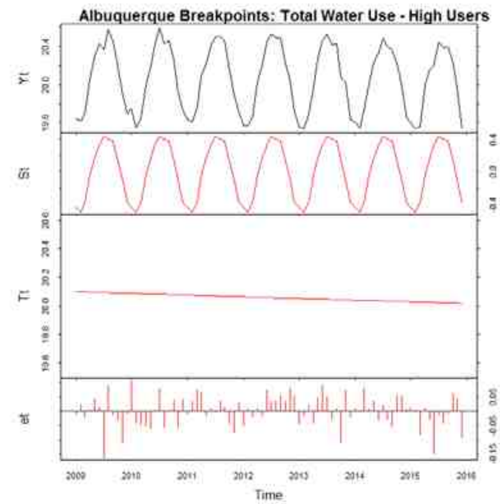
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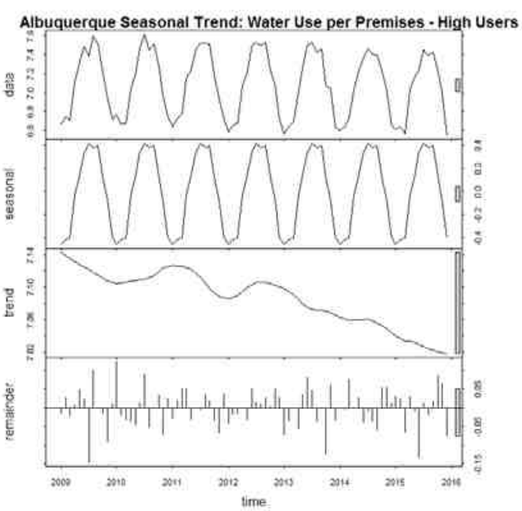
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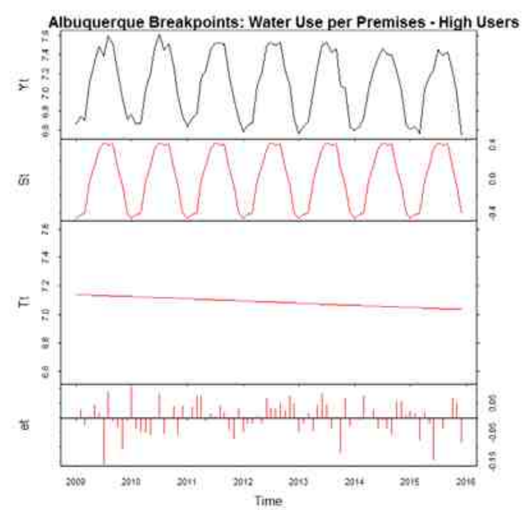
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Chapter 3: Understanding Falling Municipal Water Demand in a Small City Dependent on the Declining Ogallala Aquifer: a Case Study of Clovis, New Mexico

3.1 Introduction

> I cross over the state line into Clovis, a city with ambition but not enough water. Irrigation has drawn the aquifer down so low here that 73 wells deliver less water than what 28 wells delivered to Clovis residents in 2000. "We are in a race to the bottom," Mayor David Lansford says (Parker, 2016).

Scarce water resources and a changing climate create incentives for more efficient municipal water management, especially in areas such as the arid American southwest where climate may be affecting snowmelt run-off, mountain-front recharge, and storage (Brookshire et al., 2010; Stewart et al., 2004). Compared with historical averages, water managers must plan for projected temperatures increases, potentially greater precipitation variability, and severe drought conditions, all of which underscores the significant vulnerabilities facing municipal water supply (Deser et al., 2014; Gutzler & Robbins, 2011). This is acutely the case for the dispersed cities and towns of the high plains region over the Ogallala aquifer, where agricultural withdrawals over the past century have rapidly depleted groundwater supplies (Foster et al., 2017; McGuire, 2014; Steward & Allen, 2016). The High Plains aquifer, of which the Ogallala is a part, is the primary (or sole) source of water for a large number of municipalities and has seen average water level declines of 15 feet over the last several decades; municipalities in some states such as New Mexico, Texas, Kansas and Oklahoma in the central and southern portion of the aquifer, have fared worse (McGuire, 2014). Figure 3.1 shows a selection of municipalities that are also dependent on the High Plains aquifer.

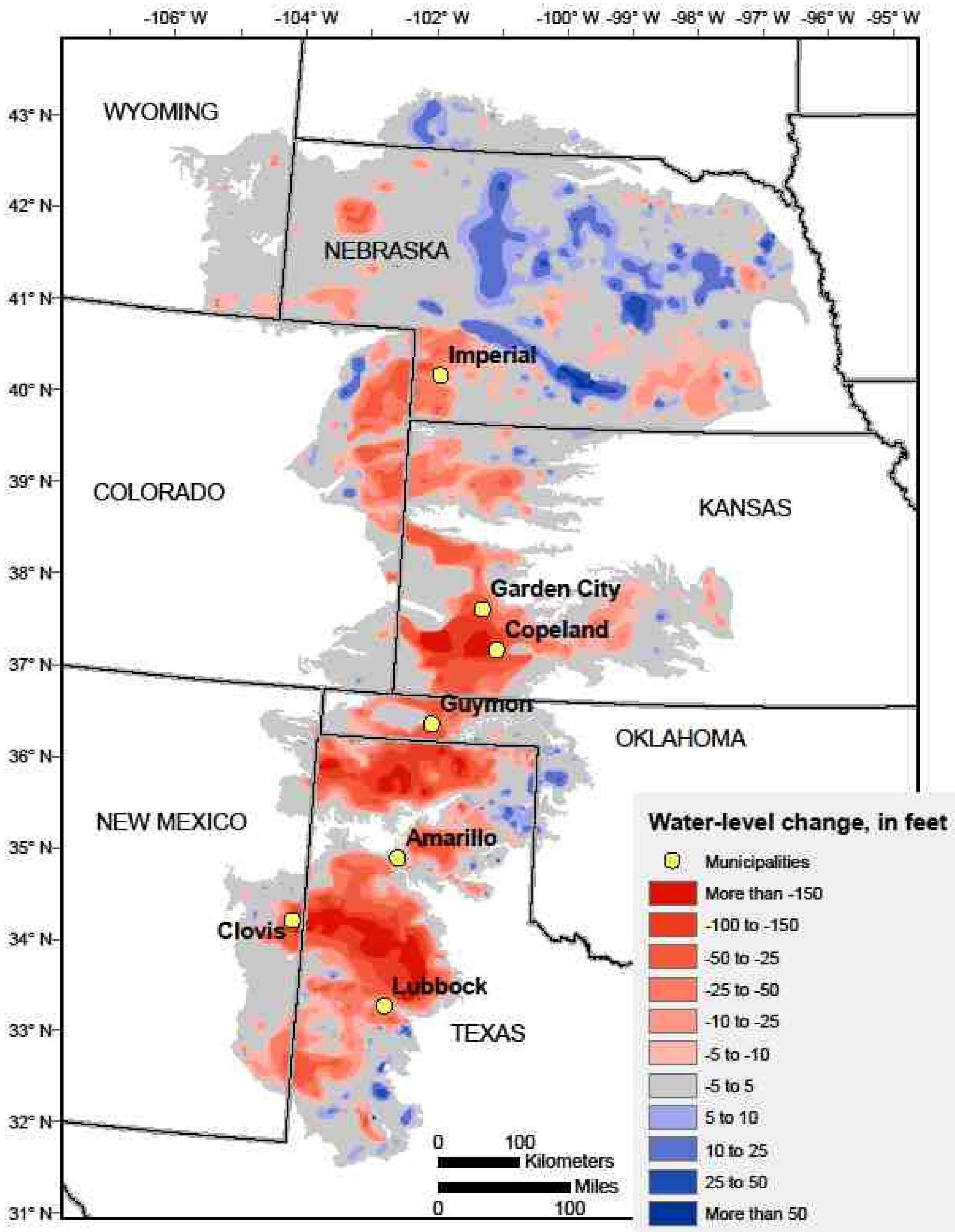

Figure 3.1 Declining High Plains Aquifer: predevelopment to 2013
Notes: High plains aquifer boundary from Qi (2010); water level change from McGuire (2014). Map based on USGS digital data. Map produced by D. Ruiz at the Bureau of Business & Economic Research, UNM.

Given population pressures and a changing climate, rapid aquifer declines have compromised the ability of municipalities to satisfy current and future demand and call for a careful evaluation of the factors that impact demand. This includes untangling the effects of complicated histories of both changing rate structures and a mix of non-price demand management programs implemented in combinations over time. Because Clovis' situation is not unique with regard to depending on a declining aquifer, a better understanding of the factors that influence water demand can be leveraged by similarly situated municipalities.

Municipal water managers regularly confront shortage and scarcity. On the demand side of the ledger, managers have both price and non-price tools at their disposal to influence user behavior (Kenney et al., 2008; Krause et al., 2003). Due in part to these efforts, per capita demand is falling in many large western cities in the US (Balling & Gober, 2007; Brelsford & Abbott, 2017; Donnelly & Cooley, 2015; Kenney et al., 2008; Price et al., 2014). In addition to the availability of demand-side response, relatively large cities, given large population and tax bases, may have a reasonable degree of maneuverability with regard to the supply side. For example, as part of a larger project, diversions of Colorado River water to the city of Tucson, Arizona, via the Central Arizona Project (CAP), became possible following aqueduct completion in 1993 and, after substantial groundwater depletion, the city began to use significant volumes of its CAP entitlement for domestic purposes in 2000 (Zuniga, 2000). Due to similar aquifer depletion, Albuquerque, New Mexico bolstered its supplies in early 2009 as a result of the San Juan Chama project; that project diverts water from the San Juan River to the Rio Grande via a series of channels and tunnels and ultimately to the city (Wickert, 2015).

While much is known about large cities, less is known about small to mid-size cities and towns (i.e., less than 50,000 residents). A number of small to mid-sized cities, especially those within the declining southern Ogallala aquifer, are dependent on the aquifer as their sole source of water. Due to constraints such as small tax bases or the inability to capture economies of scale in infrastructure investment, however, many of these municipalities must operate almost exclusively on the demand side.

Using Clovis, New Mexico as our focus, this study analyzes monthly premises-level panel data from 2006 to 2015 to quantify the effects of pricing and demand management efforts in a small municipality. Analysis accounts for factors such as household income and climate factors in an effort to estimate the relative cost efficacy of different utility actions that have contributed to declining water demand. Our focus is on a small but rapidly growing city that is located in the arid southwest, is solely dependent on the dwindling southern Ogallala aquifer, and at the present time has been unable to engage in a large scale supply enhancement project. This analysis adds to the municipal water demand literature by providing estimates of price and income elasticities, assessing the cost efficacy of water rebate programs, and providing estimates for demand responsiveness to drought conditions in a small municipality. These estimates may be used by and compared against similar localities facing similar hydrological and climate conditions as well as comparable demand management programs and resource constraints.

3.2 Background and literature review

3.2.1 Background on Clovis, NM

Clovis, which is located in Curry County, New Mexico, is a small city near the New Mexico/Texas border in the east-central part of the state whose population is growing at a rapid rate. According to estimates from the 2015 American Community

Survey, the city's population numbered 39,480 persons – up from 37,775 persons in the 2010 US Decennial Census, and up more than 7,000 persons from the 2000 Decennial Census. The climate in Clovis is arid and characterized by generally warm temperatures and relatively low precipitation. Average annual daily temperature typically ranges from around mid-30° F in the winter to the mid-70° F in the summer; meanwhile, total annual precipitation has averaged around 15 inches over the last decade. Like most of the western US, the area has recently experienced extended droughts; according to the US Drought Monitor, 100% of Curry County, the county that Clovis resides in, was under (at least) severe drought conditions from 2012 to 2014 (Simeral, 2016).

The city of Clovis is solely dependent on groundwater from the Ogallala aquifer and therefore is an important case study for other municipalities that rely on a single dwindling groundwater source or even where Ogallala water is a source within their supply mix. For example, water utilities in cities shown in figure 3.1, such as Imperial, Nebraska; Garden City, Kansas; and Guymon, Oklahoma, in the Oklahoma panhandle, each rely entirely on groundwater sources to supply its municipal customers, with most (or all) of the supply coming from the Ogallala formation. Even more populous cities such as Amarillo and Lubbock, Texas, whose utilities use some surface water in their respective supply mix, also use significant volumes of Ogallala water. However, at least in the case of Lubbock, the city recognizes that because of aquifer's relatively low water table and due to decades of agricultural pumping, municipalities must seek alternative supplies to satisfy future demand (City of Amarillo, 2012; City of Lubbock, 2013).

In Clovis, one proposed option for ensuring sufficient future supplies is via construction of the long-proposed Ute reservoir and pipeline that would divert water from the Ute Lake in eastern New Mexico southward to towns such as Clovis. Although some progress has been made along this front, the high cost of construction, which has been estimated to be in the neighborhood of USD 550 million to USD 750 million, combined with the fact that the project will require ongoing operational costs, have thus far generally stalled this large-scale investment (Suzan Montoya Bryan, 2017).

Alternatively, municipalities may attempt to bolster supplies through water trades and leases from local and regional users not supplied by the utility (Colby et al., 2010, 2014). This relatively small-scale purchase and lease activity is currently being undertaken by EPCOR, the private water utility that is contracted by the city to supply the roughly 15,000 premises (including residential, business and governmental entities) in municipal Clovis. However, while this may be an effective near-term strategy, given that irrigators are subject to the same dwindling aquifer and perhaps relatively greater stresses due to climate change (Ziolkowska & Reyes, 2017), opportunities for trade may be constrained.

Despite a general uptick in the number of premises that EPCOR services, from about 13,500 premises in 2006 to about 15,500 by 2015, total water demand and water demand per serviced premise has generally declined over the last decade. In particular, mean daily water use per premises declined from about 360 gallons per day (gdp) in 2006 to 310 gpd in 2010 and then to 250 gpd in 2015. Similarly, aggregate demand declined from about 5 million gpd to 4.7 million gpd and then to 3.9 million gpd in 2006, 2010, and 2015, respectively. This trend of falling demand has been seen in other nearby cities (Balling & Gober, 2007; Donnelly & Cooley, 2015). Fully understanding this apparent behavioral change, and what might cause it to reverse (e.g., extended drought, a warming climate, continued population growth, or altering a rebate program, etc.) is an especially critical challenge for a municipality like Clovis that does not have ready access to alternative supplies.

3.2.2 Factors under the utility's control

Strategies that utilities employ to influence water demand can broadly be described as price and non-price strategies (Kenney et al., 2008; Krause et al., 2003). With regard to price strategies, the law of demand suggests that price increases will bring about a reduction in the quantity demanded; most empirical research has borne out this expectation with regard to water use. In an analysis of the empirical water demand literature, Worthington & Hoffman (2008) note that estimated price elasticities are almost always negative and inelastic. Likewise, in a recent and large meta-analysis of water demand studies from 2002 to 2012, Sebri (2014) found a mean price elasticity of -0.37, confirming the general tendency of inelastic demand at current prices; however, given inelastic demand, price increases will only result in relatively small decrease in quantity demanded (Arbués et al., 2003; Dalhuisen et al., 2003). While most studies focus on the short-run, several studies estimate long run price elasticity. Most find the long run elasticity to be greater than the short run but still in the inelastic region (Almendarez-Hernández et al., 2016; Worthington & Hoffman, 2008), and some studies even find water demand to be price elastic in the long run (Ben Zaied & Binet, 2015; Yoo et al., 2014). Still, the finding of generally (price) inelastic demand persists in the recent literature. A collection of recent studies that have estimated price elasticity of water demand, along with key meta-analyses, is presented in Appendix 3.1.

Because water demand tends to be inelastic, non-price strategies are often favored by water utilitiess, especially when water conservation is a goal (Olmstead et al., 2007).

Non-price policies include a variety of activities such as water use restrictions, public information campaigns, rebates for the purchase (and replacement) of low-flow appliances, landscaping subsidies, and other similar strategies. Especially popular policies are rebate programs for low-flow appliances (e.g. toilets, showerheads, and washing machines). Rebate programs of this type have been shown to be effective at reducing water demand (Kenney et al., 2008; Price et al., 2014).

3.2.3 Factors not under the utility's control

Household-level characteristics have also been shown to impact water demand. For example, Arbués et al. (2003), Dalhuisen et al. (2003), and others, point out that income impacts water demand in a positive fashion, making water a "normal" good. This general result continues to be been borne out in the recent literature (see Appendix 3.1). In addition, household size has been used to explain water demand; Arbués et al. (2010) put a finer point on the topic when the authors find that smaller households are relatively more sensitive to price changes than larger households.

Weather and climate-related variables also impact water demand, although studies vary with regard to which climate variables to include or how to characterize weather. Arbués et al. (2010) used the number of days in a billing cycle over a certain temperature and no variable for precipitation; Kenney et al. (2008) included the average maximum daily temperature over a billing period and the total precipitation over that period; and Price et al. (2014) used average daily temperature over the billing period and total precipitation. Furthermore, inter-annual or seasonal variation, which may be related to outdoor activities such as gardening or pools, is likely to exist (Arbués et al., 2003).

In addition, vegetation conditions in the locality are unlikely to be under the control of the water utility but may impact water demand. Gage & Cooper (2015), for example, investigated semi-arid Aurora, Colorado and found that land cover was predictive of water use and that tree canopy cover and height reduced water use. The authors also found consistency with previous studies that demonstrated that vegetation cover was a spatially structured phenomenon; in other words, similar vegetative cover type is likely in defined spatial areas (Franczyk & Chang, 2009; House-Peters et al., 2010; Wentz & Gober, 2007).

3.3 Data

3.3.1 Water use and price

Monthly data on water use by premises from January 2006 to December 2015 was provided by EPCOR and average daily water use by premises for each month was computed. As this study is interested in measuring water user responsiveness to utility price and non-price actions, this computed variable serves as the dependent variable for all empirical estimation. Premises location was geocoded based on listed address. Water price is given on a per unit basis and is determined jointly by the size of the premises' delivery pipe and according to an increasing block rate structure. In this instance, one unit is defined as one CCF (100 ft^3) and equivalent to 748 gallons delivered to the premises. Over the ten year period, the rate (price) structure has been adjusted three times: June 2007, May 2009 and May 2012, giving four distinct rates over the period. In addition, the number of blocks has increased: for example, the residential block rate structure changed in June 2007 from two blocks to three, while the structure for commercial premises connected with a 1" water delivery pipe changed from a flat rate structure to a two block structure. The left panel in figure 3.2 shows the nominal change in the residential block rate structure through time and the right panel shows the change in the block rate structure for premises connected with a $1''$ delivery pipe. Combined, these two premises types account for approximately 97% of all observations in the dataset.

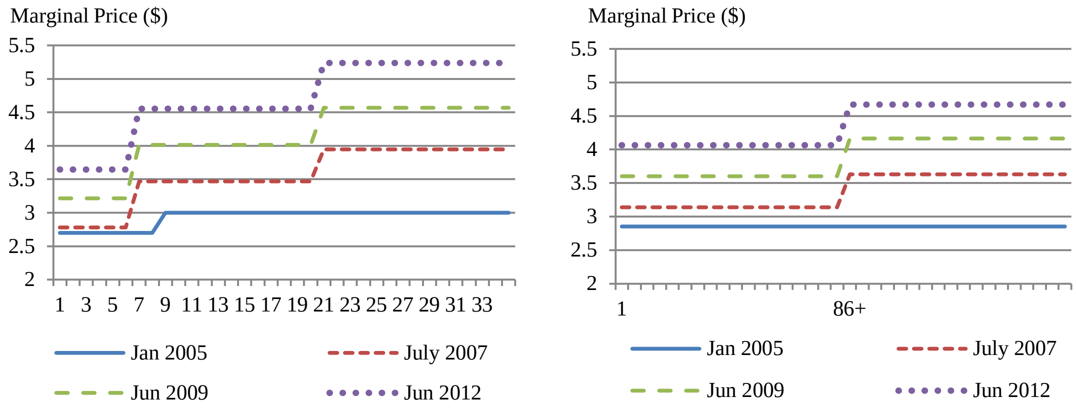

Figure 3.2 Change in block number and increase in nominal rates through time
Notes: Horizontal axis measured in CCF where 1 CCF = 748 gallons. Vertical axis measures marginal price in USD. Left panel shows residential rates. Right panel shows non-residential rates for premises that have a 1" hookup.

For estimation purposes, because the time period is relatively long (10 years), price is adjusted for inflation on an annual basis using the consumer price index (CPI) using 2015 as the base year.

3.3.2 Rebate programs

EPCOR's rebate program, which began in 2008, and is ongoing, provides rebates for toilets, washing machines and low water-use landscaping (i.e. conversion from turf to xeriscape). Rebate data are at the premises level, which allows for estimation of changes in water use due to the installation of qualifying technology or landscape change.

Nearly USD 500,000 has been spent by EPCOR on rebates over the life of the program with toilet rebates and landscaping rebates accounting for the majority of total funds spent. While 927 premises qualified for a toilet rebate, 1,686 total toilet rebates were granted; therefore, on average, 1.8 toilet rebates were granted per premises. With regard to the landscaping rebates, approximately 565,000 square feet have been converted from turf to xeriscape.

3.3.3 Climate

Daily climate data, and in particular temperature and precipitation data, were obtained from the National Oceanic and Atmospheric Administration (NOAA, 2017). Daily temperature data was used to construct average temperature for each month while daily precipitation data was summed to arrive at a monthly precipitation total. Over the study period from January 2006 to December 2015, Clovis experienced several periods of extreme drought: from a short period of drought in 2006 to extended and deep drought from 2011 to 2014. These trends are captured by the Palmer Drought Severity Index (PDSI, 2017) readings from the city shown in figure 3.3. Negative values, as those shown from about January 2011 until about January 2015 indicate dry conditions.

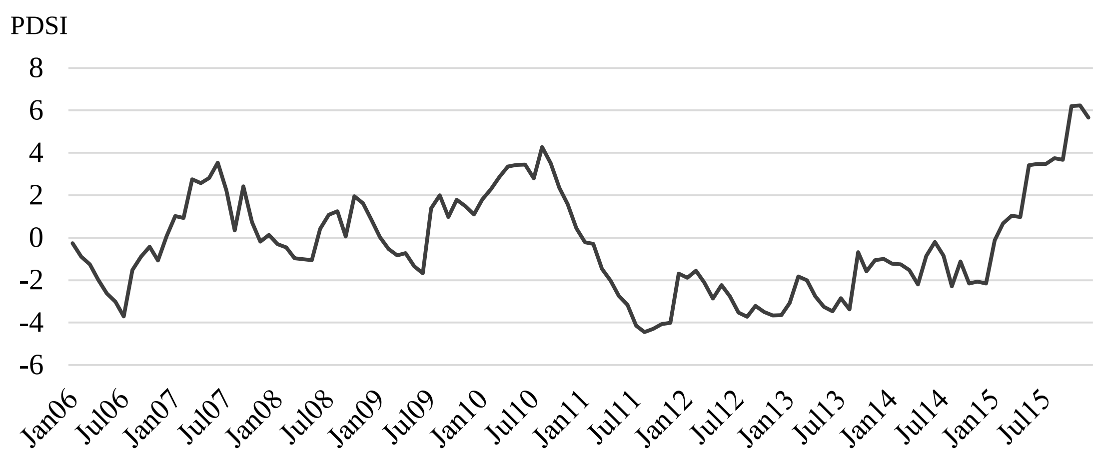

Figure 3.3 Palmer Drought Severity Index in Clovis, New Mexico by month (2006 – 2015) (PDSI, 2017)

3.3.4 Socioeconomics

Individual household-level socioeconomic data are unknown in this analysis; however, aggregate data are available through the US Census's American Community Survey program. Although individual premises-level or census tract level data would have been preferred, and have been shown to perform relatively well (Ouyang et al., 2014), this study utilizes county-level estimates for Curry county, the county that the city of Clovis resides in, because tract-level estimates are sparse. In addition, given the relatively large confidence intervals on the tract-level data, imputation was deemed to be inappropriate. As county-level data were available for most, but not all years, linear interpolation was used to interpolate between known years. The specific socioeconomic data used in this analysis are data that have been shown to impact water demand in prior studies; in particular, median household income (ACS, 2017b) and household size (ACS, 2017a), both at the county level, are included as explanatory variables. However, because these data vary over time and not space, only temporal variation is captured.

In addition to characteristics of individuals residing in the household impacting water demand, the characteristics of each or premises, or trend in aggregate premises characteristics, should also impact demand. For example, the size of the housing stock should be positively related to aggregate water use all else equal; however, it is unclear how the size of the housing stock would impact unit-level water use. Also, the age of the stock may be related to both aggregate or per capita water use (Brelsford & Abbott, 2017); if the stock ages, system losses and inefficiencies might be expected to increase water use, while a stock that is getting younger through time (through attrition of relatively old stock and replacement through new construction) are more likely to be built with water efficiency in mind. Both housing stock size and housing stock age were considered; however, preliminary analysis suggested insufficient variation in housing stock size to explain aggregate or premises-level water use. In addition, estimates of housing stock age via the American Community Survey (ACS, 2017) were correlated with other model variables. Therefore, permits granted for single family construction in the city of Clovis were used as a proxy to control for housing stock age. These monthly data were collected and compiled by the University of New Mexico's Bureau of Business & Economic Research (BBER, 2017).

3.3.5 Vegetation data

This analysis incorporates remote sensing data via the Normalized Difference Vegetation Index (NDVI), utilizing the Advanced Very High Resolution Radiometer (AVHRR) Phenology series, produced by the United States Geologic Survey (USGS, 2017). The index, which is computed from remote satellite data, measures wavelengths of light absorbed and reflected by green plants. In general, higher index values correspond to 'greener' or denser plant coverage. At the time of analysis, data were available through 2013.

This analysis specifically utilizes a measure called the time integrated NDVI, which is the cumulative value of NDVI from the start to the end of the growing season. This measure was chosen in an attempt to better capture longer-term trends over the growing season rather than other vegetation-related indices, which are more likely to capture a particular peak or valley in at a point in time. Spatial resolution is 1 km^2; each square was geocoded and overlaid on premises-level geocoding – thus matching, at the given spatial resolution, the appropriate index to each premises. The study utilizes a larger spatial scale than Gage & Cooper (2015) and is a more general interpretation of vegetation. This is done because the present analysis is interested in controlling for aggregate inter-annual vegetation trends rather than specific premises- or neighborhood-level impacts.

Descriptive statistics for variables are shown in table 3.1.

Table 3.1 Variable definitions and descriptive statistics

Variable	Description	Period	Unit	Mean	Std. dev.	Source
WU	Average daily household water use	Month	Gallons	323.6	653.5	EPCOR
AvgPrice	Average water price	Month	USD per Gallon	0.003	0.002	EPCOR
ToiletPrem	Premises toilet rebate indicator	Month	1/0	0.03	0.18	EPCOR
Washer	Washing machine rebate indicator	Month	1/0	0.02	0.13	EPCOR
Landscape	Landscape rebate indicator	Month	1/0	0.01	0.08	EPCOR
Income	Average household income in county	Ann.	Dollars	40,945	1.02	US Census (ACS, 2017)
HHsize	Average household size in county	Ann.	Persons	2.61	0.08	US Census (ACS, 2017)
BldPermit	Number of single family building permits	Month	Permits	10.37	5.47	(BBER, 2017)
Temp	Average monthly temperature	Month	Fahrenheit	56.80	14.86	(NOAA, 2017)
Precip	Average total monthly precipitation	Month	Inches	1.28	1.44	(NOAA, 2017)
VegIndex	Vegetation index	Ann.	Unitless	12.72	9.16	(USGS, 2017)
PDSI	Palmer Drought Severity Index	Month	Unitless	-0.28	2.45	NOAA (PDSI, 2017)

Note: The low standard deviation for household income occurs because the data are county-level and annual in nature; thus, income variation is solely based on interannual behavior.

3.4 Modeling approach

A primary objective of this analysis is to estimate the impact of EPCOR's price and non-price policies on water demand in Clovis. A fixed effects instrumental variable approach is used for this purpose. Although several explanatory variables are included in this analysis, some important premises-level characteristics that may impact demand, such as evaporative cooler use, yard size, irrigation type, and the like, are unknown. For this reason, a fixed effects approach is brought to bear to control for those unknown premises-level characteristics. Additionally, unlike Kenney et al. (2008), this analysis controls for household (or community) socioeconomics that are expected to relate to water demand. In that study, the authors attempted to use Decennial Census data, which did not vary through the study period and fixed effects analysis requires that explanatory variables vary through time. Therefore, to control for socioeconomic characteristic, the present study uses county-level annual estimates from the American Community Survey.

In addition, because water price is included as an explanatory variable in the demand estimation, an instrumental variable approach is applied. This is done to remove the inherent statistical bias resulting from endogeneity in the price signal when estimating water demand (Arbués et al., 2004). In other words, WU, or water use, is estimated as a function of price (among other things). However, price is also inherently a function of WU, so changes to WU can affect price. Therefore, if price was used as a regressor it would likely be correlated with the error term, which would bias the estimated parameters (Wooldridge, 2010).

To remedy this problem, a first stage estimation is undertaken where price is the dependent variable and is a function of a chosen set of instruments. In this case, marginal price, per the increasing block rate structure, is used to instrument for average price (Kenney et al., 2008; Price et al., 2014). Next, predicted prices from the first stage estimation are computed and then used as the new price variable, rather than actual price, in the main regression. This process ensures that the new (predicted) price variable is uncorrelated with the error term. Instrument validity was confirmed using the under-identification and weak identification tests.

An empirical challenge with estimating water demand stems from the block rate pricing structure employed by EPCOR and many water utilities. Because the analysis estimates the effect of pricing on water demand, choosing the correct price, or price proxy, is important. There has been considerable debate over the years concerning the management of price under a block rate structure; however, because there is not a single price for which water is sold under a block rate structure, a composite price must be developed. Common practices analysts have used to create a composite price include: marginal price, computation of an average price, or applying the so-called Nordin (1976) specification.

Economic theory suggests that demand should respond to marginal price – or the price of the last unit sold. However, for this to be the case in a municipal water demand context, consumers are required to have contemporaneous information of their water use in each period as well as an intimate understanding of the rate structure (Arbués et al., 2003; Carter & Milon, 2005; H. S. Foster & Beattie, 1979). In practice, however, both requirements are unlikely (Ito, 2014; Kenney et al., 2008). The Nordin (1976) specification utilizes marginal price as well as an additional term captured by computing the difference between the total bill and what the user would have paid if all units were charged at the marginal price; this variable is designed to proxy the income effect imposed by the block rate structure (Arbués et al., 2003). As a practical matter, this technique suffers from the same downsides as the use of straight marginal price.

Therefore, because consumers are likely to only have a general understanding of the relationship between their water use and their water bills, the present analysis employs an average price structure similar in nature to Kenney et al. (2008) and Price et al. (2014). Under this method, average price is computed by dividing the total bill amount by the water volume consumed (i.e., the volume reflected in the bill in gallons). Because a consumer is unlikely to have real-time knowledge of water use, but may change behavior from month to month based on the amount billed, this constructed variable is lagged one billing period.

While water demand studies regularly use a FEIV (or similar) empirical strategy due to its straightforward nature (Kenney et al., 2008; Porcher, 2014; Price et al., 2014; Romano et al., 2014; Wichman et al., 2016), other recent studies employ alternative methodologies in an effort to account for shortcomings associated with this approach. For example, Klaiber et al. (2014) and Wichman (2014) utilize an experimental approach and a difference-in-difference estimation methodology to account for omitted variable bias. Also attempting to account for the effect of omitted variables, Brelsford & Abbott (2017) use the decomposition procedure put forward by Gelbach (2016). Although the underlying estimation approach is FEIV in nature, Clarke et al. (2017) and Hung & Chie (2013) employ a Stone-Geary functional form, which allows for greater flexibility by allowing for non-fixed elasticities. Meanwhile, Ben Zaied & Binet (2015) and Ghavidelfar et al. (2016) harness the time series analysis literature by employing cointigration and error correction methodological approaches (Appendix 3.1contains a table of recent water demand studies along with elasticity estimates and methodological innovation). Nevertheless, and despite the situational benefits of alternative estimation, the present study uses a straightforward FEIV estimation approach.

3.4.1 The model

All estimation proceeds according to variations on the following general model

$$
\begin{aligned}
\ln\text{WU}_{it} = B_0 &+ B_1 \ln\text{AvgPrice}_{i(t-1)} + B_2\text{Temp}_{it} + B_3\text{Precip}_{it} \\
&+ B_4 \ln\text{Income}_{it} + B_5\text{HHsize}_{it} + B_6\text{BldPermit}_{it} \\
&+ \sum_{j=1}^{3} \delta_j \text{Rebate}_{jit} + \sum_{k=1}^{11} \psi_k \text{Month}_k \\
&+ \sum_{l=1}^{3} \gamma_l \text{MeterSize}_{li} + \alpha_i + \varepsilon_{it}
\end{aligned}
\tag{3.1}
$$

In this model, B_0 is the intercept term and terms from B_1 to B_6 correspond to estimated coefficients on continuous variables. On preliminary analysis, it was determined that Precip was correlated with both VegIndex ($\rho = 0.40, p < 0.000$) and PDSI ($\rho = 0.47, p < 0.000$); because precipitation is straightforward and an input into both indices, it was retained and VegIndex and PDSI were excluded. For estimation that includes the two indices, see table 3.8 in Appendix 2.2. The natural logarithm of water use is the dependent variable, and the water price and income variables are log-transformed so that their estimated coefficients can be directly interpreted as elasticities.

$\delta_j, \psi_k. \gamma_l$ are coefficients on indicators for particular states or events. The coefficient on rebates, δ_j, corresponds to three non-mutually exclusive events: receipt of toilet rebate, washing machine rebate, and landscaping rebate. The coefficient on Month, θ_k, corresponds to the billing month and is mutually exclusive; December is the base month. While one could argue that monthly control is unnecessary and behavior should be tied to actual measurable phenomena, such as temperature and precipitation (which may be correlated with months anyway), it is likely that there are both psychological and systematic calendar-based arguments, such as holidays, watering schedules, or turning off an evaporative cooler, for it use (Kenney et al., 2008).

The coefficient on MeterSize, γ_l, is mutually exclusive and controls for the size of the delivery pipe connected to the premises. Only three sizes are explicitly identified in this analysis, $\frac{5}{8}^{"}$, $1^{"}$, and $1.5^{"}$. However most observations (around 98%) occur within these three sizes; the remaining sizes are combined into a composite base category. The α_i term controls for the premise-level fixed effects, while ε_{it} is the error term. The subscripts i and t are indices that correspond to premises and time period (month), respectively.

3.5 Results & discussion

3.5.1 Model of entire dataset

Models based on equation (3.1) were estimated utilizing all available data; results are shown in table 3.2. Although not shown, controls for billing month and water delivery pipe size are employed in all cases.

Because the dependent variable (gallons of water demanded per day) is log-transformed, interpretation of the continuous explanatory variables is relatively straightforward as is the interpretation of the log-transformed continuous variables. With regard to the non-logged continuous variables (such as temperature or precipitation), the estimated coefficients correspond to a percentage change in the water use (gallons per day) for a one unit change in the variable of interest. Therefore, a one inch increase in precipitation reduces daily water use by 1.2%, all else equal. Estimated coefficients from the log-transformed variables represent elasticities. For example, the estimated coefficient on water price in model 3.1 indicates that a 1% increase in water price will reduce water demand by 0.53%, all else equal.

Table 3.2 2SLS regression results (full model)

Variable	Model 3.1
lnAvgPrice	-0.534***
	(0.0076)
ToiletPrem	-0.083***
	(0.0042)
Washer	-0.060***
	(0.0059)
Landscape	-0.100***
	(0.0071)
lnIncome	0.568***
	(0.0268)
HHsize	-0.009
	(0.0122)
BldPermit	0.007***
	(0.0001)
Temp	0.010***
	(0.00001)
Precip	-0.012***
	(0.0004)
Constant	-3.658***
	(0.2554)
Obs.	1,575,980
Premises	16,904
R^2	0.280

Note: Standard errors reported in parentheses
*Significant at 10%; **significant at 5%; *** significant at 1%.

Interpretation of the estimated coefficients on the rebate indicators (and in particular, marginal effects), however, is more complex and are computed according to Kennedy (1981),

$$\alpha_j = 100\left[e^{\left(\widehat{\delta_j} - \frac{\hat{V}(\widehat{\delta_j})}{2}\right)} - 1\right] \tag{3.2}$$

Where $\widehat{\delta_j}$ corresponds to the estimated coefficient on the j^{th} rebate and where $\hat{V}(\widehat{\delta_j})$ is the estimated variance of the estimated coefficient. Therefore, the effect on the average toilet-rebate-receiving premises is 7.9%. On a per premises basis, the average effect of the qualifying landscaping rebate on water demand is a 9.5% reduction in water demand. Because the average size of landscaping changes in the dataset is 1,960 square feet, the average effect on water demand is a reduction of 0.49% per 100 square feet. The receipt of the washing machine rebate reduces demand by 5.8%. All of these are roughly in line with the recent results found by Price et al. (2014), in the much larger city of Albuquerque, New Mexico.

Unlike Arbués et al., (2010), the estimated coefficient on the household size variable is not significant in model 3.1, while the estimated coefficient on the building permit variable is positive and significant at a 1% level. In particular, the estimated coefficient on this variable is interpreted as premises-level water use increasing by 0.7% for each additional building permit. This general result implies that, all else equal, relatively newer premises use more water than older premises. As this variable is used to proxy for housing stock age, this result is somewhat puzzling because one might expect that relatively newer constructed homes would use less water than older homes; some empirical analysis has found this to be the case (Brelsford & Abbott, 2017; Ouyang et al., 2014). This seemingly contradictory result requires additional investigation and will be discussed further in Section 3.5.3.

The estimated coefficients on temperature and precipitation are significant at a 1% level; the estimated coefficient has the expected (positive) signs for temperature in all cases and the expected (negative) signs on precipitation. Although the R^2 is on the low side (0.28), a relatively low model fit is likely due to “noisy” data associated with individual premises-level records. This includes the effects of unbalanced panels, premises entering or leaving the dataset at irregular intervals, and idiosyncratic water use patterns.

Interestingly, rebate-receiving households used more water on average than those not receiving rebates in each year (2006 to 2015). Table 3.3 shows predicted mean, standard deviation and, number of observations for premises that received at least one type of rebate at some point over the ten year period and those that never received a rebate. Median values are also reported to control for the possibility of outliers. Both the mean and median values generally trend downward; however, the data imply that relatively higher water-using premises tend to be attracted to rebates.

Table 3.3 Predicted gallons used per day per premises: non-rebate & rebate comparison

Year	Without rebate				With rebate			
	Mean	Std. Dev.	Median	Obs.	Mean	Std. Dev.	Median	Obs.
2006	240	94	226	117,716	305	98	305	13,588
2007	215	88	200	133,067	264	92	253	15,504
2008	215	101	201	139,792	269	85	261	16,243
2009	217	81	202	139,839	274	85	254	16,027
2010	202	75	188	143,189	241	77	232	16,136
2011	213	90	197	139,784	258	98	249	15,871
2012	213	152	199	144,963	253	83	239	16,356
2013	187	75	174	151,652	215	73	205	16,834
2014	180	65	170	153,297	202	65	196	16,898
2015	171	62	160	152,340	187	63	179	16,884
Total	204	94	190	1,415,639	245	89	233	160,341

Note: Without rebate subset only includes premises that never received a rebate at any time. With rebate subset only includes premises that received at least one rebate at any time.

The reason for the pattern of premises that received rebates for water-saving technology using relatively more water on average is unclear; however, it is likely that higher-use premises have more to gain by investing in water saving technology or xeriscaping precisely because they are higher demand users. In addition, it may be the case that lower-water-using households have already installed water saving technology or a xeriscape yard. However, the present data does not allow for that analysis.

To better characterize responses among different water use cohorts, data were subsetted based on whether the user was a low, medium, or high water users. Here low water users were those whose daily use averaged the lowest 25th percentile (less than 124.3 gallons per day); medium users were those whose daily use was between the 25th and 75th percentile (between 124.3 and 288.4 gallons per day) ; high water users were those whose daily use averaged over the 75th percentile (more than 288.4 gallons per day). Estimation proceeds according to equation (3.1) with the focus on estimated price and income elasticities. Key results are shown in table 3.4.

Table 3.4 Comparison of elasticities subset by low, medium and high volume users

Variable	Model 3.2 Low Water Users	Model 3.3 Medium Water Users	Model 3.4 High Water Users
lnAvgPrice	-0.596***	-0.563***	-0.434***
	(0.014)	(0.011)	(0.016)
lnIncome	0.611***	0.559***	0.462***
	(0.056)	(0.036)	(0.054)
Obs.	383,218	799,935	392,827
Premises	4,747	8,062	4,095
R^2	0.269	0.293	0.336

Note: Standard errors reported in parentheses. Low water users used less than 124.3 gallons per day; medium water users used 124.3 gallons to 288.4 gallons on average per day; high water users used more than 288.4 gallons per day. Price and income elasticities shown; remaining variables suppressed.
*Significant at 10%; **significant at 5%; *** significant at 1%.

Estimation demonstrates that low water users are less price inelastic than high water users. In other words, low water users are relatively more impacted by water rate changes compared to medium and high water users. In addition, low water users are more income elastic than medium and high water users meaning that a marginal change in income will constitute a relatively larger change in water use by low water users.[11] Although data are not available to better understand the composition of each group (i.e. socioeconomic composition), it stands to reason that the low water-using group is likely the most economically disadvantaged group. This is inferred because the low water user group is the most impacted by marginal income changes. Similarly, this group is also most heavily impacted by water rate changes. If it is indeed true that the low water user group is indeed the most economically disadvantaged, then water rate changes – and in particular rate increases – may operate to be regressive. In terms of policy and equity considerations, the water utility and regulator should investigate how groups are differentially impacted prior to adjusting water rates.

3.5.2 Subset analysis: rebate models

To further isolate the effects of the rebates, additional regression analyses were conducted on three data subsets. Only included in each regression were premises from the original data set that had participated in the toilet, washing machine, and landscape rebate programs, respectively. Overall, the estimated coefficients on rebates, water price, temperature and precipitation are highly significant and have the expected signs in all

[11] Two things to note are that although the point estimates are nominally different, the 95% confidence intervals for the price elasticity estimate overlap for the low- and medium- volume users and the 95% confidence interval overlaps for the income elasticity estimate for the low- and high-volume users. Specifically, the 95% price elasticity confidence intervals for the low, medium, and high users are: -0.623 to -0.567; -0.583 to -0.541; and -0.464 to -0.404, respectively. The fact that the confidence intervals for the low and medium users slightly overlap may not be surprising given that there is no definitive data separation between the two groups (i.e. the cutoff for each group is somewhat arbitrary and they flow into each other). The 95% income elasticity confidence intervals for the low, medium, and high users are: 0.502 to 0.720; 0.490 to 0.631; and 0.356 to 0.568, respectively. Overlap in the confidence intervals is also probably unsurprising given that the income data has no spatial variation; in other words, income is not defined at the premises level. Nevertheless, the key result related to the direction of the nominal estimates remains and makes consideration of the disparate impacts on various groups an important consideration for policy makers.

cases. With regard to temperature and precipitation, estimated coefficient magnitudes are similar to those shown in the estimation original estimation.

Table 3.5 2SLS regression results (subset model)

Variable	Model 3.5 ToiletPrem	Model 3.6 Washer	Model 3.7 Landscape
Rebate	-0.098***	-0.098***	-0.049***
	(0.007)	(0.010)	(0.010)
lnAvgPrice	-0.426***	-0.303***	-0.712***
	(0.032)	(0.050)	(0.047)
lnIncome	0.374***	0.644***	0.251
	(0.101)	(0.150)	(0.167)
HHsize	-0.146**	-0.207**	-0.01
	(0.048)	(0.070)	(0.076)
Temp	0.020***	0.020***	0.020***
	(0.000)	(0.000)	(0.000)
Precip	-0.012***	-0.010***	-0.014***
	(0.002)	(0.002)	(0.003)
BldPermit	0.009***	0.008***	0.009***
	(0.000)	(0.001)	(0.001)
Constant	-1.668	-3.689**	-2.335
	(0.949)	(1.405)	(1.576)
Obs.	100,870	47,460	34,616
Premises	926	459	328
R^2	0.3504	0.3541	0.4242

Note: Standard errors reported in parentheses
Month and MeterSize indicators not shown.
*Significant at 10%; **significant at 5%; *** significant at 1%.

The estimated coefficient (elasticity) on water price in the toilet rebate model is -0.43 and -0.30 in the washing machine model; both elasticities are similar to those found in Price et al. (2014): -0.34 for toilet rebates and -0.30 for washing machine rebates in that case. The estimated coefficient on water price in the landscape model is -0.71, which makes that group more price elastic than the toilet and washing machine rebate groups. This result is consistent with prior analyses showing that outdoor water use is more responsive to price change than indoor use (Dandy et al., 1997; Lyman, 1992; Price et al., 2014).

Application of equation (3.2) to the estimated coefficient of the rebate variable in the toilet rebate model indicates that a premise with a low-flow toilet reduces water use by 9.3%. This is a stronger effect than the whole model estimation, which was estimated to be 7.9%. Following the same procedure, the average effect of the qualifying landscaping change on water demand is a 4.8% reduction in monthly water demand; this effect is much lower than the one estimated in the whole dataset. Because the average size of landscaping changes in the dataset is 1,960 square feet, the effect on water demand is a reduction of 0.24% per 100 square feet. The receipt of the washing machine rebate reduces demand by 9.3%; this is larger in magnitude than with the whole dataset.

The difference between the computed marginal effects using the entire dataset and the subsetted models, which were targeted at the individual rebate programs, illustrates why selecting the proper data subset is important if the particular question of interest is the impact of the individual (voluntary) rebate programs. To make this point more concrete, when the entire dataset is used, the control (or base) group includes premises that never received a rebate at any point in addition to premises that had not yet received a rebate. As a result, the estimation for the rebate variable of interest is likely to be imprecise because it is subject to the additional statistical noise resulting from including the extraneous premises that never participated in the rebate program. However, when the data are subsetted to only include premises that received a rebate at some point, the control group is premises that had not yet received a rebate but at some point receive a rebate. Therefore, the estimated coefficient in the subset analysis for the relevant rebate variable more accurately captures the rebate effect, which is the primary goal of this analysis.

Interestingly, as the number of premises (and observations) decline from 926 (100,870) in the toilet rebate case, to 459 (47,460) in the washing machine rebate case and 328 (34,161) in the landscape rebate case, the model fit tends to improve (with an R^2 of 0.35, 0.35 and 0.42, respectively). This is likely due to increasing homogeneity with regard to the type of premises that are likely to participate in the various types of rebate programs.

3.5.3 Subset analysis: premises age

Because premise-level analysis is conducted, it is possible to discern trends based on when the premises began to receive water from the water utility. A possible contributor to declining demand is rebalancing of the housing stock such that newer construction is likely to use less water than relatively older construction all else equal (Brelsford & Abbott, 2017; Ouyang et al., 2014). To investigate this issue, the data are subsetted into premises served by EPCOR prior to 2007 and into premises that began receiving water from EPCOR after 2008. A two-year gap in data (2007 and 2008) is used to ensure temporal separation between subsets. In addition, estimation is confined to the 84-month period from January 2009 to December 2015 in an effort to compare periods where premises in both data subsets were present.

Most premises in the analysis existed in 2006 at the start of the series and only an additional 10% was added over the period from 2009-2015; however, estimation results suggest group differences with older premises appearing to be relatively more price elastic than newer premises and older premise being relatively less income elastic than newer premises. In addition, although washing machine and landscaping rebates significantly reduced water demand for both older and newer premises, toilet-rebate premises only significantly reduced demand in older premises. Based on the estimations results, table 3.6 shows estimated water demand for each subset.

Table 3.6 Gallons used per day per premises: prior to 2007 versus post-2008

Year	In dataset prior to 2007				Entered dataset post-2008			
	Mean	Std. Dev.	Median	Obs.	Mean	Std. Dev.	Median	Obs.
2009	219	65	210	149,907	219	141	160	1,136
2010	203	60	197	150,780	229	141	172	3,623
2011	215	76	202	145,764	247	161	189	5,401
2012	212	108	199	148,682	260	159	196	7,705
2013	188	64	179	151,374	228	141	174	11,299
2014	180	53	174	150,884	211	126	160	13,377
2015	169	50	165	149,242	199	120	153	14,199
Total	198	73	190	1,046,633	223	139	170	56,740

It is clear that premises in the dataset prior to 2007 and premises that entered after 2008 both experienced declining water demand over the period from 2009 to 2015. However, it is also true that premise-level demand, in terms of average gallons per day, is lower for pre-2007 premises, indicating that relatively newer premises use more water than older premises. This result is inconsistent with the expectation that newer premises tend to be more water-efficient than older premises, but it explains the positive coefficient on the estimated building permit (BldPermit) variable seen in model 3.1. On the other hand, water use for the median premises is relatively lower for the new premises, implying that outliers in the new premises group are likely pulling up the average. The contradictory results, and the fact that average use does not conform to expectations, indicates a need for better understanding the idiosyncratic characteristics of each premises, such as number of bathrooms, lot or premises size, etc.; in this case, the data are not available for that type of premises-level detail.

3.6 Cost effectiveness of rebate programs

While it is clear that each rebate program reduces the quantity of water demanded, less clear is cost-effectiveness of each program. Given constrained budgets, evaluating the cost-effectiveness of rebate programs is a critical element to effective municipal water demand management. In order to rank the effectiveness of this type of rebate program, at least with regard to cost effectiveness from the perspective of the utility, Fane & White (2003) and Price et al. (2014) suggest the use of the following levelized cost formula,

$$\text{Levelized cost} = \frac{\sum \frac{C_{kn}}{(1+r)^n}}{\sum \frac{S_{kn}}{(1+r)^n}} \tag{3.3}$$

In this case, levelized cost is given as the present value of costs divided by the present value of water conserved. Here C_{kn} denotes the cost of rebate-type k in year n, S_{kn} the annual volume reduction in water demand resulting from rebate-type k in year n, and r is the annual discount rate. Because the purpose of the assessment is to compare the relative cost-effectiveness of rebate programs and not absolute cost-effectiveness, it is assumed that the nominal value for water reduction is USD1 at time $t = 0$. In addition, note that this calculation does not take into consideration the cost outlays by the consumer for the purchase of water saving technologies (or landscaping changes) nor does it account for reduced payments by the consumer for the purchase of water that accrue due to lowered water demand. Rather, the levelized cost calculation only contemplates the utility's outlays for qualifying rebates and the water saved due to reduced demand.

Marginal effects, based on the estimated coefficients and standard errors from equation 3.1, are computed from the appropriate rebate outcomes presented in table 3.5 (i.e. subset analysis). However, in the case of toilet rebates, data type and availability make it impossible to accurately compute the marginal effect of a single installation; in particular, the premises-level effect is likely inaccurate because the average premises received more than one rebated toilet. This problem is mitigated somewhat because it is probable that the first toilet installation provides the greatest water use reduction since it is likely replacing the most frequently used or most inefficient toilet. And as Price et al. (2014) found, the marginal benefit of the second toilet rebate was much lower than the marginal benefit of the first toilet rebate.

Therefore, in order to improve the accuracy of this assessment, the estimated impact of the first toilet rebate is computed as follows. First, because the average rebate-receiving premises received 1.8 toilet rebates, or 90% of 2.0 toilet rebates, the marginal effect calculation is inflated by 11.1% (i.e. $\frac{1}{0.9}$) to arrive at a likely marginal effect assuming that premises received a full 2.0 toilet rebates. Price et al. (2014) provides estimated water demand reductions for the first and second toilet installation, in this case: 37.98 gallons per day for the first installation and a total reduction of 46.87 gallons per day for the first and second installation. Therefore, the first toilet accounts for approximately 81% of impact for the first and second toilet installation. This percentage is applied to the computed marginal effect in order to better estimate the impact of a the first toilet. It is important to note that the reported results therefore assume that the relative impact of first and subsequent toilet use in Clovis is similar to the relative impact in Albuquerque.

Change in daily water use is computed by applying the marginal impact to mean estimated water use for each premise prior to obtaining the rebate. Rebate value is the rebate amount paid by EPCOR per device: USD150 for toilets and washing machines and

USD 40 per 100 ft^2 converted to xeriscape. Device lifespan is assumed to be 25 years for a toilet, 12 years for a washing machine (Gleick, 2003a), and 25 years for xeriscape (Price et al., 2014). Outcomes are given under the assumption of 5%, 7% and 10% rates of interest. While 10% rates of interest are high, this rate is included to show how high the rate must be before a washing machine rebate begins to overtake the toilet rebate as the most cost effective. Results are shown in table 3.7.

Table 3.7 Change in water use due to low-flow device and levelized cost

Rebate	Marginal effect per device (percent)	Change in water use (gal/day)	Rebate value per device (USD)	Device lifespan (years)	Cost r=5% (USD per 1000 gal.)	Cost r=7% (USD per 1000 gal.)	Cost r=10% (USD per 1000 gal.)
ToiletPrem	-8.36	-31.74	150	25	0.87	1.04	1.30
Washer	-9.21	-37.70	150	12	1.17	1.28	1.45
Landscape (100 ft^2)	-0.24	-0.98	40	25	7.55	8.96	11.19

Notes: Marginal effects computed by applying equation (3.2) to estimated coefficients in model 3.1. Change in water use computed by applying marginal effects per device to the mean water use prior to receipt of water rebate.

The results suggest that on a device-by-device comparison, washing machine rebates are more effective at reducing water use than toilet rebates and both toilet rebates and washing machine rebates are more effective at reducing water use than the average premises that received a 1960 ft^2 landscaping rebate. Given the rebate prices and the respective expected lifespans, the most cost effective rebate type is the toilet rebate which, at a 5% discount rate, costs less than USD 1.00 per every 1,000 gallons of water conserved.[12]

[12] A related issue that is not directly considered here, but is discussed in Appendix 3.4, is the notion of peak day demand. Peak day demand corresponds to the highest, or peak, demand in a particular year and typically occurs in the summer months. Since landscaping changes are likely to reduce water use primarily in the summer months – when the peak day is likely to occur – it may be the case that landscaping rebates are undervalued in this analysis in terms of cost-effectiveness.

In contrast, washing machine rebates cost about 20% more than toilet rebates at just under USD 1.20 per 1,000 gallons conserved. Although washing machine rebates are more effective than toilet rebates in terms of reducing water use, the expected lifespan of only 12 years make those rebates more costly per volume conserved. Landscaping rebates are significantly more expensive per volume conserved.

3.7 Conclusion

This analysis investigated factors contributing to declining water demand in Clovis, New Mexico, a small but growing municipality that has an arid climate and depends on the dwindling southern Ogallala aquifer. While Clovis is the focus of our case study, its experience can be used as a benchmark for other small to mid-sized municipalities in the region that may also be confronting declining demand, a changing climate, are dependent on rapidly dwindling groundwater supplies, and that do not have sufficient resources or population bases to enhance supplies. While this appears to be a very particular set of characteristics, Clovis' experience is far from unique for many municipalities that sit atop of the declining Ogallala. We argue that detailed understanding of the effects of various demand-side factors will be especially critical for these municipalities going forward, and cannot just be the purview of large-scale water utilities; hence the need for detailed case studies.

With regard to rebates for water-saving technology, results indicate that rebate programs successfully reduce premises-level water use. Overall, after controlling for confounding factors such as temperature and precipitation, the installation of a rebated toilet reduced water use by an average of nearly 32 gallons per day, installation of a water saving washing machine reduced water use by an average of about 38 gallons per day, and an average household receiving a landscaping rebate saved 19 gallons per day. While it might be surprising that landscaping rebates save so little water, it is likely due to the fact that irrigation only takes place in part of the year; washing machines and toilets, on the other hand, are used year-round.

In addition, this analysis confirmed that water demand is price inelastic at current prices in Clovis; however, elasticity varies depending on which data are studied, with data subsets based on rebate type experiencing different levels of (in)elasticity. Elasticity for the entire dataset, as well as those households that did not receive a rebate, was around 0.50. When the data is subset to only include premises that received toilet or washing machine rebates, price becomes relatively more inelastic; however, premises that received landscaping rebates, while still price inelastic, were much less so, indicating the relative ease at which premises can reduce their outdoor water consumption in the face of price increases.

Given the likely effects of climate change (e.g. longer more prolonged droughts, Deser et al., 2014; Gutzler & Robbins, 2011), this analysis confirmed that climate plays an important role in influencing water demand; as the temperature increases water use increases and as precipitation increases, water use declines. This result provides useful information which can be brought to bear in times of high temperature or low precipitation, such as the period from 2011 to 2014 when Clovis experienced prolonged drought. In general, income variables show that water is a normal good – as income increases, water demand increases.

It is important to note that this analysis only looks at part of the story. Building upgrades, such as pipe and plumbing replacement and new efficient building practices may also play a role in reducing water demand, but the data in this analysis lacks the richness to fully investigate this issue. Causing additional confusion is the subset analysis that showed that the mean premises built prior to 2007 used relatively less water than the mean premises built after 2008, while the median behavior shows the opposite. Further research could be devoted to better understating the premises-level characteristics that are likely driving this result. In addition, changes to preferences, or an increasing desire of the population to conserve, may also play a role in declining demand. Future work could include an assessment of some of those factors. For example, panel or repeated cross section surveying methods may be used to uncover true household-level responses. In addition, improved accuracy with regard to spatial scale, especially with regard to vegetation, could better pinpoint landscaping changes and its impact on water use.

Although the cost of the washing machine rebate and the toilet rebate is the same (USD 150), toilet rebates are the most cost effective rebate program of the three programs. However, as the discount rate increases to around 10%, the washing machine begins to approach the toilet rebate program in terms of cost effectiveness. Despite initially appearing to be inexpensive (USD 0.40 per ft^2), landscaping rebates are the most expensive per unit of water conserved. This implies that toilet rebates should generally be prioritized before washing machine rebates and both should be prioritized before landscaping rebate. However, it is important to note that it is not uncommon for premises that received landscaping rebates to have already participated in other rebate programs. So if a water user has a relatively high propensity to participate in rebate program and they have already received a toilet or washing machine rebate, the landscaping rebate program may be the only way to significantly reduce that user’s actual demand.

Furthermore, it is important to note that the analysis really only considered the cost-effectiveness from the standpoint of the utility and did not consider the rebate type that is most attractive to the consumer. In general, one would expect that toilets are likely to be less costly than qualifying washing machines (and also landscaping changes), so toilet changes are likely to be the most attractive to consumers, strictly in terms of cost savings.

It is clear that rebates for water-saving technology induce water savings by water users. However, from the utility's perspective, a question remains as to why it would subsidize the purchase of products that effectively reduce the demand for the product that it sells (namely, water). Therefore, the Chapter 4 introduces a theoretical justification for the provision of rebates for water-saving technology. Additionally, a model is developed demonstrating some of the tradeoffs that a utility faces when deciding to engage in that type of problem. Finally, an empirical model is developed that may be used to test whether utilities participating in water rebate programs are behaving optimally.

Appendix 3.1 Recent studies estimating price and income elasticity

Author	Study Location	Estimated Price Elasticity of Demand	Estimated Income Elasticity of Demand	Empirical Methodology or Innovation
Clarke et al., 2017	Tucson, Arizona, USA	-0.12 to -0.37		Stone Geary model, investigating seasonal elasticities
Brelsford & Abbott, 2017	Las Vegas, Nevada, USA			Decomposition of drivers of declining demand using Gelbach (2016)
O'Donnell & Berrens, 2017	Clovis, New Mexico, USA	-0.29 to -0.53	0.57 to 0.83	Spatial fixed effects instrumental variable estimation
Hung et al., 2017	Taipei, Taiwan	-0.23 to -0.45	0.23	Agent-based modeling using Stone Geary model
Cabral et al., 2017	Nuevo León, Mexico	-0.40 to -0.60	0.12 to 0.16	Understanding residential price perception under increasing block rates using Shin (1985)
Almendarez-Hernández et al., 2016	El Vizcaino Biosphere Reserve, Mexico	Short run: -0.26 to -0.28 Long run: -0.67 to -0.71	Short run: 0.10 to 0.13 Long run: 0.27 to 0.29	Understanding short- and long-run residential price elasticities using Shin (1985)
Ghavidelfar et al., 2016	Auckland, New Zealand	Short run: -0.14 Long Run: -0.12		Multifamily (high-rise) residence analysis using cointigration & error correction models
Mieno & Brozović, 2016	Southwestern Nebraska, USA	-0.12 to -0.76		Examination of biased price elasticity estimation for irrigator groundwater consumption
Ghimire et al., 2016	Oklahoma City, Oklahoma, USA	-0.38 to -0.66	0.28 to 0.30	Two-stage least squares model with random effects used to assess effects of drought and seasonality

Author	Study Location	Estimated Price Elasticity of Demand	Estimated Income Elasticity of Demand	Empirical Methodology or Innovation
Ashoori et al., 2016	Los Angeles, California, USA	Negative	Ambiguous based on user type	Analysis of water demand by water user type
Wichman et al., 2016	Municipalities in North Carolina, USA	-0.15 to -0.30		Assessment of demand responsiveness to prescriptive versus price strategies using fixed effects instrumental variable approach
Zuo et al., 2016	Murray-Darling Basin, Australia	-0.53 to -0.69		Combination of irrigator stated and revealed preference data to estimate elasticities given different water entitlement types
Fullerton Jr. et al., 2016	El Paso, Texas, USA	-0.32		Development of municipal water demand forecasting model
Ben Zaied & Binet, 2015	Tunisia	Short run: -0.07 to -0.37 Long run: -1.95	0.08 to 0.23	Seasonal and non-seasonal modeling using cointigration analysis
Lee & Tanverakul, 2015	East Los Angeles and South San Francisco, California, USA	-0.22 to -0.44		Comparison of price responsiveness in two California cities with different pricing structures
Galaitsi et al., 2015	Palestinian West Bank	-0.19 to -0.37		Household survey methodology focusing on water security
Yoo et al., 2014	Phoenix, Arizona, USA	Short run: -0.66 Long run: -1.16	0.14 to 0.58	A difference in consumption design with direct measures of price

Author	Study Location	Estimated Price Elasticity of Demand	Estimated Income Elasticity of Demand	Empirical Methodology or Innovation
Klaiber et al., 2014	Phoenix, Arizona, USA	-0.12 to -1.83		A quasi-experimental research approach using a difference in consumption design to assess seasonal effects, climate conditions, and water use
Price et al., 2014	Albuquerque, New Mexico, USA	-0.28 to -0.48		Evaluation of low-flow appliances and demand-side water management
Ouyang et al., 2014	Phoenix, Arizona, USA	-0.04	0.19 to 0.34	Analysis of demand on multiple spatial scales
Binet et al., 2014	Réunion (French Territory)	-0.31	0.25	Updated version of Shin (1985) to estimate water price perceptions
Baerenklau et al., 2014	Western Riverside County, California, USA	-0.76	0.16	Investigation of increasing block rate structure on residential water demand
Romano et al., 2014	Key town in Italian provinces	Negative	Positive, but small	Linear mixed-effects model estimated using maximum likelihood methods
Sebri, 2014b	N/A	-0.37	0.21	Meta-analysis from 2002 to 2012
Porcher, 2014	Municipalities in France	-0.22 to -0.60		Fixed effects regression to estimate welfare changes
(Brelsford & Abbott, 2017)	Chapel Hill, North Carolina, USA	-0.43 to -1.14		Difference in difference approach
Hung & Chie, 2013	Taipei, Taiwan	-0.22 to -0.61		Proposal for using augmented price signal to resolve conflicting residential uses

Author	**Study Location**	**Estimated Price Elasticity of Demand**	**Estimated Income Elasticity of Demand**	**Empirical Methodology or Innovation**
Polycarpou & Zachariadis, 2013	Urban Cyprus	-0.25 to -0.45	0.53 to 0.75	Novel geographic analysis; assessment of effect of interrupted supply on demand
Worthington & Hoffman, 2008	N/A	Short run: 0.0 to -0.5 Long run: -0.5 to -1.0	Positive and less than unity	Review of literature
Dalhuisen et al., 2003	N/A	-0.41 (mean) -0.35 (median)	0.43 (mean) 0.24 (median)	Meta-analysis from 1963 to 2001
Espey et al., 1997	N/A	-0.51		Meta-analysis from 1967 to 1993

Note: Short run elasticities are displayed unless stated otherwise

Appendix 3.2 Robustness checks

Variations of equation (3.4) were estimated in an effort to also include explanatory variables VegIndex and PDSI.

$$\begin{aligned}\mathrm{lnWU}_{it} = {} & B_0 + B_1\mathrm{lnAvgPrice}_{i(t-1)} + B_2\mathrm{Temp}_{it} + B_3\mathrm{Precip}_{it} \\ & + B_4\mathrm{lnIncome}_{it} + B_5\mathrm{HHsize}_{it} + B_6\mathrm{VegIndex}_{it} \\ & + B_7\mathrm{BldPermit}_{it} + B_8\mathrm{PDSI}_{it} + \sum_{j=1}^{3}\delta_j\mathrm{Rebate}_{jit} \\ & + \sum_{k=1}^{11}\psi_k\mathrm{Month}_k + \sum_{l=1}^{3}\gamma_l\mathrm{MeterSize}_{li} + \alpha_i + \varepsilon_{it}\end{aligned} \tag{3.4}$$

Specifically, four models were estimated: model 3.1 (i.e. the same model 3.1 estimated in the main text) controls for water price, rebate type, household income and size, building permits in the city, and temperature and precipitation. Model 3.7 also includes controls for PDSI; model 3.8 is the same as model 3.1 but also controls for vegetation index values; model 3.9 controls for both PDSI and vegetation index. The number of observations (and premises) declines when moving from model 3.1 to 3.8 because only eight years of vegetation index data were available (whereas ten years of data was available for other series). Nevertheless, estimated coefficients, in terms of signs, levels and significance are generally similar across most models. Because VegIndex and PDSI were found to correlate to temperature and precipitation, the focus will be on those variables.

Table 3.8 2SLS regression results (full model including VegIndex and PDSI)

Variable	Model 3.1	Model 3.8	Model 3.9	Model 3.10
lnAvgPrice	-0.534***	-0.584***	-0.448***	-0.494***
	(0.0076)	(0.0074)	(0.0084)	(0.0083)
ToiletPrem	-0.083***	-0.080***	-0.079***	-0.078***
	(0.0042)	(0.0041)	(0.0049)	(0.0049)
Washer	-0.060***	-0.060***	-0.048***	-0.048***
	(0.0059)	(0.0058)	(0.0069)	(0.0068)
Landscape	-0.100***	-0.094***	-0.009	-0.019
	(0.0071)	(0.0071)	(0.0114)	(0.0113)
lnIncome	0.568***	0.301***	0.387***	0.064*
	(0.0268)	(0.0264)	(0.0295)	(0.0296)
HHsize	-0.009	0.067***	0.055***	0.029*
	(0.0122)	(0.0123)	(0.0134)	(0.0134)
BldPermit	0.007***	0.006***	0.004***	0.004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Temp	0.010***	0.010***	0.010***	0.010***
	(0.00001)	(0.00001)	(0.00002)	(0.00002)
Precip	-0.012***	0.005***	-0.006***	0.005***
	(0.0004)	(0.0008)	(0.0007)	(0.0008)
PDSI		-0.018***		-0.015***
		(0.0003)		(0.0003)
VegIndex			-0.001***	0.000
			(0.0001)	(0.0001)
Constant	-3.658***	-2.111***	-1.114***	2.111***
	(0.2554)	(0.2862)	(0.2827)	(0.2862)
Obs.	1,575,980	1,575,980	1,173,761	1,173,761
Premises	16,904	16,904	15,533	15,533
R^2	0.280	0.292	0.254	0.265

Note: Standard errors reported in parentheses

*Significant at 10%; **significant at 5%; *** significant at 1%.

The estimated coefficients have the expected (positive) signs, levels of significance, and magnitudes for temperature in all cases. However, the expected (negative) signs on precipitation are present only in models 3.1 and 3.9. The common denominator in models 3.8 and 3.9, however, is the inclusion of PDSI, which is likely causing the sign to flip due to the expected correlation between precipitation and PDSI. Therefore, either PDSI or precipitation should be chosen as explanatory variables, but not both. Because of the straightforward nature of the precipitation variable, the present analysis prefers precipitation over PDSI.

To further isolate the effect of rebate programs on water demand, an additional regressor (RebateControl) is introduced that controls for the presence of other rebates. For example, the toilet rebate subset is based on premises that received a toilet rebate; however, an indicator is assigned to that premises if they participated in an additional rebate program (i.e. washing machine or landscaping). This step is undertaken because the presence of additional rebate programs could conceivably bias the estimated rebate coefficient.

Applying equation (3.2) from the full analysis renders marginal effects similar to those already reported. According to the toilet rebate model, the average premises with a low-flow toilet reduces water use by 9.3%. On a per premises basis, the average effect of the qualifying landscaping change on water demand is a 4.7% reduction in water demand. Because the average size of landscaping changes in the dataset is 1960 square feet, the effect on water demand is a reduction of 0.24% per 100 ft^2. The receipt of the washing machine rebate reduced demand by 9.2%.

Table 3.9 2SLS regression results (sub-model: rebate type and additional control)

Variable	Model 3.14 ToiletPrem	Model 3.15 Washer	Model 3.16 Landscape
Rebate	-0.097***	-0.097***	-0.048***
	(0.007)	(0.010)	(0.010)
RebateControl	-0.036***	-0.044***	-0.040**
	(0.009)	(0.012)	(0.013)
lnAvgPrice	-0.411***	-0.278***	-0.690***
	(0.032)	(0.051)	(0.048)
lnIncome	0.368***	0.633***	0.24
	(0.101)	(0.150)	(0.167)
HHsize	-0.141**	-0.195**	0.003
	(0.048)	(0.070)	(0.076)
Temp	0.020***	0.020***	0.020***
	(0.000)	(0.000)	(0.000)
Precip	-0.012***	-0.010***	-0.014***
	(0.002)	(0.002)	(0.003)
BldPermit	0.009***	0.008***	0.009***
	(0.000)	(0.001)	(0.001)
Constant	-1.538	-3.467*	-2.111
	(0.952)	(1.410)	(1.579)
Obs.	100,870	47,460	34,616
Premises	926	459	328
R^2	0.3479	0.3497	0.4226

Standard errors reported in parentheses
Month and MeterSize indicators not shown.
*Significant at 10%; **significant at 5%; *** significant at 1%.

All other estimated coefficients are also generally similar to the full model. In addition, the estimated coefficient on the RebateControl indicator is negative and significant (at a 5% level or better) indicating that households engaging in more than one rebate program reduce their water use by an additional amount due to that program. That outcome is probably not surprising given the results shown in the original estimation.

While the previous models provide insight into the behavior of rebate-receiving premises, they clearly do not explain the behavior of premises that did not receive rebates. Table 3.12 shows the results from estimations that only include premises that did not receive any type of rebate. While there are fewer regressors (because no premises received a rebate), remaining estimated coefficients are similar to those from the full model.

Table 3.10 2SLS regression results (sub-model: no rebates)

Variable	Model 3.17
lnAvgPrice	-0.544***
	(0.008)
lnIncome	0.587***
	(0.028)
HHsize	0.0034
	(0.013)
Temp	0.010***
	(0.000)
Precip	-0.012***
	(0.001)
BldPermit	0.007***
	(0.000)
Constant	-4.119***
	(0.269)
Obs.	1,415,639
Premises	15,394
R^2	0.273

Standard errors reported in parentheses
Month and MeterSize indicators not shown.
*Significant at 10%; **significant at 5%; *** significant at 1%.

Of particular interest is that the estimated coefficient on the price variable are negative and in the neighborhood of 0.50. Like the other models, this implies inelastic demand, although that figure makes non-rebate premises relatively more price elastic than premises receiving toilet or washing machine rebates and less price elastic than premises receiving landscaping rebates.

Appendix 3.3 Spatial panel econometric analysis

While spatial effects have been acknowledged to impact demand (Brelsford and Abbott 2017), and spatial panels used to assess water utilization efficiency (Sun et al., 2014), only static spatial demand analysis has been undertaken (de Maria André & Carvalho, 2014). Using monthly municipal consumption data (2006-2015) in Clovis, New Mexico, this analysis applies spatial panel econometrics to water demand estimation, and compares to non-spatial estimations. Results inform future empirical strategies as well as future data collection requirements.

Appendix 3.3.1: Data and modeling approach

As shown in table 3.12, monthly premises-level data on water use (2006-2015) were provided by EPCOR, Clovis' water utility, as were rebate and price data. Average unit price was computed and adjusted for inflation using the consumer price index. County-level monthly average temperature and precipitation data was obtained from the National Oceanic and Atmospheric Administration. County-level median income estimates from the American Community Survey were used.

Table 3.11 Variable definitions and descriptive statistics

Variable	Description	Period	Unit	Mean	Std. dev.	Source
WU	Average daily household water use	Month	Gallons	190.6	2.75	EPCOR
AvgPrice	Average water price	Month	$/Gallons	0.002	1.54	EPCOR
ToiletPrem	Toilet rebate indicator	Month	1/0	0.03	0.18	EPCOR
Washer	Washing machine rebate indicator	Month	1/0	0.02	0.13	EPCOR
Landscape	Landscape rebate indicator	Month	1/0	0.01	0.08	EPCOR
Income	Average household income in county	Annual	Dollars	40,945	1.02	US Census (ACS)
Temp	Average monthly temperature	Month	Fahrenheit	56.80	14.86	NOAA
Precip	Average total monthly precipitation	Month	Inches	1.28	1.44	NOAA

A fixed effects instrumental variable (FEIV) approach at the premises and Census block group levels is employed. Instrumental variable estimation is undertaken to remove bias from price endogeneity (Arbués et al., 2004). Spatial weights matrices are constructed based on the nearest 2, 3, and 4 neighbors and are applied in spatial estimations.

Estimation follows:

$$\begin{aligned}\text{lnWU}_{it} = B_0 + B_1\text{lnAvgPrice}_{i(t-1)} + B_2\text{Temp}_{it} + B_3\text{Precip}_{it} \\ + B_4\text{lnIncome}_{it} + \sum_{j=1}^{3}\delta_j\text{Rebate}_{jit} + \sum_{k=1}^{11}\psi_k\text{Month}_k + \alpha_i \\ + \varepsilon_{it}\end{aligned} \tag{3.5}$$

lnWU is logged monthly water consumption. B_0 to B_5 are estimated coefficients. $\text{lnAvgPrice}_{i(t-1)}$, is lagged water price (Arbués et al., 2010). δ_j corresponds to premise receipt of one or more available rebates. θ_k is the coefficient on month (December base). α_i controls for fixed effects; ε_{it} is the error term. i and t are indices for location and time period, respectively.

Rewritten in matrix form:

$$\text{lnWU} = (\iota_T \otimes I_N)\alpha + X\beta + lnAvgPrice\varphi + \varepsilon \tag{3.6}$$

lnWU is a vector if size $(NT \text{ x } 1)$, stacked by location, N, and then time period, T. $\otimes$ represents the Kronecker Product, ι_T is a ones vector sized T, I_N is an $(N \text{ x } N)$ identity matrix; $\iota_T \otimes I_N = \iota_{NT}$ is a $(NT \text{ x } NT)$ matrix; α is a $(NT \text{ x } 1)$ vector of fixed effects. X is a $(NT \text{ x } K)$ matrix; K is the number of non-endogenous explanatory variables; β is a $(K \text{ x } 1)$ vector of estimated coefficients. $lnAvgPrice$ is a $(NT \text{ x } 1)$ vector of price, with estimated coefficient φ. ε is a $(NT \text{ x } 1)$ vector of residuals, $\varepsilon \sim IID[0,\ \sigma_\varepsilon^2 I_{NT}]$.

Simplifying:

$$\ln\text{WU} = \iota_{NT}\alpha + Z\delta + \varepsilon \tag{3.7}$$

Z is a $(NT \text{ x } (K+1))$ matrix; $Z = [lnAvgPrice\ X]$ and δ is a $\left((K+1) \text{ x } 1\right)$ vector of coefficients.

Equation (3.8) illustrates the spatial lag model:

$$\ln\text{WU} = \lambda W_{NT}\text{WU} + \iota_{NT}\alpha + Z\delta + \varepsilon \tag{3.8}$$

W_{NT} is a $(NT \text{ x } NT)$ spatial weights matrix for N locations across T periods. λ is an estimated spatial lag coefficient and $\varepsilon \sim IID[0,\ \sigma_\varepsilon^2 I_{NT}]$. Failure to account for spatial lag can lead to biased and inconsistent estimation (Anselin et al., 2008; Elhorst, 2010).

In (3.9), the error structure is given by $\rho W_{NT}\varepsilon$, where ρ is estimated, plus u; $u{\sim}IID[0, \sigma_u^2 I_{NT}]$. Spatial error leads to inefficient estimation (Anselin et al., 2008; Elhorst, 2010).

$$\begin{gathered} \ln\text{WU} = \iota_{NT}\alpha + Z\delta + \varepsilon \\ \varepsilon = \rho W_{NT}\varepsilon + u \end{gathered} \tag{3.9}$$

If neither spatial lag nor spatial error exists estimation simplifies to (3.5).

Several methods of panel balancing were considered including multiple imputation, deletion, and temporal and geographical aggregation. Due to a large amount of missing data, imputation and deletion methods were discarded. Estimation was undertaken by averaging key variables across Census block groups while retaining all time periods producing a 3,960 x3,960 weights matrix (33 block groups, 120 months). Census block estimation was disregarded due to missing data and high computational requirements. Centroids were computed for each block group and spatial weights matrices were computed for the nearest two, three, and four neighbors $(k = 2, k = 3, and\ k = 4)$.

The *splm* package in R is used to estimate spatial models (Kapoor et al., 2007; Millo and Piras, 2012). The *spgm* command accounts for endogenous price (Millo & Piras, 2012). Although Akaike's information criterion is typically the preferred measure of model fit for spatial models, an R^2 measure according to Elhorst (2010) is instead computed for consistency and to facilitate comparability with non-spatial models.

Appendix 3.3.2: Results and discussion

As shown in table 3.13, FEIV estimation in models 3.1 and 3.15 provide baselines for comparing spatial models (3.16-3.20). Fixed effects are applied in spatial models as the Hausman specification test was rejected in the lag model ($\chi^2 = 41.8, p < 0.01$); although not rejected in the error model ($\chi^2 = 1.1, p = 0.999$), fixed effects were retained for comparability. Lagrange Multiplier tests for spatial dependence could not rule out the presence of either spatial error or spatial lag ($LM = 217.2, p < 0.01; LM = 248.1, p < 0.01, \text{respectively}$).

Price is negative (inelastic) and significant in models 3.1 and 3.15, which is consistent with prior research (Sebri, 2014) and significant in all cases except model A14 (positive but insignificant). Estimated coefficients on rebate variables are negative implying that they decrease demand; however, coefficients, especially on ToiletPrem are insignificant in models 3.15-3.18. lnIncome is positive and significant in nearly every case and the temperature and precipitation variables retain the expected signs and are significant in most cases.

The spatial lag parameter, λ, is positive in all cases, nominally increases with k and is statistically significant when $k = 3$ and $k = 4$. Similarly, the spatial error coefficient, ρ, increases with k. R^2 in models 3.1 and 3.15 are 0.280 and 0.581, respectively. Improved fit in model 3.15 is likely due to data aggregation which reduces noise, but may limit accuracy; e.g., ToiletPrem which is insignificant in the model 3.15. R^2 in the spatial error models is about 0.630, whereas it ranges from 0.652 to 0.963 and increases with k in the spatial lag estimations.

The spatial lag effect dominates other explanatory variables as k increases. Price loses significance when $k = 4$, and given the weight of evidence suggesting significant inelastic demand (Sebri, 2014), spatial lag estimation is difficult to justify. Spatial proximity may be correlated with factors impacting demand and overshadowing other meaningful signals. Spatial dependence may explain demand because each location confronts similar factors.

Appendix 3.3.3 Conclusion

Although spatial panel analysis has been understudied in a water demand, diagnostics suggest that demand is subject to spatial error and lag. Controlling for spatial error produces estimates similar to the analogous non-spatial analysis. Although spatial lag models appear to fit well, given reduced statistical significance of key variables, there is little justification for spatial lag estimation in this context. This is especially true where premises are subject to similar exogenous factors such as climate and pricing. Furthermore, due to data constraints such as incomplete panels and high computational requirements in panel spatial estimation, the benefits may not outweigh the costs of losing the additional detail from a more fine-grained premises-level analysis. Nevertheless, if data are only available at relatively large geographic scales, testing and controlling for spatial effects, and particularly spatial error, is prudent.

Table 3.12 FEIV and spatial models

Variable	Model 3.1 FEIV Premises-Level	Model 3.15 FEIV Block Group	Model 3.15 Spatial Lag	Model 3.16 Spatial Error	Model 3.17 Spatial Lag	Model 3.18 Spatial Error	Model 3.19 Spatial Lag	Model 3.20 Spatial Error
			$k = 2$		$k = 3$		$k = 4$	
lnAvgPrice	-0.534***	-0.406***	-0.407***	-0.392***	-0.285***	-0.389***	0.0358	-0.383***
	(0.0076)	(0.0386)	(0.0967)	(0.0423)	(0.0823)	(0.0445)	(0.0924)	(0.0471)
ToiletPrem	-0.083***	-0.123	-0.107	-0.156	-0.152	-0.148	-0.268**	-0.176*
	(0.0042)	(0.1061)	(0.1140)	(0.1047)	(0.1112)	(0.1046)	(0.1215)	(0.1031)
Washer	-0.060***	-0.613***	-0.595***	-0.683***	-0.659***	-0.769***	-0.836***	-0.738***
	(0.0059)	(0.1567)	(0.1601)	(0.1570)	(0.1628)	(0.1531)	(0.1794)	(0.1490)
Landscape	-0.100***	-0.937***	-0.921***	-0.864***	-0.856***	-0.814***	-0.670***	-0.722***
	(0.0071)	(0.1697)	(0.1698)	(0.1688)	(0.1739)	(0.1700)	(0.1933)	(0.1650)
lnIncome	0.568***	0.829***	0.806***	0.829***	0.635***	0.821***	0.229	0.826***
	(0.0268)	(0.1415)	(0.1744)	(0.1704)	(0.1705)	(0.1838)	(0.1888)	(0.2004)
Temp	0.010***	0.011***	0.010***	0.011***	0.008***	0.011***	0.003**	0.011***
	(0.0001)	(0.0009)	(0.0016)	(0.0011)	(0.0015)	(0.0012)	(0.0016)	(0.0013)
Precip	-0.012***	-0.012***	-0.011***	-0.012***	-0.010***	-0.012***	-0.001	-0.011**
	(0.0004)	(0.0028)	(0.0034)	(0.0034)	(0.0032)	(0.0036)	(0.0036)	(0.0039)
λ			0.021		0.227**		0.738***	
			(0.1337)		(0.1146)		(0.1309)	
ρ				0.183		0.246		0.321
N	1,575,980	3,960	3,960	3,960	3,960	3,960	3,960	3,960
R^2 (FEIV)	0.280	0.581						
R^2 (Spatial)			0.652	0.631	0.776	0.630	0.963	0.630

Standard errors reported in parentheses

*Significant at 10%; **significant at 5%; *** significant at 1%

Appendix 3.4 Peak Day Demand Estimation

In this analysis, peak day demand volume is estimated. One peak day data point per year was provided and regression analysis was conducted. Several variables, and sets of variables, were tested to determine which fit best. Tested variables included temperature, precipitation, Pacific Decadal Oscillation (PDO), Atlantic Multidecadal Oscillation (AMO), Palmer Drought Severity Index (PDSI), Palmer Drought Hydrologic Index (PDHI) and others. The more 'exotic' series like PDO and PDSI were tested because it was hoped that those series could be leveraged several months prior to the peak day volume in order to prepare well in advance; however, in most cases those series produced relatively poor fit. The variables that tended to fit best were straightforward temperature and precipitation variables. The upshot is that those variables are fairly contemporaneous, intuitive, and easy to defend.

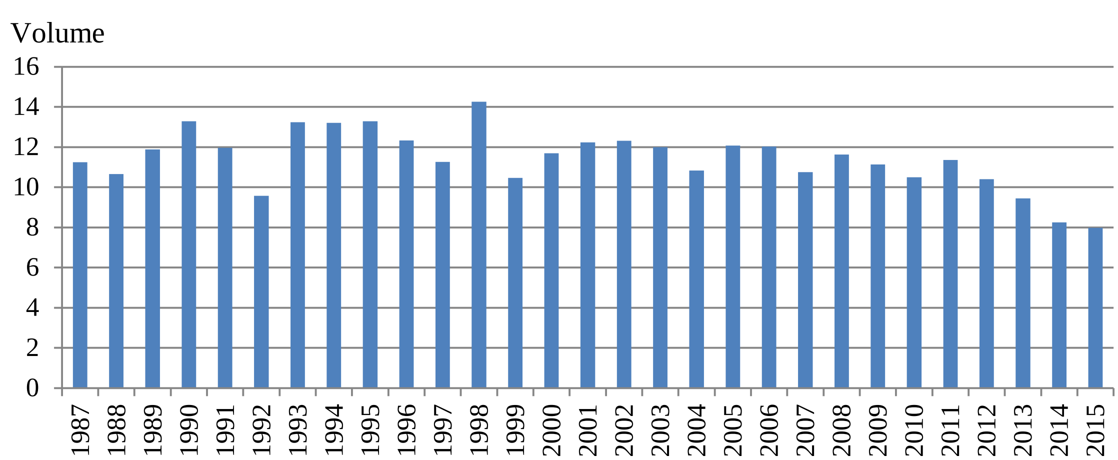

Figure 3.4 Peak day volume in each year (1987-2015)

Variations of the following model are estimated:

$$lnPD_t = \beta_0 + \beta_1 Precip_t + \beta_2 Temp_t + \tau Trend_t + \delta Indicator_t + \mu_t \qquad (3.10)$$

Where $lnPD$ is peak demand volume, $Precip$ is the sum of precipitation over the prior six months (in inches), $Temp$ is average temperature over the last fourteen days (in Fahrenheit), $Trend$is a trend series beginning in 1987 through 2015 (1-29), $Indicator$is a dummy variable indicating 2013 to 2015, which experienced sharp declines in peak day demand. β_0, β_1, β_2, τ, and δ are estimated coefficients. The subscript t corresponds to the particular data point in a particular year.

The first model presented includes all listed variables (shown in table 3.14). As the table shows, all variables are highly significant and the model fits well (adjusted R^2 is 0.74).

Table 3.13 Peak day model: best fit

Regression Statistics	
Multiple R	0.879
R Square	0.773
Adjusted R Square	**0.735**
Standard Error	0.069
Observations	29

Variable	*Coefficients*	*Standard Error*	*t Stat*	*P-value*
Intercept	8.640	0.241	35.889	0.00
Precipitation (Inches last 6 months)	-0.012	0.004	-3.370	0.00
Temperature (Average last 14 Days)	0.009	0.003	3.515	0.00
Trend (1-29)	-0.004	0.002	-2.319	0.03
Indicator (2013 - 2015)	-0.190	0.055	-3.467	0.00

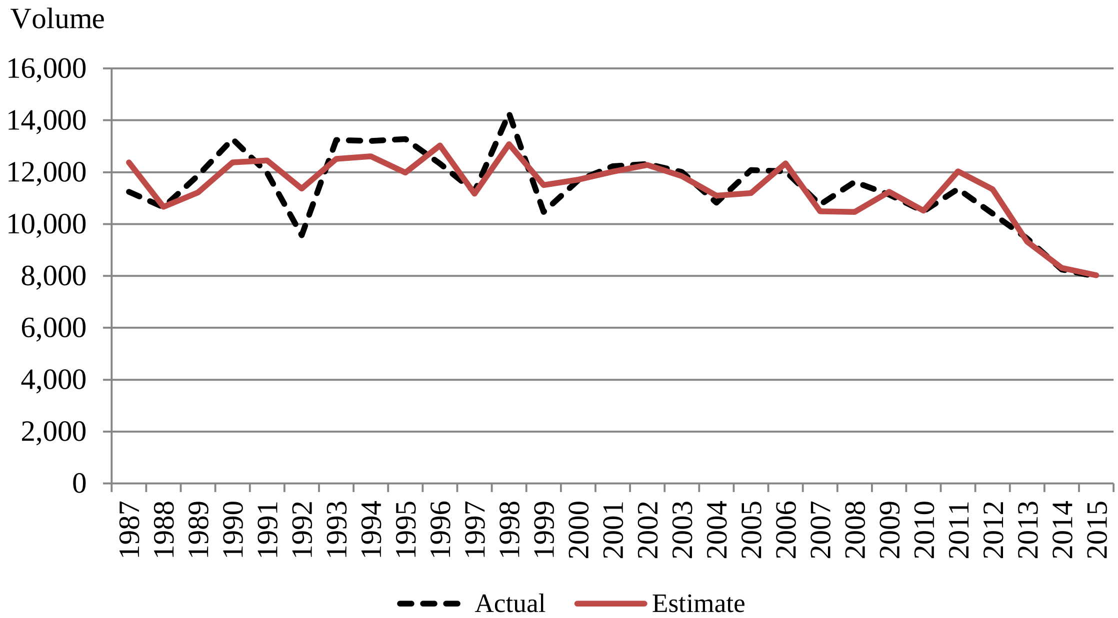

Figure 3.5 Predicted vs. actuals: best fit model

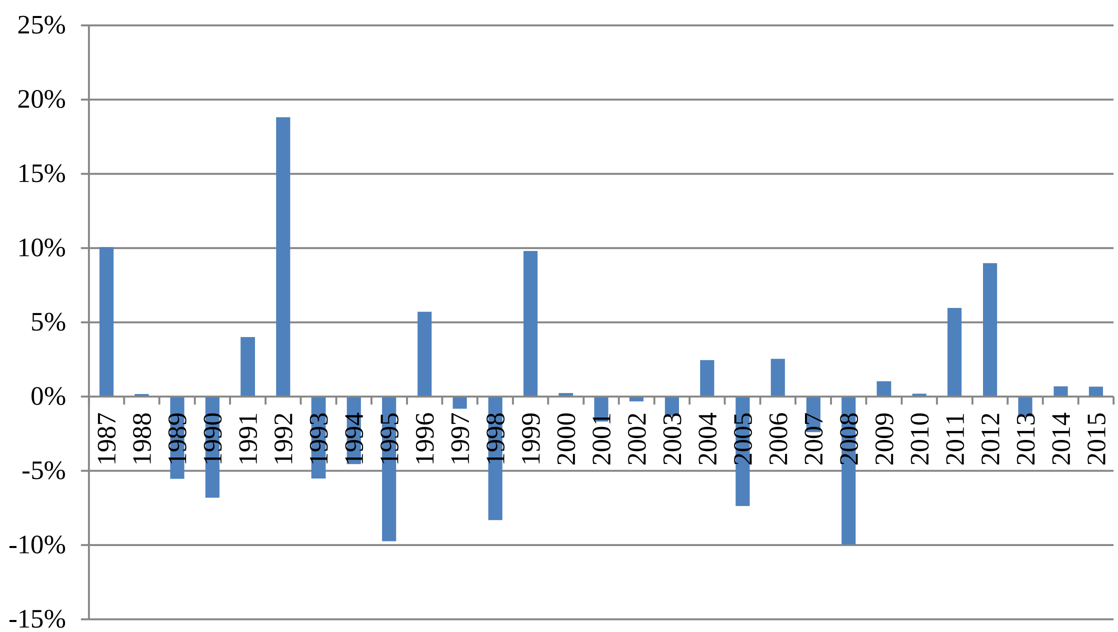

Figure 3.6 Errors: best fit model

Although the prior model fits well, it is difficult to justify the indicator to control for the years from 2013 to 2015 because it is not clear that there was anything systematic that should (in principle) cause the series to decline over that period. The inclusion of a trend variable is also atheoretical; however, given the declining trend found in the demand analysis (as well as the seasonal trend and breakpoint analysis) it stands up to more scrutiny. As a result, the next model only includes the simple trend.

Table 3.14 Peak day model: trend

Regression Statistics	
Multiple R	0.537
R Square	0.288
Adjusted R Square	0.262
Standard Error	0.115
Observations	29

Variable	*Coefficients*	*Standard Error*	*t Stat*	*P-value*
Intercept	9.462	0.044	215.560	0.000
Trend (1-29)	-0.008	0.003	-3.305	0.003

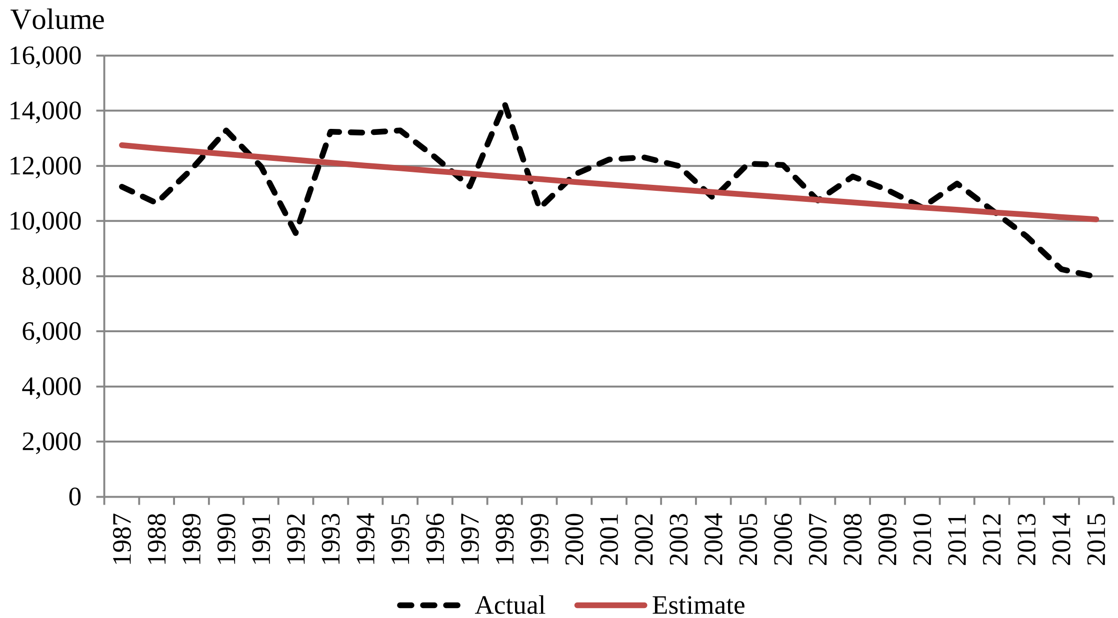

Figure 3.7 Predicted vs. actuals: trend model

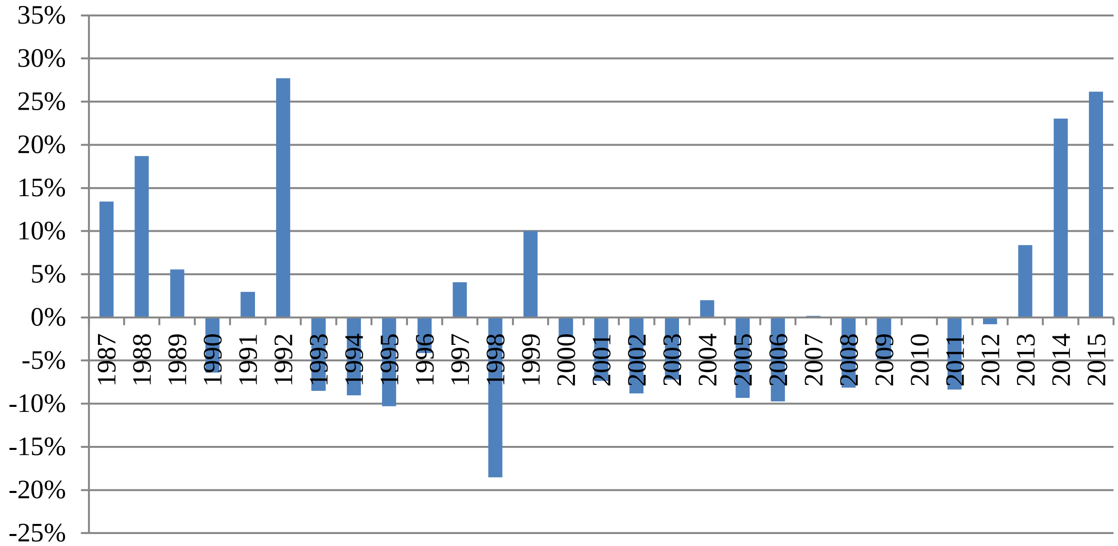

Figure 3.8 Errors: trend model

The trend model captures the declining trend over time in peak use, which is consistent with the general trend of declining use in the city of Clovis. However, the model only explains about 26% of the variation and it is not uncommon for errors to be greater than 15% in any given year. The next model includes temperature and precipitation but excludes the trend.

Table 3.15 Peak day model: temperature & precipitation

Regression Statistics	
Multiple R	0.641
R Square	0.411
Adjusted R Square	0.365
Standard Error	0.107
Observations	29

Variable	*Coefficients*	*Standard Error*	*t Stat*	*P-value*
Intercept	8.162	0.340	24.038	0.000
Precipitation (Inches last 6 months)	-0.014	0.006	-2.409	0.023
Temperature (Average last 14 Days)	0.014	0.004	3.702	0.001

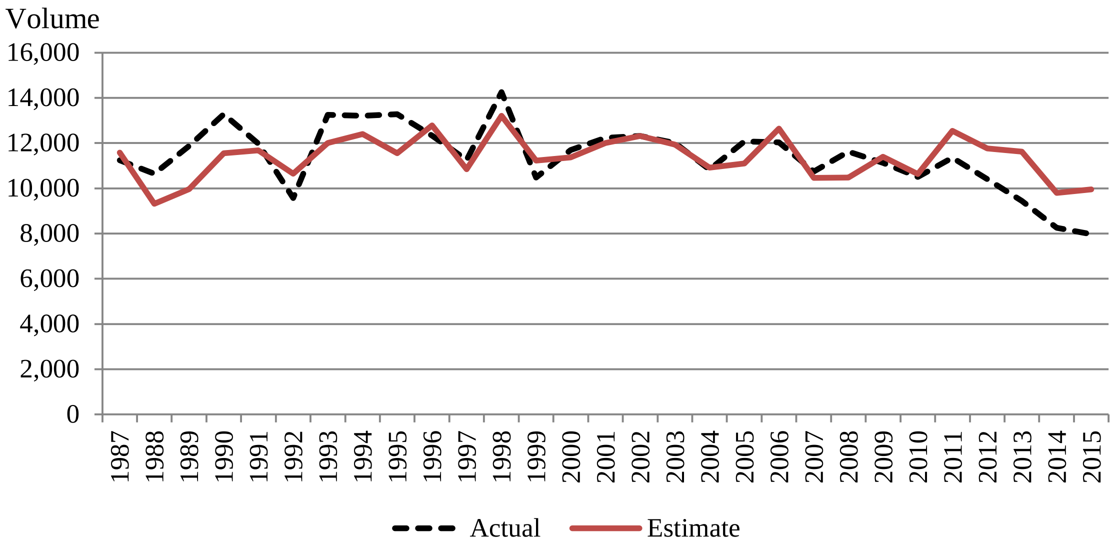

Figure 3.9 Predicted vs. actuals: temperature & precipitation model

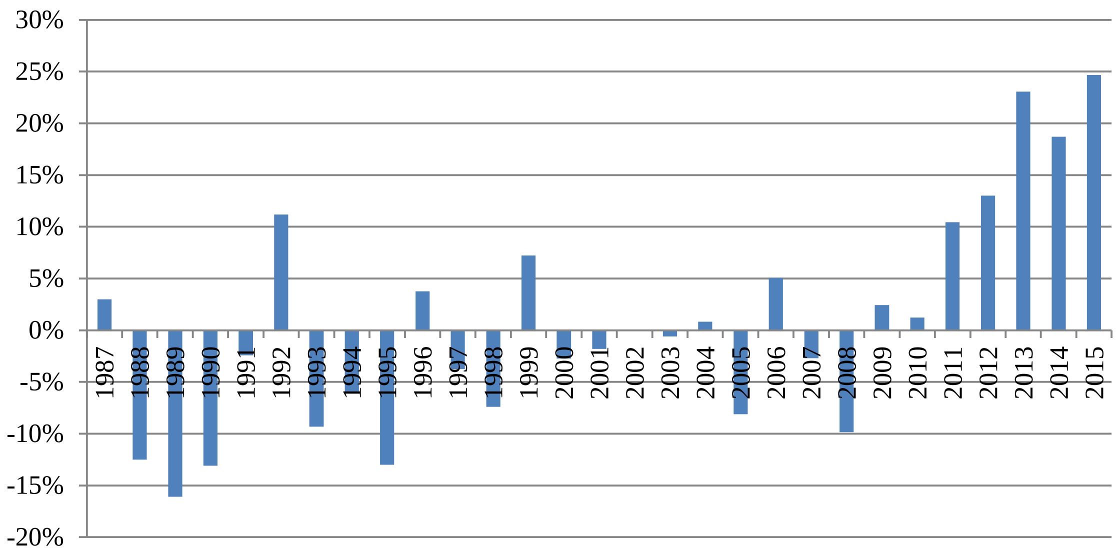

Figure 3.10 Errors: temperature & precipitation model

Fit in the temperature and precipitation model is better overall than the trend model (given a higher R^2 value); however, it begins to overestimate beginning in 2011 in a fairly significant fashion. Therefore, the following model incorporates temperature, precipitation and the trend.

Table 3.16 Peak day model: temperature, precipitation and trend

Regression Statistics	
Multiple R	0.812
R Square	0.659
Adjusted R Square	0.618
Standard Error	0.083
Observations	29

Variable	*Coefficients*	*Standard Error*	*t Stat*	*P-value*
Intercept	8.312	0.266	31.281	0.000
Precipitation (Inches last 6 months)	-0.012	0.004	-2.824	0.009
Temperature (Average last 14 Days)	0.013	0.003	4.615	0.000
Trend (1-29)	-0.008	0.002	-4.267	0.000

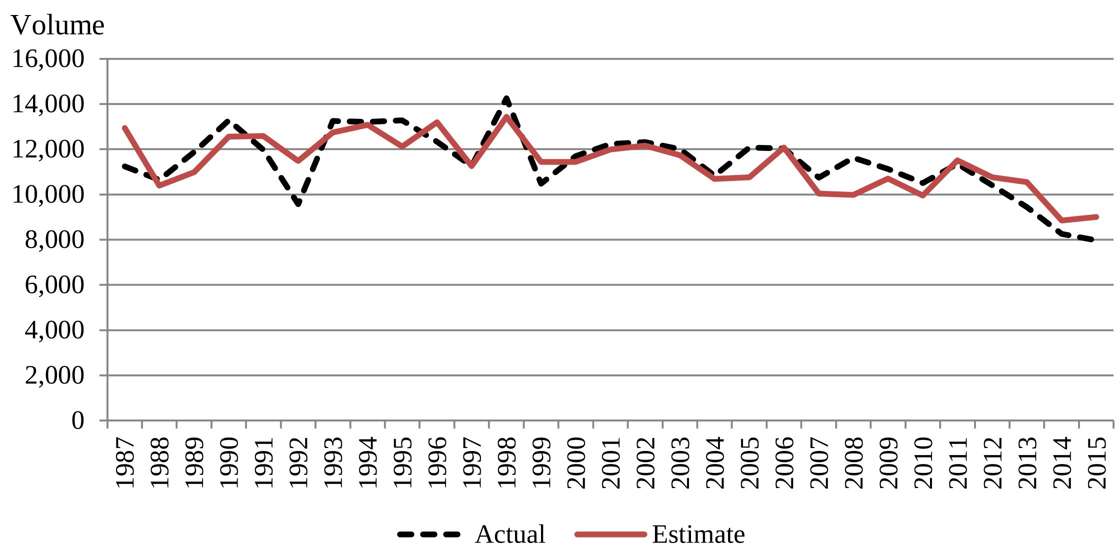

Figure 3.11 Predicted vs. actuals: temperature, precipitation & trend model

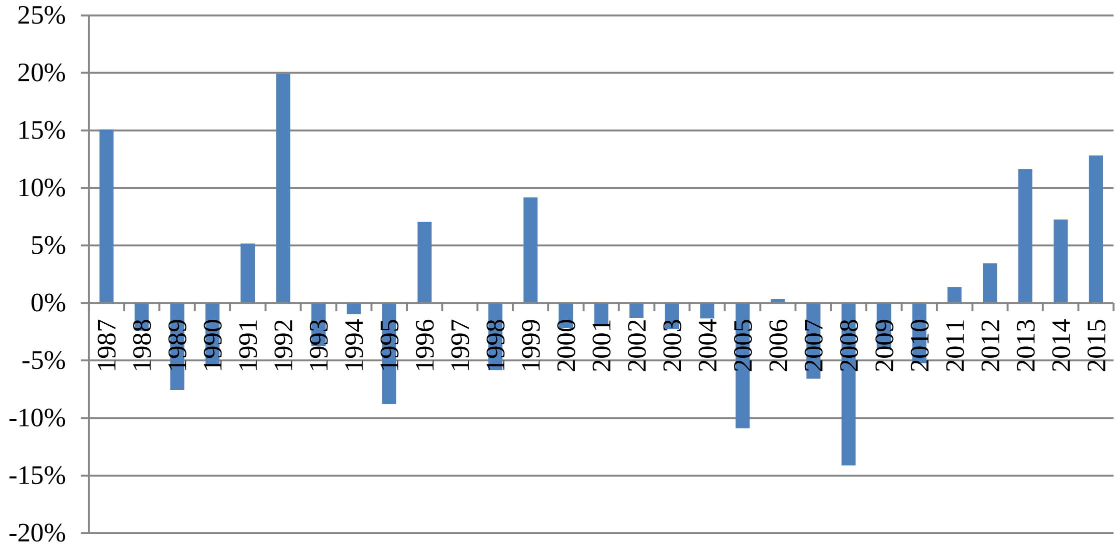

Figure 3.12 Errors: temperature, precipitation & trend model

While the last estimation does not provide the best fit, it is probably the most practical model. In order for this estimation to work, it would be necessary to basically compute expected demand each day based on temperature and precipitation while controlling for the annual trend. As final error figure shows, this method generally preformed within +/- 10% (at least in-sample). It is also important to reiterate that it is peak day demand that is being estimated; in other words, the relevant question is: if today is a peak day, level of demand should we expect? It is clear that most days will not be in the neighborhood of the peak day, but knowing what it could be should help to safeguard against inadequate supply.

In any event, because temperature and precipitation data are available through the summer of 2016 (but the actual peak day volume is unknown), it is possible to estimate the maximum day volume for the year as well as estimate the date at which it was likely to have occurred. Specifically, the models shown in table 3.17 and table 3.14 are used to predict the date of max day as well as the volume.

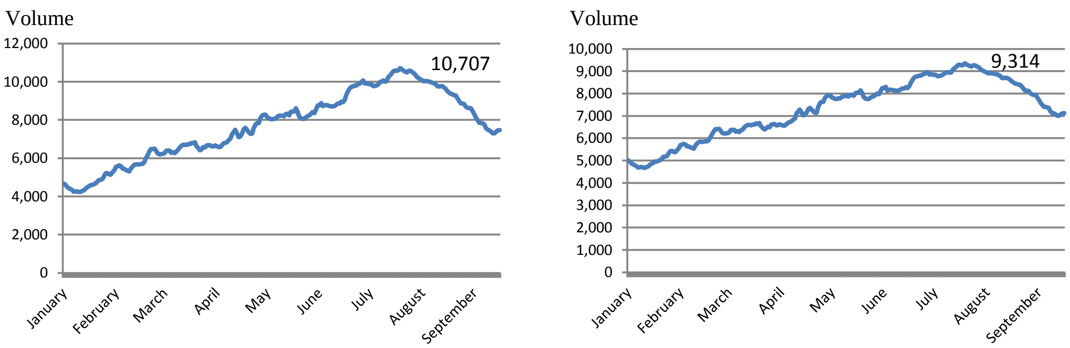

Figure 3.13 Max day volume: left panel without additional indictor (from Table 3.17), right panel with additional indicator (from Table 3.14)

In both cases, the models predict that the max day occurred on about July 19, 2016 and near-peak day volumes are likely to have been demanded in the several days prior to and post July 19. The model that does not include an indicator from 2013 through the current date estimates that peak day volume was about 10.7 million gallons while the model that includes the atheoretical indicator for the period 2013 forward predicts that the volume was about 9.3 million gallons. In both cases, the predictions are above the 2014 and 2015 volumes, while the prediction from the model that includes the indicator is near to the peak day volume experienced in 2013 (of about 9.4 million gallons).

To improve the estimation, having information in addition to peak demand in a particular year would be useful. In particular, having daily data even at an aggregate level, would help to provide insight into rapid behavioral responses (rapid in the face of changing temperature and precipitation). It would also help in providing estimates of general daily demand because then it would simply be a model of demand – which, given drivers of behavioral response should still help to predict peak demand. Other factors such as day of the week, presence of holidays, and even items discussed in the demand models such as rebates (and especially landscaping rebates) could also be brought into the analysis. If daily data was brought to bear, it might be advisable to include a lagged term or control for autocorrelation. In other words, yesterday's demand may impact demand today. In the present case, that was not necessary because of the temporal differences between data points.

Another strategy would be to study the composition of the premises on each peak day. It might be the case that certain premises contribute most to the peaks while other premises do not change demand much even in the face of the conditions that bring about the peaks. If the premises that contribute the most to the peaks can be identified, and other premises are only marginal contributors, focus can be put on the high-contribution premises and characteristics governing behavior may be uncovered and leveraged.

Chapter 4: Advertising Rebates for Water-Saving Technology: An Optimal Control Model for Utility Investment Decisions and Demand Management

4.1 Introduction

Water utilities regularly engage in advertising campaigns to promote public awareness for water conservation and manage demand. These campaigns may include investments in billboards, mailers that are included with water bills, television and radio advertisements – all of which are designed to influence consumer preferences. At the same time, some utilities also engage in advertising to entice water users to purchase and install water-saving technologies, and in some cases, utilities provide rebates for replacement of old, and relatively less efficient, technologies. These types of advertising and rebate programs have undoubtedly played a role in reducing municipal water use (Heiman, 2002; Kenney et al., 2008; Price et al., 2014). However, given that advertisement encourages conservation, and conservation reduces demand, how does a utility justify investing scarce resources to reduce the demand for the product that it sells?

This research investigates the conditions under which advertising investment by a water utility, for the purpose of inducing water users to purchase and install water saving technology, makes economic sense from the utility's perspective. Along this front, one state engineer offers some guidance when it notes that the potential benefits of rebate programs (for the purchase and installation of water-saving technology) is that they effectively reduce water demand and thus eliminate some otherwise necessary water and wastewater treatment construction costs (OSE 2001, p. 76). In other words, by the utility engaging in demand management, including advertising for water rebate programs, costly investment and maintenance decisions can be delayed.[13]

To assess this claim, a dynamic analytical framework using a capital accumulation approach that outlines the tradeoffs that a water utility faces when advertising for and engaging in a water rebate program is developed. In particular, infrastructure maintenance and expansion are costly, so the focus is on how advertising may be leveraged by an optimizing utility and how a utility may tradeoff between regular maintenance or investment and advertising for the purchase and installation of water saving technology. Specifically contemplated in this analysis are private water utilities.[14] The choice of investigating this issue from the perspective of a private utility informs the model design as behavior is assumed to flow directly from a private utility's objective to profit maximize.[15]

In this dissertation chapter, Chapter 4.2 provides a brief literature review on rebates, advertising, and water infrastructure. Chapter 4.3 develops the various elements considered by an optimizing utility, specifies the private utility's objective, and develops the utility's maximization problem. After solving the utility's maximization problem,

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[13] A key issue not considered in this analysis is that of conservation and delaying future supply augmentation. For example, a utility may be interested in advertising technologies that reduce demand and therefore slow the current rate of groundwater extraction so that it can postpone future supply investments. This issue is not addressed here but presents an additional economic justification for a utility to engage in advertising for water-saving technologies.

[14] In the United States, approximately 85% of all water utilities are publicly owned and about 15% are privately owned. This research focuses on private ownership due to its increasing popularity (Griffin, 2006).

[15]As discussed by Griffin (2006, p. 339-343), the two extreme ownership cases for a water utility are public ownership and private ownership. In the case of a publicly owned water utility, its objective, at least in principle, is a cost-minimizing one. In other words, given the demand for water, an efficient utility will provide the resource at the lowest cost. In the case of a privately owned water utility, the utility's objective is to maximize profits. As the utility is typically a natural monopoly sanctioned by the state to provide service in a given territory, private utilities are incentivized to engage in typical monopolistic behavior, for which the state generally finds reason to regulate.

Chapter 4.4 provides a qualitative assessment of optimal utility action under several scenarios. Chapter 4.5 develops an empirical model with hypothesized outcomes that can be tested with appropriate data and Chapter 4.6 concludes by enumerating limitations of the current work and offering possible directions for future investigation.

4.2 Background & Literature Review

Advertising for the purposes of water demand management is common among water utilities and has been demonstrated to reduce demand (Heiman, 2002). Similarly, water rebate programs, or utility subsidization of water-saving technologies, have also been shown to reduce demand (Kenney et al., 2008; Price et al., 2014). While the general impact of advertising in terms of altering preferences and shifting demand is well known in the marketing and economics literature (e.g. Dorfman & Steiner, 1954; Hamilton, 1972; Krugman, 1965), the economic analysis of rebates is somewhat more arcane; and in particular, the analysis of rebates for the purchase of water-saving technology from the perspective of a cost minimizing or profit maximizing water utility has not yet been undertaken. While the model that is developed and presented in this dissertation assumes that the utility directly controls advertising efforts and not uptake of rebated technology, in order to frame the relevant issues, a brief discussion of the economics of rebates follows.

Rebates offered by a producer or seller effectively reduce the purchase price of products for the individuals taking advantage of the rebate. In the economics literature, rebates are said to allow a business to price discriminate and thus extract greater surplus (Gerstner & Hess, 1991; Lu & Moorthy, 2007). According to Edwards (2007), a rebate is a “delayed incentive offered by either a product manufacturer or retailer that requires consumers to: (1) make a purchase at a pre-rebate shelf price; (2) submit a request for refund amount by mail or the Internet to the rebate offeror…; and (3) wait some period of time after the purchase and rebate submission for the rebate offeror… to send a rebate check or something of value…" Rebates are often distinguished with coupons based on the time at which the refund is provided with a coupon being instituted at the time of sale and a rebate being at a later date.

Commentators have generally concluded that the economic purpose of rebates is that they offer a seller a means of price discrimination, thereby granting the seller larger surplus (Lu and Moorthy 2007; Pindyck and Rubinfeld 1995; Gerstner and Hess 1991). In other words, some individuals will pay full price and either not know or not care about the rebate offer while other individuals, that would have not purchased the product at the listed shelf price, may be induced to purchase the product given the rebate opportunity. Of course, some consumers that would have purchased the product without the rebate will apply for the rebate, but the additional revenues obtained from induced customers will be greater than the loss from customers that would have purchased the product at the un-rebated price given the optimal rebate. However, at least one strand of research has suggested that rebates may be profitable even when all purchasers are induced to participate in the rebate program (Gerstner & Hess, 1991).

Rebates for the purchase of water saving technology functionally operate in a similar fashion to other rebate programs at least from the perspective of the consumer. In that case, a water utility makes a public offer to the community whereby the utility agrees to remunerate consumers that purchase products that qualify for the rebate program and replace existing products in their homes or businesses. Qualifying products often include water saving showerheads, low flow toilets, high efficiency washing machines, or any device that the utility chooses to include in its program, each with stated purpose of reducing household water use. A distinguishing feature between a rebate granted by a manufacturer or retailer and a water utility, however, is that the utility does not build or sell the product for which it is rebating; rather, the utility is essentially providing a subsidy for the purchase of qualified technology produced and sold by another entity. Nevertheless, the "rebate" terminology generally persists.

Whereas a typical rebate effectively reduces the product price and provides a means of price discrimination, a rebated product that lowers water use, effectively reduces the demand for the product that the utility sells: namely, water. Furthermore, rebates are costly because they are subsidized by the water utility. So, it would seem that with reduced water demand and increased costs to the utility, its profitability would be negatively impacted. For example, administration of the Albuquerque Bernalillo County Water Authority's toilet rebate program from 1995 to 2002 was estimated to cost the utility more than $2.3 million (Smith, 2004; WRA, 2008). Meanwhile, from 2002 to 2006, the city of Aurora, Colorado's water utility spent nearly $1 million on toilet and high efficiency washing machine rebate programs (Aurora, 2007; WRA, 2008). Similar programs to those described above exist in other cities and municipalities across the United States.

In addition, the utility, by encouraging the installation of water saving technology, effectively reduces the demand for the good that it sells – this has been demonstrated in theory as well as in practice (Kenney et al., 2008; Price et al., 2014). As a result, water rebate programs simultaneously impact the revenue and cost sides of the ledger in a negative manner. Therefore, it begs the question as to why an optimizing utility would engage in this type of activity.

Several hypotheses could be offered that in some cases reducing demand may be optimizing. For example, a utility may be supply-constrained and if demand exceeds current supply, the utility may be obligated to engage in costly supply enhancement. Similarly, and especially for utilities reliant on a declining aquifer with little opportunity for supply augmentation, a forward-looking utility may directly or indirectly consider the value of the remaining underground stock (the shadow value), which rises as the available volume falls. It is clear that in the first case, rebated technology, and demand management in general, offers a near-term solution to excess demand. In the latter case, the focus is having adequate supplies over a relatively longer period and, by considering the value of the remaining water, the utility can extend the useful life of the aquifer.

While these rationales likely play a role, the highly regulated nature of the water utility, and its inability to effectively set price, makes it difficult for the utility to adequately cover the rebate investment costs. Furthermore, a utility's inability to adjust price in the face of changing supply and demand conditions can create operational difficulties for the utility and those conditions may run counter to the city or municipalities' stated conservation goals (Timmins, 2003).

An alternative hypothesis that may explain how rebate investment may be optimal for a utility is that reduced system and infrastructure demands that occurs due to lowered water demand, reduces the investment that is required by the utility for infrastructure replacement and expansion. In this chapter, the term infrastructure is used to generally describe various municipal water utility capital assets including water reservoirs, treatment facilities, groundwater wells, and any other component of the utility's water collection, management and distributions systems. This rationale, at least with regard to a desire to put off investment, has particular merit given the current state of water infrastructure. As water infrastructure in the United States nears the end of its useful life (American Water Works Association 2012), rebate and demand management programs can help postpone costly maintenance, replacement, and expansion. However, this attitude has led to underfunding: according to the American Society of Civil Engineers (2017), United States' drinking water infrastructure is currently underfunded to the tune of about $100 million nationwide in 2017, earning it a grade of "D" in annual report card. In addition, as a result of continued infrastructure underinvestment, as well as population shifts in some parts of the country (which requires infrastructure expansion in some cases), the investment costs are projected to total $1 trillion over the next 25 years (American Water Works Association 2012). These statistics make attempting to better understating optimal utility investment all the more critical.

4.3 The Model

To determine whether an advertising program that promotes the purchase of water saving technology is optimal for a water utility in the face of infrastructure costs and investment, a capital accumulation model is developed. Because the focus is on the utility's capital infrastructure and its ability to adequately supply the customer base, this research also applies an adjustment cost model to the capital accumulation problem (Carey & Zilberman, 2002; Hansen, 2009; Rubio, 1992). The practical effect of this model is that investment decisions by the water utility constrain the utility's production capacity in the current period and therefore does not positively affect instantaneous output (Hansen, 2009). In an effort to analyze this problem, the following sub-chapters develop relevant aspects of the model in per capita terms (Chapter 4.3.1), specify the private utility's objective (Chapter 4.3.2), and define and solve the utility's profit maximization problem (Chapter 4.3.3).

4.3.1 Model development in per capita terms

It is natural to assume that the objective for a generic publically owned and optimally-performing utility is to minimize its costs given a particular level of production or output. In other words, the volume demanded by water users must be fulfilled by the utility, and the optimizing utility seeks to satisfy demand at the lowest possible cost. This cost-minimizing approach makes particular sense for a public utility that is uninterested in profit. However, there exist a set of private water utilities that are indeed driven by profits rather than cost minimization.[16]

While duality between cost minimization and profit maximization should generate identical results, the present research focuses on profit maximization rather than cost minimization; this approach is taken for two main reasons. First, and most obvious, is that a private business is generally expected to be driven by the profit motive, making the profit maximization problem the most direct avenue of study. Second, some model parameters, such as water price, for example, do not appear in a cost minimization problem but are included in a profit maximization problem.[17] In an effort to retain those parameters of interest, this analysis focuses on profit maximization. The examination of a

[16] EPCOR, the water utility that provides service to Clovis and Edgewood, New Mexico is an example of a private utility that arguably seeks to maximize profit. Private water utilities are discussed in Griffin (2006).
[17] Conceptually, this is because in a cost minimization problem, demand must be fulfilled regardless of water price. Focusing in the dual profit maximization problem retains that key parameter in the analysis and could allow for further comparative static analysis.

water utility from the perspective of a profit maximizing firm is not new and has been used in similar contexts (Hansen, 2009; Timmins, 2003).

Additionally, in an effort to proxy for a socially optimal outcome, the water utility is assumed to operate in a perfectly competitive market. While the market is not perfectly competitive in practice, due to the highly regulated environment that a water utility operates in, this framework allows for the utility to act as a price taker, where water price is taken as given and the regulator sets the price p.

Water production, $Q(t)$, at any point in time is a function of existing capital, $K(t)$, labor, $L(t)$,[18] direct capital infrastructure investment, $M(t)$, and indirect investment via advertising for rebated water saving technology, $A(t)$. The utility's production function is given by

$$Q(t) = F[K(t), M(t), L(t), A(t)] \tag{4.1}$$

The utility seeks to choose its optimal level of investment $M^*(t)$ and advertising $A^*(t)$ such that it maximizes the present value of it stream of profits. The firm uses $M(t)$ to replace worn out existing capital, if needed, and to expand capital to meet the demands of a growing consumer base. The firm uses $A(t)$ to effectively reduce demand on its existing capital.

Consistent with economic theory, $F_K > 0$, $F_{KK} < 0$, $F_L > 0$, $F_{LL} < 0$. In other words, production increases with greater levels of capital and larger populations, but each increase at a decreasing rate. The theory of the adjustment cost model says that $F_M \leq 0$, $F_{MM} \leq 0$. Similarly, $F_A \leq 0$, $F_{AA} \leq 0$. Because budgets are assumed to be fixed in each

[18] In this analysis, labor is assumed to be synonymous to population. Similarly labor growth is assumed to equal population growth.

time period, these assumptions suggest that by spending costly resources on $M(t)$ or $A(t)$, production in the current period is reduced commensurate with the amount invested or spent. This model is similar to Hansen (2009), however, in the current model, $A(t)$ is included in the production function; the inclusion of $A(t)$ recognizes that advertising assists the transition to water saving technologies, which reduces stress on existing capital and may delay costly investment in capital expansion.

The effect of population growth[19] enters the production function and translates the utility's decisions into per capita terms. Assuming homogeneity of degree one in the production function

$$F[\mu K(t), \mu M(t), \mu L(t), \mu A(t)] = \mu F[K(t), M(t), L(t), A(t)] \quad \forall \; \mu > 0 \qquad (4.2)$$

Given, $L(t) > 0$, let $\mu = \frac{1}{L(t)}$, $k(t) = \frac{K(t)}{L(t)}$, $m(t) = \frac{M(t)}{L(t)}$, $a(t) = \frac{A(t)}{L(t)}$. Substituting into equation (4.2), and assuming that the production function is multiplicatively separable

$$f[k(t), m(t), a(t), 1] = L(t)^{-1} F[K(t), M(t), L(t), A(t)] \qquad (4.3)$$

such that

$$F[K(t), M(t), L(t), A(t)] = L(t) f[k(t), m(t), a(t), 1] \qquad (4.4)$$

The right hand side of equation (4.4) is the population weighted production function in per capita terms.

Advertising, $A(t)$ induces the purchase of water saving technologies that are rebated by the utility. This produces a stock of rebated technology that changes according to

$$\dot{O} = D\big(A(t)\big) \qquad (4.5)$$

[19] Again, population growth and labor growth are assumed to be equivalent.

Where $O(t)$ is the stock of rebated low-flow technology installed as a result of utility advertising efforts. $O(t)$ is functionally related to $A(t)$ via $D(\cdot)$, which corresponds to uptake of rebated water saving technologies that occurs as a result of advertising efforts. Assuming constant returns to scale, dividing through by the population size, $L(t)$, to express the equation in per-capita terms produces

$$\frac{\dot{O}(t)}{L(t)} = d\big(a(t)\big) \tag{4.6}$$

$\frac{\dot{O}(t)}{L(t)}$ is the path of rebated technology expressed in per-capita terms and $d\big(a(t)\big)$ is uptake of advertised technology per capita.

Next, define the stock of rebated technology in per-capita terms as: $o(t) = \frac{O(t)}{L(t)}$. Rearranging this equation produces $O(t) = L(t)o(t)$, which is a new equation for the stock of rebated technology that, for the moment, is no longer in per-capita terms. In particular, the left hand side of the equation corresponds to the stock of rebated technology and the right hand side is the population weighted per capita stock of rebated technology. Differentiating with respect to time elicits equation (4.7).

$$\dot{O}(t) = L(t)\dot{o}(t) + \dot{L}(t)o(t) \tag{4.7}$$

The left hand side of equation (4.7) shows the time-path of the stock of rebated technology and must be equal to the sum of the product of the per-capita path of rebated technology and population size ($L(t)\dot{o}(t)$), and the product of the population path and per-capita rebated technology ($\dot{L}(t)o(t)$). Dividing both sides by the population size $L(t)$, to formulate a new equation in per-capita terms produces

$$\frac{\dot{O}(t)}{L(t)} = \dot{o}(t) + \frac{\dot{L}(t)}{L(t)}o(t) \tag{4.8}$$

Defining the rate of population growth as $\frac{\dot{L}(t)}{L(t)} = \eta$, and substituting, yields

$$\frac{\dot{O}(t)}{L(t)} = \dot{o}(t) + \eta o(t) \tag{4.9}$$

Equations (4.6) and (4.9) are now both expressed in terms of the time path of rebated technology stock in per capita terms $\left(\frac{\dot{O}(t)}{L(t)}\right)$, so setting them equal and solving for $\dot{o}(t)$ produces the per capita time path for rebated technology

$$\dot{o}(t) = d\big(a(t)\big) - \eta o(t) \tag{4.10}$$

In equation (4.10), $\eta o(t)$ corresponds to the additional per capita rebated technology required to accommodate the rate of population growth. Therefore, at the steady state, when $\dot{o}(t) = 0 \Rightarrow o(t) = \frac{d(a(t))}{\eta}$. In other words, per capita rebated technology, $o(t)$, must equal the per capita uptake in advertised technology, $d\big(a(t)\big)$, while accounting for the effect of population growth, $\frac{1}{\eta}$.

Investment (i.e. capital replacement and expansion), $M(t)$, in any period impacts the utility's capital stock, $K(t)$, as does the rate of depreciation, δ; for simplicity, only used capital is assumed to depreciate. Additionally, water saving technology $O(t)$ reduces the demand on capital and therefore effectively reduces the amount of capital used (or consumed) and that is subject to deprecation. Therefore

$$\dot{K}(t) = M(t) - \delta\big(K(t) - O(t)\big) \tag{4.11}$$

Next, define investment and capital stock in per capita terms as $m(t) = \frac{M(t)}{L(t)}$ and $(t) = \frac{K(t)}{L(t)}$, respectively. Dividing both sides of equation (4.11) by population, $L(t)$, produces

$$\frac{\dot{K}(t)}{L(t)} = m(t) - \delta\big(k(t) - o(t)\big) \tag{4.12}$$

Next, recall that capital per capita is defined as $k(t) = \frac{K(t)}{L(t)}$. Rearranging in terms of total capital stock produces $K(t) = L(t)k(t)$, which sets the capital stock equal to the population weighted per capita capital stock. Taking a time derivative elicits

$$\dot{K}(t) = L(t)\dot{k}(t) + \dot{L}(t)k(t) \tag{4.13}$$

Dividing by $L(t)$ and using the definition of the population growth rate, $\frac{\dot{L}(t)}{L(t)} = \eta$ produces equation (4.14).

$$\frac{\dot{K}(t)}{L(t)} = \dot{k}(t) + \eta k(t) \tag{4.14}$$

In other words, the change in capital divided by population size is equal to the change in capital in per capita terms plus the current level of capital multiplied by the rate of population growth.

Equations (4.12) and (4.14) provide equations expressed in terms of the time path of the total capital stock divided by the population size $\left(\frac{\dot{K}(t)}{L(t)}\right)$. Setting the equations equal and solving for $\dot{k}(t)$ produces equation (4.15), which is the time path for $k(t)$ and is a function of per capita infrastructure investment, per capita capital, and water saving technology stock $o(t)$.

$$\dot{k}(t) = m(t) - (\delta + \eta)k(t) + \delta o(t) \tag{4.15}$$

In steady state, $\dot{k}(t) = 0 \Rightarrow k(t) = \frac{m(t)+\delta o(t)}{(\delta+\eta)}$. In other words, for $\dot{k}(t) = 0$, per capita capital $k(t)$, must be fulfilled by a combination of direct per capita investment, $m(t)$, per capita rebated technology that takes the place of capital that would have been depreciated but for the technology, $\delta o(t)$, and the combined effect of depreciation and population growth, $\frac{1}{(\delta+\eta)}$.

4.3.2 The (private) utility's objective

With all of the key pieces in per capita terms, it is helpful to briefly take stock of the utility's objective before developing the utility's dynamic problem. Recall that a private water utility is interested in maximizing its profits (Π), or the difference between its total revenue (TR) and (TC) total costs (i.e. $\Pi = TR - TC$). In this case, the utility's total revenue is given by $TR = pL(t)f\big(k(t), m(t), a(t)\big)$, where total revenue is the product of unit price, p, population size $L(t)$, and the volume produced by the utility per the utility's production function (e.g. $f\big(k(t), m(t), a(t)\big)$). The utility charges price p for water, which is exogenous and determined by the regulator.

The volume produced by the utility is a function of capital stock, $k(t)$, infrastructure investment, $m(t)$, and advertising investment, $a(t)$ (all in per capita terms). The utility will choose the optimal levels of infrastructure investment, $m^*(t)$, and advertising, $a^*(t)$. Due to the application of the adjustment cost model, both $f_m, f_a \leq 0$, meaning that investment is costly in terms of foregone production in the current period; resources that are expended are not part of current revenues, since according to the adjustment cost model, current period investment does not bring about instantaneous adjustment (Hansen, 2009).[20]

[20] Following the adjustment cost model in per capita terms, $f_{mm}, f_{aa} \leq 0$ (Hansen, 2009). While the second derivative of production with regard to investment or advertising appears to be somewhat abstract, the direction is needed for appropriately signing the investment and advertising time paths.

The utility's total costs are given by $TC = ck(t) + gm(t) + sa(t)$, where $c \geq 0$, $g \geq 0$, and $s \geq 0$ are the unit costs for repair, infrastructure investment, and advertising, respectively. In other words, investment, $m(t)$, is costly and comes at g dollars per unit of capital investment, resulting in a capital investment expenditure of *gm(t).* Similarly, advertising, $a(t)$, is costly and comes at s dollars per unit investment, resulting in an advertising expenditure of *sa(t).*[21] Therefore, the utility maximizes profit according to $\Pi = pL(t)f\big(k(t), m(t), a(t)\big) - \big(ck(t) + gm(t) + sa(t)\big)$, and, to reiterate, does so by choosing the optimal level of infrastructure investment, $m(t)$, and advertising, $a(t)$.[22]

4.3.2 The utility's dynamic maximization problem in continuous time

In order to construct the dynamic model a few other assumptions are required. First, the utility anticipates that the population grows according to the logistic equation $L(0)e^{\eta t}$ where $L(0)$ is the population size at time $t = 0$ and η is the rate of population growth. In addition, the utility's internal discount rate is ρ. Accounting for the utility's profit maximizing objective (i.e. the revenues and costs discussed in the prior section), the utility maximizes the following model in continuous time

$$\max_{m(t),a(t)} V = \int_0^T e^{-\rho t} L(0) e^{\eta t} \Big(pf\big(k(t), m(t), a(t)\big) - ck(t) - gm(t) - sa(t)\Big)\, dt \tag{4.16}$$

Setting $L(0) = 1$, the objective function becomes,

[21] Clearly repair is also costly and comes at c dollars per unit of repair, resulting in repair expenditure of $ck(t)$, but capital is not directly chosen by the utility so is ignored for the purpose of highlighting the choice variables.
[22] For simplicity, it is assumed that the utility advertises the purchase of water saving technology but does not subsidize it.

$$\max_{m(t),a(t)} V = \int_0^T e^{rt} \Big(pf\big(k(t), m(t), a(t)\big) - ck(t) - gm(t) - sa(t)\Big)\, dt \qquad (4.17)$$

Where $r = \eta - \rho$ and for $r < 0$, $\rho > \eta$.

The maximization problem is constrained by the various stocks described in equations (4.10) and (4.15), as well as the additional starting, terminal, and range conditions shown in (4.18).

$$\begin{aligned}
&\dot{k} = m(t) - (\delta + \eta)k(t) + \delta o(t) \\
&\dot{o} = d\big(a(t)\big) - \eta o(t) \\
&k(0) = k_0;\ \underline{k} \le k(t) \le \overline{k};\ k(T) = k_t \\
&o(0) = o_0;\ 0 \le o(t) \le \overline{o}; o(T) = o_t \\
&\lambda_i(T) = 0, \forall i \\
&T \text{ fixed}
\end{aligned} \qquad (4.18)$$

In other words, the utility chooses $m(t)$ and $a(t)$ in order to maximize its stream of profits over the planning horizon T under the constraints given by $k(t)$ and $o(t)$. As the planning horizon is fixed at terminal time T, this can be also be interpreted as a management horizon over which a utility operates. Minimum and maximum values of $k(t)$ and $o(t)$ are given, indicating that per capita levels of capital and rebated technology must be contained within the given intervals. In addition, r, which is given by the difference between the population growth rate (η) and the utility's internal discount rate (ρ), is the social discount rate and is assumed to be less than zero. This condition requires that the utility's internal discount rate, ρ, be greater than the rate of population growth, η. Given this framework, the current value Hamiltonian is:

$$H = pf\big(k(t), m(t), a(t)\big) - ck(t) - gm(t) - sa(t)$$
$$+ \lambda_1[m(t) - (\delta + \eta)k(t) + \delta o(t)] \tag{4.19}$$
$$+ \lambda_2\big[d\big(a(t)\big) - \eta o(t)\big]$$

$\lambda_1$and λ_2 represent the shadow (or option) values of capital and water saving technology (or the state variables) respectively. Dropping the time subscripts for simplicity, the first order necessary conditions are:

$$\frac{\partial H}{\partial m} = 0 \iff pf_m - g + \lambda_1 = 0 \tag{4.20}$$

$$\frac{\partial H}{\partial a} = 0 \iff pf_a - s + \lambda_2 d_a = 0 \tag{4.21}$$

$$-\frac{\partial H}{\partial k} = \dot{\lambda}_1 - r\lambda_1 \iff \dot{\lambda}_1 = -pf_k + c + \lambda_1(\delta + 2\eta - \rho) \tag{4.22}$$

$$-\frac{\partial H}{\partial o} = \dot{\lambda}_2 - r\lambda_2 \iff \dot{\lambda}_2 = \lambda_2(2\eta - \rho) - \delta\lambda_1 \tag{4.23}$$

$$\frac{\partial H}{\partial \lambda_1} = \dot{k} \iff \dot{k} = m - (\delta + \eta)k - \delta o \tag{4.24}$$

$$\frac{\partial H}{\partial \lambda_2} = \dot{o} \iff \dot{o} = d(a) - \eta o \tag{4.25}$$

$$\lim_{t \to T} e^{rt} H(k, m, a, o, \lambda_1, \lambda_2) = 0 \tag{4.26}$$

Assuming that an interior solution exists, and solving equations (4.20) and (4.21), yields equations in terms of pf_m and pf_a, or the marginal revenue products of investment and advertisement, respectively. Because $pf_m, pf_a < 0$ correspond to production in the current period that is given up in favor of investment, pf_m and pf_a therefore represent opportunity costs of investment and imply tradeoffs between production in the current period and investment (or advertising). Additionally, $d_a > 0$, or the marginal impact of advertising on rebate uptake, enters equation (4.21) and plays a key role in the optimal advertising decision.

Given the potentially costly tradeoffs that a utility must make in terms of investment decisions and production, at the optimum the utility invests up to the point where the costs of investment are equal to the benefits from investment. As such, solving for λ_1 in equation (4.20) gives

$$\lambda_1 = g - pf_m \tag{4.27}$$

In this case, g is the unit cost of infrastructure investment and pf_m is the opportunity cost of investing. Therefore, given that $g - pf_m$ is the marginal cost of investment, λ_1 represents the marginal benefit, or marginal value, to the utility of infrastructure investment.

Similarly, the utility optimally chooses advertising investment such that the marginal costs of advertising equal the marginal benefits of advertising. Solving for λ_2 in equation (4.21)

$$\lambda_2 = \frac{s - pf_a}{d_a} \tag{4.28}$$

The term $s - pf_a$ corresponds to the combined costs of the direct and opportunity cost of advertising. The term in the denominator, d_a, scales the marginal cost by marginal advertising effectiveness In particular, as d_a increases, relatively less advertising is required to achieve the same marginal cost outcome, all else equal. As a result, λ_2 represents the marginal value to the utility of advertising, or the marginal value of rebated technology.

Critical to the analysis is that $\lambda_1, \lambda_2 > 0$.[23] In the case of λ_1, the unit cost of investment, $m(t)$, is positive ($g > 0$) and because the opportunity cost of infrastructure investment is negative ($pf_m < 0$), the shadow (or option) value of infrastructure investment is positive ($\lambda_1 > 0$). Similarly, because the unit cost of advertising, $a(t)$, is positive ($s > 0$), the opportunity cost of advertising investment is negative ($pf_a < 0$), and the marginal effect of advertising on technology uptake is positive ($d_a > 0$), the shadow (or option) value of advertising is also positive ($\lambda_2 > 0$).

Taking the time derivative of equation (4.27) produces a time path for the shadow value of investment, λ_1

$$\dot{\lambda}_1 = -p\left(f_{mk}\dot{k} + f_{mm}\dot{m} + f_{ma}\dot{a}\right) \tag{4.29}$$

Taking the time derivative of equation (4.28) produces a time path for the shadow value of advertising, λ_2

$$\dot{\lambda}_2 = -\frac{p\left(f_{ak}\dot{k} + f_{am}\dot{m}\right) + \dot{a}(pf_{aa} + \lambda_2 d_{aa})}{d_a} \tag{4.30}$$

Equations (4.29) and (4.30) must hold if m and a are optimally chosen.

Equations (4.22) and (4.23) also provide time paths for the shadow values of investment and infrastructure (λ_1 and λ_2, respectively) and correspond to how the objective changes given changes in the respective stocks, $k(t)$ and $o(t)$. These time paths can be used in conjunction with equations (4.29) and (4.30), respectively, to solve for time paths of the choice variables, $\dot{m}$ and $\dot{a}$. Therefore, setting equation (4.23) equal to equation (4.30) and solving for $\dot{a}$ produces and equation that is a function of the time path of infrastructure investment, $\dot{m}$

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[23] Recall that $\lambda_1 = g - pf_m$ and $\lambda_2 = \frac{s - pf_a}{d_a}$.

$$\dot{a} = -\frac{d_a(\lambda_2(2\eta - \rho) - \delta\lambda_1) + pf_{ak}\dot{k}}{(pf_{aa} + \lambda_2 d_{aa})} - \frac{pf_{am}}{(pf_{aa} + \lambda_2 d_{aa})}\dot{m} \tag{4.31}$$

Similarly, setting equation (4.22) equal to equation (4.29) and solving for $\dot{m}$ produces and equation that is a function of advertising time path, $\dot{a}$

$$\dot{m} = \frac{[pf_k - c] - [\lambda_1(\delta + 2\eta - \rho)] - [pf_{mk}\dot{k}]}{pf_{mm}} - \frac{f_{am}}{f_{mm}}\dot{a} \tag{4.32}$$

Equations (4.31) and (4.32) provide a system of equations that can be solved for both $\dot{a}$ and $\dot{m}$. Equation (4.32) is particularly noteworthy because it similar to the result found in (Hansen, 2009), but because the present analysis incorporates the effect of advertising, it includes the additional term $\frac{f_{am}}{f_{mm}}\dot{a}$. In addition, this term is subtracted on the right hand side of equation (4.32) implying that as advertising investment increases, the optimal infrastructure investment path decreases because the utility is effectively trading off between the two investment types. Plugging equation (4.31) into (4.32) and solving $\dot{m}$ for produces

$$\begin{aligned}\dot{m} = \frac{(pf_{aa} + \lambda_2 d_{aa})}{p\left(f_{mm}(pf_{aa} + \lambda_2 d_{aa}) - {f_{am}}^2\right)}\Bigg([pf_k - c] - [\lambda_1(\delta + 2\eta - \rho)] \\ - [pf_{mk}\dot{k}] + \frac{pf_{am}\left(d_a(\lambda_2(2\eta - \rho) - \delta\lambda_1) + pf_{ak}\dot{k}\right)}{(pf_{aa} + \lambda_2 d_{aa})}\Bigg)\end{aligned} \tag{4.33}$$

Equation (4.33) is the optimal path for m.

Substituting equation (4.33) back into (4.31) and solving for $\dot{a}$ produces the optimal path for a.

$$\dot{a} = -\left[\frac{(1 + pf_{am})\left(d_a(\lambda_2(2\eta - \rho) - \delta\lambda_1) + pf_{ak}\dot{k}\right)}{(pf_{aa} + \lambda_2 d_{aa})} + \frac{f_{am}}{(f_{mm}(pf_{aa} + \lambda_2 d_{aa}) - (f_{am})^2)}\left([pf_k - c] - [\lambda_1(\delta + 2\eta - \rho)] - \left[pf_{mk}\dot{k}\right]\right)\right] \tag{4.34}$$

For complete solutions, the shadow values of infrastructure investment and advertising, $\lambda_1$and λ_2, respectively, should be substituted into optimal m and a paths and $\dot{k}$ should be replaced by the restriction given in equation (4.18); however, those terms are left in the present analysis for compactness. Furthermore, because $\lambda_1, \lambda_2 > 0$, they pose no special difficulty with regard to understanding the behavior of each path.[24]

4.4 Signing and Analysis

In an effort to better characterize the optimal choice for a utility (given a variety of underlying assumptions), this section provides qualitative results for key terms, parameters, and relationships. To facilitate this discussion, assume that $f_{am} = 0$, or that the cross partial derivatives of the production function with respect to both control variables are equal to zero.[25] Simplifying equation (4.32) yields

$$\dot{m} = \frac{1}{pf_{mm}}\left([pf_k - c] - [\lambda_1(\delta + 2\eta - \rho)] - \left[pf_{mk}\dot{k}\right] + p\left[\frac{f_{ak}}{(pf_{aa} + \lambda_2 d_{aa})}\right]\dot{k}\right) \tag{4.35.1}$$

[24] Although, depending on the assumed signs for augmented depreciation $(\delta + 2\eta - \rho)$ and the population effect $(2\eta - \rho)$, the relative magnitudes for λ_1, λ_2 may make a difference.
[25] This is indeed a strong assumption. However, simplification is required to make meaningful qualitative comparisons.

Equation (4.35.1) is in the same general form given in (Hansen, 2009) but it includes the additional term $p\left[\frac{pf_{ak}}{(pf_{aa}+\lambda_2 d_{aa})}\right]\dot{k}$, which accounts for the effect of advertising on the changing capital. Equation (4.35.1) is rearranged in equation (4.35.2) in order to capture the full effect of $\dot{k}$ in the path for m.

$$\dot{m} = \frac{1}{pf_{mm}}\Bigg([pf_k - c] - [\lambda_1(\delta + 2\eta - \rho)] \\ - \left[\frac{f_{mk}(pf_{aa} + \lambda_2 d_{aa}) - f_{ak}}{(pf_{aa} + \lambda_2 d_{aa})}\right]p\dot{k}\Bigg) \tag{4.35.2}$$

In addition, applying the assumption $f_{am} = 0$ to equation (4.34) produces equation (4.36.1)

$$\dot{a} = -\frac{d_a(\lambda_2(2\eta - \rho) - \delta\lambda_1) + pf_{ak}\dot{k}}{pf_{aa} + \lambda_2 d_{aa}} \tag{4.36.1}$$

For comparability, equation (4.36.1) is rearranged in equation (4.36.2) to be consistent with equation (4.35.1). In particular, each contain the same $p\left[\frac{f_{ak}}{pf_{aa}+\lambda_2 d_{aa}}\right]\dot{k}$ term. This demonstrates that both the infrastructure $(\dot{m})$ and advertising $(\dot{a})$ paths are subject to similar offsetting factors.

$$\dot{a} = -\left(\frac{d_a(\lambda_2(2\eta - \rho) - \delta\lambda_1)}{pf_{aa} + \lambda_2 d_{aa}} + p\left[\frac{f_{ak}}{pf_{aa} + \lambda_2 d_{aa}}\right]\dot{k}\right) \tag{4.36.2}$$

However, for the purpose of analyzing the a path, equation (4.36.3) is derived,

$$\dot{a} = -\frac{d_a(2\eta - \rho)\lambda_2}{pf_{aa} + \lambda_2 d_{aa}} + \frac{d_a\delta\lambda_1}{pf_{aa} + \lambda_2 d_{aa}} - p\left[\frac{f_{ak}}{pf_{aa} + \lambda_2 d_{aa}}\right]\dot{k} \tag{4.36.3}$$

By assumption, $\eta - \rho < 0$ (i.e. the social discount rate $r < 0$); however, the sign of $\delta + 2\eta - \rho$, which essentially accounts for the combined effects of population augmented depreciation (augmented depreciation) and the utility's internal discount rate, in the $\dot{m}$ path in equation (4.35.2), is unknown. Similarly the direction of $\dot{a}$ turns in part on the sign of $2\eta - \rho$, which is essentially the difference between the scaled rate of population growth rate (population effect) and the utility's internal rate of discount, and is also unknown. In both cases, empirical data are necessary to uncover the true signs for the augmented depreciation and population effect terms. Nevertheless, the following scenarios demonstrate the various relationships given the various possible signs of $\delta + 2\eta - \rho$ and $2\eta - \rho$; in other words, the paths depend on the strength and direction of the effects of augmented depreciation and the population effect.

4.4.1 Scenario 1:Population effect greater than utility discount rate ($\boldsymbol{2\eta - \rho > 0}$) *and augmented depreciation greater than utility discount rate* ($\boldsymbol{\delta + 2\eta - \rho > 0}$)

Based on the m path shown in equation (4.35.1), there exist several possible directions of $\dot{m}$ depending on whether capital is accumulating or declining; i.e. given the sign of $\dot{k}$.

Define $A = \frac{pf_k - c}{pf_{mm}}$; $B = \frac{\lambda_1(\delta + 2\eta - \rho)}{pf_{mm}}$; and $C = \frac{f_{mk}\dot{k}}{f_{mm}}$; and $D = \frac{1}{pf_{mm}}\left[\frac{f_{ak}}{(pf_{aa} + \lambda_2 d_{aa})}\right]\dot{k}$. A can be described as the marginal net benefit (MNB_m) of repairing existing infrastructure. A prudent manager would not spend more fixing existing infrastructure than it receives in benefits, so $pf_k - c \geq 0$. However, $pf_{mm} < 0$, so $A < 0$.

Because $\lambda_1 = g - pf_m$, B is the marginal value of infrastructure investment (MVI_m). The marginal benefit of infrastructure investment is equal to the costs of investment, so it must be that $\lambda_1 = g - pf_m > 0$. However, the relationship between augmented depreciation and the utility's internal discount rate ($\delta + 2\eta - \rho$) is unknown, which makes assessing the sign of B and empirical question. In this case it is assumed that $\delta + 2\eta - \rho > 0$, or that augmented depreciation is positive; therefore, $B > 0$.

C and D both capture effects from the change in capital stock modeled through $\dot{k}$. Specifically, C accounts the marginal capital changes occurring due to infrastructure investment and D accounts for marginal changes in capital due to advertising investment. With regard to C, $f_{mk} < 0$ and $f_{mm} < 0$; however, because of the leading negative sign on C, the sign is opposite of $\dot{k}$. For D, $\frac{f_{ak}}{(pf_{aa}+\lambda_2 d_{aa})} > 0$ and $pf_{mm} < 0$, so like C, the sign is opposite of $\dot{k}$. Table 4.1 shows the optimal direction for infrastructure investment given the assumptions already described.

Table 4.1 Summary of impacts for optimal path of $\dot{\boldsymbol{m}}$ when $\boldsymbol{\delta + 2\eta - \rho > 0}$

	$\dot{k} < 0$	$\dot{k} = 0$	$\dot{k} > 0$
$\dot{m} < 0$	$A > (B + C + D)$	$A > B$	$(A + C + D) > B$
$\dot{m} = 0$	$A = (B + C + D)$	$A = B$	$(A + C + D) = B$
$\dot{m} > 0$	$A < (B + C + D)$	$A < B$	$(A + C + D) < B$

In situations when the change in capital stock is negative, i.e. when $\dot{k} < 0$, the optimal path for infrastructure investment, or the direction of $\dot{m}$, depends on the magnitude of the MNB_m from repairs. If the MNB_m from repairs exceeds the MVI_m and the joint effects from the change in capital stock (i.e. capital stock changes coming from direct investment and advertising), then the utility should shift its focus away from new capital investment and toward repairs. However, if MNB_m from repairs is less than the MVI_m and the joint effects from the change in capital stock, then the utility should shift its focus to capital investment.

When changes to capital stock are positive, i.e. when $\dot{k} > 0$, the MVI_m tends to dominate. For example, if the combined MNB_m from repairs and the joint effects from change in capital stock are less than the MVI_m, the utility should focus its efforts on new investment; however, if the combined impact is greater than MVI_m then the utility should focus on repairs. Finally, the $\dot{m} = 0$ row provides steady state relationships for each instance of $\dot{k}$ when net infrastructure investment is equal to zero – in other words, it provides situations when a utility would be indifferent between infrastructure investment and repairs.[26]

Similarly, to outline the various possible directions of $\dot{a}$ given the various signs of $\dot{k}$, define $X = \frac{d_a(2\eta-\rho)\lambda_2}{pf_{aa}+\lambda_2 d_{aa}}$, $Y = \frac{d_a\delta\lambda_1}{pf_{aa}+\lambda_2 d_{aa}}$ and $Z = p\left[\frac{f_{ak}}{pf_{aa}+\lambda_2 d_{aa}}\right]\dot{k}$. Because $\lambda_2 = \frac{s-pf_a}{d_a}$, X is the marginal value of advertising investment (MVA_a); Y, in a manner of speaking, is the marginal value of infrastructure investment (MVI_a) put in advertising terms; and Z is the impact on the $\dot{a}$ path due to changing capital stock. Because $f_{aa}, d_{aa} < 0$, the denominator for each quantity, $X, Y,$ and Z is negative. Due to the increasing effect of advertising on rebate uptake, $d_a > 0$, the positive shadow value for advertising, $\lambda_2 > 0$, and given the assumption that the population effect outweighs the effect of the utility's internal discount rate, $2\eta - \rho > 0$, the $MVA_a < 0$. By similar logic, because the depreciation term is positive, $\delta > 0$, the $MVI_a < 0$. Finally, because $f_{ak} < 0$, $p\left[\frac{f_{ak}}{pf_{aa}+\lambda_2 d_{aa}}\right] < 0$, so the sign for Z depends on the direction of the capital effect $\dot{k}$.

[26] Note that the critical comparison in this case is between the marginal benefit of repair and the marginal benefit of investment – the effect of advertising only indirectly enters through the capital effect, and specifically through $D = \frac{1}{pf_{mm}}\left[\frac{f_{ak}}{(pf_{aa}+\lambda_2 d_{aa})}\right]\dot{k}$. However, the following paragraphs describe the advertising relationship and specifically how the marginal value of advertising is compared against the marginal value of investment (i.e. how they are traded off). To put this in a concise fashion, in order for the utility to behave optimally, it must choose the proper directions for $\dot{m}$ and $\dot{a}$ given the various assumptions already described regarding the population effect and augmented depreciation, as well as the observed direction of $\dot{k}$. In other words, the qualitative results describe whether it is optimal for a utility to increase (or decrease or keep level) investment or advertising.

Given the relations as shown in equation (4.36.3), and the assumption $2\eta > \rho$, the possible directions for the $\dot{a}$ path are shown in table 4.2.

Table 4.2 Summary of impacts for optimal path of $\dot{\boldsymbol{a}}$ assuming $\boldsymbol{2\eta > \rho}$

	$\dot{k} < 0$	$\dot{k} = 0$	$\dot{k} > 0$
$\dot{a} < 0$	$(X + Z) < Y$	$X > Y$	$X < (Y + Z)$
$\dot{a} = 0$	$(X + Z) = Y$	$X = Y$	$X = (Y + Z)$
$\dot{a} > 0$	$(X + Z) > Y$	$X < Y$	$X > (Y + Z)$

In this case, there is no analogue to MNB_m; rather, the relevant comparisons are based on the marginal values of advertising and infrastructure investment. In this case, when $\dot{k} < 0$, the optimal path for advertising investment, or the direction of $\dot{a}$, depends on the magnitude of the MVA_a and the capital effect. Specifically, if the MVA_a and the capital effect are less than MVI_a, then it makes sense to shift resources away from advertising and toward infrastructure investment. However, if the MVA_a and the capital effect are greater than MVI_a, then it makes sense to shift resources toward advertising.

In cases when $\dot{k} > 0$, the magnitude of MVA_a dominates. If MVA_a is less than the joint impact of MVI_a and the capital effect, then it makes sense to invest in infrastructure. However, if MVA_a is greater than the joint impact of MVI_a and the capital effect, then it makes sense to invest in advertising. The $\dot{a} = 0$ row provides steady state relationships for each instance of $\dot{k}$. These steady state outcomes occur when the MVA_a of repairs equals the MVI_a of investment.

Of particular interest for $\dot{a}$ and $\dot{m}$ is that both depend on $\lambda_1$and λ_2; in other words, the marginal value of both investment-types play a role in determining optimal investment paths and illustrates that tradeoffs between investments depend on the marginal values of each. The $\dot{a}$ path is the most direct version of this and, as the signing results suggest, it allows for a direct comparison of the various values of each investment type and provides qualitative guidance for when investment tradeoffs should occur. However, even the $\dot{m}$ path includes a correction for advertising as that path incorporates the shadow value (or option value) of advertising, illustrating that both investment types should be considered when attempting to achieve the optimal paths.

4.4.2 Scenario 2: Population effect equal to utility discount rate ($\boldsymbol{2\eta - \rho = 0}$) *or augmented depreciation equal to utility discount rate* ($\boldsymbol{\delta + 2\eta - \rho = 0}$)

Although Scenario 1 produces the most likely set of outcomes, given the assumed signs for $2\eta - \rho$ and $\delta + 2\eta - \rho$, nothing in principle prevents those expressions taking on different signs. In this particular scenario, either (twice) the population growth rate is equal to the utility's internal rate of discount ($2\eta = \rho$) or the rate of augmented deprecation is equal to the utility's internal rate of discount ($\delta + 2\eta = \rho$), but not both (assuming that $\delta > 0$). If the utility's rate of augmented depreciation is equivalent to its internal discount rate, then the various time paths for $\dot{m}$, given the three conditions for $\dot{k}$, are given in table 4.3.

Table 4.3 Summary of impacts for optimal path of $\boldsymbol{\dot{m}}$ when $\boldsymbol{\delta + 2\eta - \rho = 0}$

	$\dot{k} < 0$	$\dot{k} = 0$	$\dot{k} > 0$
$\dot{m} < 0$	$0 > (B + C + D)$	$0 > B$	$(C + D) > B$
$\dot{m} = 0$	$0 = (B + C + D)$	$0 = B$	$(C + D) = B$
$\dot{m} > 0$	$0 < (B + C + D)$	$0 < B$	$(C + D) < B$

In this case, because the effects of augmented depreciation are offset against the utility's internal discount rate, A, or the marginal net benefit of repairs (MNB_m), is zero. Therefore, outcomes shown in the table do not offer insight into a meaningful tradeoff between repairs and investment, but rather show conditions that must exist when the directions for $\dot{k}$ and $\dot{m}$ and known.

Similarly, if the population's growth rate is equivalent to its internal discount rate, then X in the $\dot{a}$ path, or the marginal value of advertising (MVA_a), is equal to zero. The various time paths for a, given the three conditions for $\dot{k}$, are given in table 4.4. Like table 4.3, the results demonstrate that there is no meaningful tradeoff between investment types and instead provides conditions that must exist for an optimally managed utility given the various directions for $\dot{a}$ and $\dot{k}$.

Table 4.4 Summary of impacts for optimal path of $\dot{\boldsymbol{a}}$ when $\mathbf{2\boldsymbol{\eta} - \boldsymbol{\rho} = 0}$

	$\dot{k} < 0$	$\dot{k} = 0$	$\dot{k} > 0$
$\dot{a} < 0$	$Z < Y$	$0 > Y$	$0 < (Y + Z)$
$\dot{a} = 0$	$Z = Y$	$0 = Y$	$0 = (Y + Z)$
$\dot{a} > 0$	$Z > Y$	$0 < Y$	$0 > (Y + Z)$

4.4.3 Scenario 3: Population effect less than utility discount rate $(\mathbf{2\boldsymbol{\eta} - \boldsymbol{\rho} < 0})$

In this scenario, it is assumed that the population growth is outweighed by the utility's discount rate $2\eta < \rho$. This term enters into the $\dot{a}$ time path, but not the $\dot{m}$ time path, and effectively changes the sign of X, or the MNB_m. In essence, this change forces X to the opposite side of the inequality compared to table 4.2.

Table 4.5 Summary of impacts for optimal path of $\dot{\boldsymbol{a}}$ when $\mathbf{2\boldsymbol{\eta} - \boldsymbol{\rho} < 0}$

	$\dot{k} < 0$	$\dot{k} = 0$	$\dot{k} > 0$
$\dot{a} < 0$	$Z < (X + Y)$	$0 > (X + Y)$	$0 < (X + Y + Z)$
$\dot{a} = 0$	$Z = (X + Y)$	$0 = (X + Y)$	$0 = (X + Y + Z)$
$\dot{a} > 0$	$Z > (X + Y)$	$0 < (X + Y)$	$0 > (X + Y + Z)$

In this instance, there is no tradeoff between MVA_a and MVI_a and the results simply illustrate the conditions that must be true given various directions for $\dot{a}$, conditions for $\dot{k}$, and assuming that the utility is behaving optimally. However, the implication of the utility's discount rate being larger than the population growth rate is that it incentivizes the acquisition of near-term profits at the expense of any other type of investment – including advertising investment, which are expected to reduce future capital demands.

4.4.4 Scenario 4: Augmented depreciation less than utility discount rate ($\boldsymbol{\delta + 2\eta - \rho < 0}$)

The logic for the $\dot{m}$ path, assuming that augmented depreciation is less than the utility's discount rate, is similar to scenario 3; when $\delta + 2\eta < \rho$, the utility no longer trades off between repairs and capital investment. Results are shown in table 4.6.

Table 4.6 Summary of impacts for optimal path of $\dot{\boldsymbol{m}}$ when $\boldsymbol{\delta + 2\eta - \rho < 0}$

	$\dot{k} < 0$	$\dot{k} = 0$	$\dot{k} > 0$
$\dot{m} < 0$	$0 > (A + B + C + D)$	$0 > (A + B)$	$(C + D) > (A + B)$
$\dot{m} = 0$	$0 = (A + B + C + D)$	$0 = (A + B)$	$(C + D) = (A + B)$
$\dot{m} > 0$	$0 < (A + B + C + D)$	$0 < (A + B)$	$(C + D) < (A + B)$

When the utility's internal discount rate exceeds the rate of depreciation and the population effect, near-term profits are encouraged, which disincentives investment because investment will bring the utility profits at a later date.

4.4.5 Scenario discussion

While the most interesting set of results occur when $\delta + 2\eta - \rho > 0$ and when $2\eta - \rho > 0$, the previous analysis demonstrate the possible outcomes when those conditions are not met. Additionally, the results provide some bounds when some pieces of information are known and may make it possible to deduce, or at least narrow down, the list of possible options if some information is unknown. For example, if it is known that $2\eta - \rho = 0$, then it must be the case that $\delta + 2\eta - \rho \geq 0$ because $\delta \geq 0$. In addition, if $\dot{k} > 0$, for instance, then that only leaves a limited set of possible relations for an optimally behaving utility for $\dot{a}$ and $\dot{m}$. While this assessment provides the possible list of outcomes, the actual set of outcomes expected in a particular case is ultimately an empirical question.

4.5 Developing Testable Empirical Models

While previous analysis qualitatively describes the conditions that must be satisfied to determine the directions of the various paths given the proposed models, and produces generally intuitive results, it does not mean that the proposed models necessarily behave in in the manner suggested in practice. Therefore, the time paths (for $\dot{m}$, $\dot{a}$, and $\dot{k}$ are manipulated in an effort to develop statistical models that may be tested empirically and compared against expected parameter outcomes. Beginning with equation (4.35.2) and distributing $\frac{1}{pf_{mm}}$ produces equation (4.37)

$$\dot{m} = \frac{[pf_k - c] - [\lambda_1(\delta + 2\eta - \rho)]}{pf_{mm}} - \frac{[pf_{mk}\dot{k}]}{pf_{mm}} + \frac{pf_{ak}\dot{k}}{pf_{mm}(pf_{aa} + \lambda_2 d_{aa})} \tag{4.37}$$

Substituting $\lambda_1 = g - pf_m$ and $\lambda_2 = \frac{s - pf_a}{d_a}$ and collecting like terms yields

$$\begin{aligned}\dot{m} = \frac{f_k + f_m(\delta + 2\eta - \rho)}{f_{mm}} - \frac{(\delta + 2\eta - \rho)}{f_{mm}}\left(\frac{g}{p}\right) - \frac{f_{mk}}{f_{mm}}(\dot{k}) \\ + \left(\frac{1}{f_{mm}}\right)\left(\frac{d_a f_{ak}}{(p(d_a f_{aa} - d_{aa} f_a) + s d_{aa})}\dot{k} - \frac{c}{p}\right)\end{aligned} \tag{4.38}$$

Similarly, distributing $-\frac{1}{pf_{aa} + \lambda_2 d_{aa}}$ in equation (36.2) produces

$$\dot{a} = -\frac{([d_a(\lambda_2(2\eta - \rho) - \delta\lambda_1)] + [pf_{ak}\dot{k}])d_a}{pd_a f_{aa} + d_{aa}(s - pf_a)} \tag{4.39}$$

Substituting $\lambda_1 = g - pf_m$ and $\lambda_2 = \frac{s - pf_a}{d_a}$ and collecting like terms

$$\dot{a} = \frac{\left(f_a d_a(2\eta - \rho) - {d_a}^2 \delta f_m\right)}{p(d_a f_{aa} - d_{aa} f_a) + s d_{aa}} p - \frac{d_a(2\eta - \rho)}{p(d_a f_{aa} - d_{aa} f_a) + s d_{aa}} s + \frac{{d_a}^2 \delta}{p(d_a f_{aa} - d_{aa} f_a) + s d_{aa}} g - \frac{d_a f_{ak}}{p(d_a f_{aa} - d_{aa} f_a) + s d_{aa}} p\dot{k} \tag{4.40}$$

$\dot{k}$ is straightforward,

$$\dot{k} = m - (\delta + \eta)k + \delta o \tag{4.41}$$

Full algebraic derivations are provided in Appendix 4.1.1.

In equation (4.38), the $\frac{1}{f_{mm}}$ term is estimated econometrically but requires knowing $\frac{d_a f_{ak}}{p(d_a f_{aa} - d_{aa} f_a) + s d_{aa}}$. While the unit costs p and s are likely to be known from underlying data, the various embedded partial derivatives and cross-partial derivatives of $d(\cdot)$ and $f(\cdot)$ are unknown. However, $\frac{d_a f_{ak}}{p(d_a f_{aa} - d_{aa} f_a) + s d_{aa}}$ is estimated directly in equation (4.40) using known data; that estimate can be applied in the estimation of equation (4.38).

To develop models that can be estimated econometrically, the continuous time paths are converted into discrete time where, generally, $\dot{G} = G_{t+1} - G_t = \Delta G$. In other words, the time paths are first-differenced. Therefore, the following three models are estimated econometrically

$$\Delta a = \tau_0 + \tau_1 p_t - \tau_2 s_t + \tau_3 g_t - \tau_4 (p_t \Delta k) + \epsilon_{1t} \tag{4.42}$$

$$\Delta m = \beta_0 + \beta_1 \frac{g_t}{p_t} - \beta_2 \Delta k + \beta_3 \left(\widehat{\tau_4} \Delta k - \frac{c_t}{p_t}\right) + \epsilon_{2t} \tag{4.43}$$

$$\Delta k = \gamma_0 + \gamma_1 m_t - \gamma_2 k_t + \gamma_3 o_t + \epsilon_{3t} \tag{4.44}$$

Table 4.7 describes signs that are expected for each estimated coefficient given variables used in the estimation as well as the underlying theory described by each coefficient.

In this case, the data variables for the Δa estimation are unit price, p_t, advertising cost, s_t, infrastructure investment cost, g_t, and the change in capacity multiplied by price, $p_t \Delta k$. With regard to the Δm estimation, data variables include the infrastructure investment price ratio, $\frac{g_t}{p_t}$, the change in capacity, Δk, and the negative of the sum of capacity change times the appropriate estimated parameter from the Δa estimation plus the capital repair cost to price ratio, $-\left(\widehat{\tau_4} \Delta k - \frac{c_t}{p_t}\right)$. For the Δk estimation, the data variables include the levels at each point in time for infrastructure investment, m_t, capacity, k_t, and rebated technology, o_t. ϵ_{1t}, ϵ_{2t}, and ϵ_{3t} are model errors from the Δa, Δm, and Δk estimations, respectively. Signs on estimated coefficients can be compared against the column of expected signs to test for model consistency. However, in four cases, the expected signs are ambiguous. Contributing to the ambiguity is the fact that $2\eta - \rho$ and $\delta + 2\eta - \rho$ could take on positive or negative values depending on the relative sizes of the respective elements. Additionally, because the underlying data and models were defined in per capita terms, population effects enter the model through τ_4, β_2, γ_1, γ_2, and γ_3. Capital effects come into the model via τ_4 and β_3. And policy effects enter from τ_2, τ_3, and β_1.

Table 4.7 Summary of coefficients, theory, variables, and expected signs

Model & Coefficients	Theory	Data Variable	Expected sign
For Δa estimation			
τ_0	0	$Constant$	$Null$
τ_1	$\frac{f_a d_a(2\eta-\rho)-{d_a}^2\delta f_m}{p(d_a f_{aa}-d_{aa}f_a)+sd_{aa}}$	p	$Ambiguous$
τ_2	$-\frac{d_a(2\eta-\rho)}{p(d_a f_{aa}-d_{aa}f_a)+sd_{aa}}$	s	$Ambiguous$
τ_3	$\frac{{d_a}^2\delta}{p(d_a f_{aa}-d_{aa}f_a)+sd_{aa}}$	g	$-$
τ_4	$-\frac{d_a f_{ak}}{p(d_a f_{aa}-d_{aa}f_a)+sd_{aa}}$	$p\Delta k$	$-$
For Δm estimation			
β_0	$\frac{f_k+f_m(\delta+2\eta-\rho)}{f_{mm}}$	$Constant$	$Ambiguous$
β_1	$-\frac{(\delta+2\eta-\rho)}{f_{mm}}$	$\frac{g}{p}$	$Ambiguous$
β_2	$-\frac{f_{mk}}{f_{mm}}$	Δk	$-$
β_3	$\frac{1}{f_{mm}}$	$-\left(\widehat{\tau_4}\Delta k+\frac{c}{p}\right)$	$-$
For Δk estimation			
γ_0	0	$Constant$	$Null$
γ_1	1	k	$+$
γ_2	$-(\delta+\eta)$	m	$-$
γ_3	δ	o	$+$

Because there are multiple equations to be estimated and because they are likely to be related either directly or through their error structure, proper estimation suggests the use of simultaneous estimation or seemingly unrelated regression techniques as well as the integration of additional model controls. In order to commence estimation, data are needed for each variable and Hansen (2009) provides some direction with regard to this analysis; however, the inclusion of advertising makes estimation challenging. In order to estimate the proposed models, advertising budgets and advertising unit costs would need to be collected.

4.6 Conclusions

The act of advertising is costly to a profit maximizing business or entity. However, while advertising is typically done for the purpose of encouraging the purchase of the product or service that the entity sells, and effectively shifting the demand curve rightward, utility-level advertising for water-saving technology does the opposite: it reduces the demand for the product that it sells. The fact that this activity increases a utility's cost and reduces demand for the product it sells operates to make the rationale for the activity unclear at least on the surface, especially in the case of a profit maximizing private utility. One justification that is often given is that by encouraging the purchase of water-saving technology, the utility can put off infrastructure investment and repairs. To investigate this claim, a capital accumulation framework is utilized that illustrates the conditions that must be present for this type investment.

A key result from this analysis is that the optimal path for each investment type depends on the other. This is immediately apparent from equations (4.31) and (4.32), as $\dot{a}$ is a function of $\dot{m}$ and vice-versa. In addition, after substituting to find the optimal paths and simplifying (equations (4.35.1) and (4.36.3)), it is clear that each path contains the same capital accumulation term: $p\left[\frac{f_{ak}}{pf_{aa}+\lambda_2 d_{aa}}\right]\dot{k}$. Furthermore, in the $\dot{m}$ path, that term is positive and in the $\dot{a}$ path it is negative, implying that there is an inverse relationship between the two paths and suggesting that there are tradeoffs between investment types. Additionally, supporting this conclusion is that embedded in both paths are λ_1 and λ_2, which are essentially the marginal values (or option values) associated with both investment types. Therefore, in order to assure that the optimal paths are reached, it is critical to not only consider how that investment compares against the benefits of repairs, but also how one investment type impacts the other.

One element that is not included in the model is utility payment for qualifying rebated technology. This analysis essentially assumed that the cost to the utility was zero; however, because the utility subsidizes the purchase, the cost to the utility should be included. This assumption was used for simplicity as adding another element to the model significantly increases its complexity and reduces its ability to be easily understood. Future work could be done to add this element. In addition, the simplifying assumption that the cross partial derivative of production with respect to advertising and direct investment is equal to zero (i.e. $f_{am} = 0$) was employed to facilitate the qualitative signing analysis. In a future investigation, this assumption could be relaxed.

While the analytical model and qualitative results provide some insight into when a utility should invest in infrastructure or advertising, they provide no assistance with regard to determining whether the model accurately describes the utility decision. Therefore, empirical models were developed which, assuming the availability of appropriate data, can be compared against expected outcomes. While the empirical methodology will likely require estimation by a system or a similar method, the inclusion of various controls, and the testing of various model specifications, the necessary data are not currently available. Specifically, although Hansen (2009) provides insight into some data that could be used to estimate the models, the current unavailability of advertising costs and budget data, rebate uptake data (or how advertising translates into purchases), and rebated water-saving technology stock data make estimation impossible. Future work could be devoted to attempting to collect or estimate this data and simulation methodology may be employed for certain variables.

Appendix 4.1 Detailed Mathematical Appendix

Appendix 4.1.1: Developing time paths

Take the time derivative of equation (4.27) to produce equation (4.30),

$$\lambda_2 d_a = s - pf_a \tag{4.27}$$

$$\dot{\lambda}_2 d_a + \lambda_2 d_{aa}\dot{a} = -p\left(f_{ak}\dot{k} + f_{am}\dot{m} + f_{aa}\dot{a}\right)$$

$$\dot{\lambda}_2 d_a = -p\left(f_{ak}\dot{k} + f_{am}\dot{m} + f_{aa}\dot{a}\right) - \lambda_2 d_{aa}\dot{a}$$

$$\dot{\lambda}_2 d_a = -p\left(f_{ak}\dot{k} + f_{am}\dot{m}\right) - pf_{aa}\dot{a} - \lambda_2 d_{aa}\dot{a}$$

$$\dot{\lambda}_2 d_a = -p\left(f_{ak}\dot{k} + f_{am}\dot{m}\right) - \dot{a}(pf_{aa} + \lambda_2 d_{aa})$$

$$\dot{\lambda}_2 = -\frac{p\left(f_{ak}\dot{k} + f_{am}\dot{m}\right) + \dot{a}(pf_{aa} + \lambda_2 d_{aa})}{d_a} \tag{4.30}$$

Set equation (4.22) equal to equation (4.28) and solve for $\dot{m}$ to produce equation (4.32)

$$\dot{\lambda}_1 = -pf_k + c + \lambda_1(\delta + 2\eta - \rho) \tag{4.22}$$

$$\dot{\lambda}_1 = -p\left(f_{mk}\dot{k} + f_{mm}\dot{m} + f_{ma}\dot{a}\right) \tag{4.29}$$

$$-p\left(f_{mk}\dot{k} + f_{mm}\dot{m} + f_{ma}\dot{a}\right) = pf_k + c + \lambda_1(\delta + 2\eta - \rho)$$

$$-pf_{mk}\dot{k} - pf_{mm}\dot{m} - pf_{ma}\dot{a} = -pf_k + c + \lambda_1(\delta + 2\eta - \rho)$$

$$pf_k - pf_{mk}\dot{k} - pf_{ma}\dot{a} - c - \lambda_1(\delta + 2\eta - \rho) = pf_{mm}\dot{m}$$

$$pf_{mm}\dot{m} = pf_k - pf_{mk}\dot{k} - pf_{ma}\dot{a} - c - \lambda_1(\delta + 2\eta - \rho)$$

$$\dot{m} = \frac{1}{pf_{mm}}\left[pf_k - pf_{mk}\dot{k} - pf_{ma}\dot{a} - c - \lambda_1(\delta + 2\eta - \rho)\right]$$

$$\dot{m} = -\frac{1}{pf_{mm}}\left[c - pf_k + pf_{mk}\dot{k} + pf_{ma}\dot{a} + \lambda_1(\delta + 2\eta - \rho)\right]$$

$$\dot{m} = -\frac{1}{pf_{mm}}\Big[c - pf_k + pf_{mk}\big(m - (\delta + \eta)(k - o)\big) + pf_{ma}\dot{a}$$
$$+ \lambda_1(\delta + 2\eta - \rho)\Big]$$

$$\dot{m} = -\frac{1}{pf_{mm}}\left[c - pf_k + pf_{mk}\big(m - (\delta+\eta)(k-o)\big) + \lambda_1(\delta + 2\eta - \rho)\right]$$

$$-\frac{1}{pf_{mm}} pf_{ma}\dot{a}$$

$$\dot{m} = \frac{[pf_k - c] + [(\delta + 2\eta - \rho)(pf_m - g)] - \left[pf_{mk}\dot{k}\right]}{pf_{mm}} - \frac{f_{ma}}{f_{mm}}\dot{a} \qquad (4.32)$$

Set equation (4.23) equal to equation (4.30) and solve for $\dot{m}$ to produce equation (4.31)

$$\dot{\lambda}_2 = \lambda_2(2\eta - \rho) - \delta\lambda_1 \qquad (4.23)$$

$$\dot{\lambda}_2 = -\frac{p\big(f_{ak}\dot{k} + f_{am}\dot{m}\big) + \dot{a}(pf_{aa} + \lambda_2 d_{aa})}{d_a} \qquad (4.30)$$

$$\lambda_2(2\eta - \rho) - \delta\lambda_1 = -\frac{p\big(f_{ak}\dot{k} + f_{am}\dot{m}\big) + \dot{a}(pf_{aa} + \lambda_2 d_{aa})}{d_a}$$

$$d_a(\lambda_2(2\eta - \rho) - \delta\lambda_1) = -\Big(p\big(f_{ak}\dot{k} + f_{am}\dot{m}\big) + \dot{a}(pf_{aa} + \lambda_2 d_{aa})\Big)$$

$$\dot{a}(pf_{aa} + \lambda_2 d_{aa}) = -p\big(f_{ak}\dot{k} + f_{am}\dot{m}\big) - d_a(\lambda_2(2\eta - \rho) - \delta\lambda_1)$$

$$\dot{a} = -\frac{p\big(f_{ak}\dot{k} + f_{am}\dot{m}\big) + d_a(\lambda_2(2\eta - \rho) - \delta\lambda_1)}{(pf_{aa} + \lambda_2 d_{aa})}$$

$$\dot{a} = -\frac{pf_{ak}\dot{k} + pf_{am}\dot{m} + d_a(\lambda_2(2\eta - \rho) - \delta\lambda_1)}{(pf_{aa} + \lambda_2 d_{aa})} -$$

$$\dot{a} = -\frac{d_a(\lambda_2(2\eta - \rho) - \delta\lambda_1) + pf_{ak}\dot{k}}{(pf_{aa} + \lambda_2 d_{aa})} - \frac{pf_{am}}{(pf_{aa} + \lambda_2 d_{aa})}\dot{m} \qquad (4.31)$$

Substitute equation (4.31) into equation (4.32) to produce equation (4.33)

$$\dot{m} = \frac{[pf_k - c] + [(\delta + 2\eta - \rho)(pf_m - g)] - \left[pf_{mk}\dot{k}\right]}{pf_{mm}} - \frac{f_{ma}}{f_{mm}}\dot{a} \qquad (4.32)$$

$$\dot{m} = \frac{[pf_k - c] - [\lambda_1(\delta + 2\eta - \rho)] - [pf_{mk}\dot{k}]}{pf_{mm}} + \frac{f_{ma}}{f_{mm}}\left(\frac{d_a(\lambda_2(2\eta - \rho) - \delta\lambda_1) + pf_{ak}\dot{k}}{(pf_{aa} + \lambda_2 d_{aa})} + \frac{pf_{am}}{(pf_{aa} + \lambda_2 d_{aa})}\dot{m}\right)$$

$$\dot{m} = \frac{[pf_k - c] - [\lambda_1(\delta + 2\eta - \rho)] - [pf_{mk}\dot{k}]}{pf_{mm}} + \frac{f_{ma}}{f_{mm}}\left(\frac{d_a(\lambda_2(2\eta - \rho) - \delta\lambda_1) + pf_{ak}\dot{k}}{(pf_{aa} + \lambda_2 d_{aa})}\right) + \frac{{f_{am}}^2}{f_{mm}(pf_{aa} + \lambda_2 d_{aa})}\dot{m}$$

$$\dot{m} - \frac{{f_{am}}^2}{f_{mm}(pf_{aa} + \lambda_2 d_{aa})}\dot{m} = \frac{[pf_k - c] - [\lambda_1(\delta + 2\eta - \rho)] - [pf_{mk}\dot{k}]}{pf_{mm}} + \frac{f_{ma}}{f_{mm}}\left(\frac{d_a(\lambda_2(2\eta - \rho) - \delta\lambda_1) + pf_{ak}\dot{k}}{(pf_{aa} + \lambda_2 d_{aa})}\right)$$

$$\dot{m}\left(\frac{f_{mm}(pf_{aa} + \lambda_2 d_{aa}) - {f_{am}}^2}{f_{mm}(pf_{aa} + \lambda_2 d_{aa})}\right) = \frac{[pf_k - c] - [\lambda_1(\delta + 2\eta - \rho)] - [pf_{mk}\dot{k}]}{pf_{mm}} + \frac{f_{ma}}{f_{mm}}\left(\frac{d_a(\lambda_2(2\eta - \rho) - \delta\lambda_1) + pf_{ak}\dot{k}}{(pf_{aa} + \lambda_2 d_{aa})}\right)$$

$$\dot{m} = \frac{(pf_{aa} + \lambda_2 d_{aa})}{p\left(f_{mm}(pf_{aa} + \lambda_2 d_{aa}) - {f_{am}}^2\right)}\left([pf_k - c] - [\lambda_1(\delta + 2\eta - \rho)] - [pf_{mk}\dot{k}] + \frac{pf_{am}\left(d_a(\lambda_2(2\eta - \rho) - \delta\lambda_1) + pf_{ak}\dot{k}\right)}{(pf_{aa} + \lambda_2 d_{aa})}\right) \tag{4.33}$$

Substitute equation (4.33) into equation (4.31) to produce equation (4.34)

$$\dot{a} = -\frac{d_a(\lambda_2(2\eta-\rho)-\delta\lambda_1)+pf_{ak}\dot{k}}{(pf_{aa}+\lambda_2 d_{aa})} - \frac{pf_{am}}{(pf_{aa}+\lambda_2 d_{aa})}\dot{m} \tag{4.31}$$

$$\begin{aligned}\dot{a} = &-\frac{d_a(\lambda_2(2\eta-\rho)-\delta\lambda_1)+pf_{ak}\dot{k}}{(pf_{aa}+\lambda_2 d_{aa})} \\ &- \frac{pf_{am}}{(pf_{aa}+\lambda_2 d_{aa})}\left(\frac{(pf_{aa}+\lambda_2 d_{aa})}{p\left(f_{mm}(pf_{aa}+\lambda_2 d_{aa})-f_{am}{}^2\right)}\left([pf_k\right.\right. \\ &- c] - [\lambda_1(\delta+2\eta-\rho)] - \left[pf_{mk}\dot{k}\right] \\ &\left.\left.+ \frac{pf_{am}\left(d_a(\lambda_2(2\eta-\rho)-\delta\lambda_1)+pf_{ak}\dot{k}\right)}{(pf_{aa}+\lambda_2 d_{aa})}\right)\right)\end{aligned}$$

$$\begin{aligned}\dot{a} = -\Bigg[&\frac{d_a(\lambda_2(2\eta-\rho)-\delta\lambda_1)+pf_{ak}\dot{k}}{(pf_{aa}+\lambda_2 d_{aa})} \\ &+ \frac{f_{am}}{\left(f_{mm}(pf_{aa}+\lambda_2 d_{aa})-f_{am}{}^2\right)}\Bigg([pf_k - c] \\ &- [\lambda_1(\delta+2\eta-\rho)] - \left[pf_{mk}\dot{k}\right] \\ &+ \frac{pf_{am}\left(d_a(\lambda_2(2\eta-\rho)-\delta\lambda_1)+pf_{ak}\dot{k}\right)}{(pf_{aa}+\lambda_2 d_{aa})}\Bigg)\Bigg]\end{aligned} \tag{4.34}$$

Appendix 4.1.2: Developing empirical models

To develop testable empirical models, substitute for λ_1 and λ_2 and collect terms for variables for which data are likely to be available. To derive the empirical model for $\dot{m}$, begin with equation (4.35.2).

$$\dot{m} = \frac{1}{pf_{mm}}\left([pf_k - c] - [\lambda_1(\delta + 2\eta - \rho)] - \left[\frac{f_{mk}(pf_{aa} + \lambda_2 d_{aa}) - f_{ak}}{(pf_{aa} + \lambda_2 d_{aa})}\right]p\dot{k}\right) \tag{4.35.2}$$

$$\dot{m} = \left(\frac{[pf_k - c] - [\lambda_1(\delta + 2\eta - \rho)]}{pf_{mm}} - \frac{f_{mk}\dot{k}}{f_{mm}} + \frac{f_{ak}\dot{k}}{f_{mm}(pf_{aa} + \lambda_2 d_{aa})}\right)$$

$$\dot{m} = \left(\frac{[pf_k - c] - [\lambda_1(\delta + 2\eta - \rho)]}{pf_{mm}} + \left(-\frac{f_{mk}}{f_{mm}} + \frac{f_{ak}}{f_{mm}(pf_{aa} + \lambda_2 d_{aa})}\right)\dot{k}\right)$$

$$\dot{m} = \left(\frac{[pf_k - c] - [\lambda_1(\delta + 2\eta - \rho)]}{pf_{mm}} + \left(-\frac{f_{mk}}{f_{mm}} + \frac{f_{ak}}{f_{mm}(pf_{aa} + \lambda_2 d_{aa})}\right)\dot{k}\right)$$

$$\dot{m} = \frac{[pf_k - c]}{pf_{mm}} - \frac{[\lambda_1(\delta + 2\eta - \rho)]}{pf_{mm}} + \left(\frac{f_{ak} - (pf_{aa} + \lambda_2 d_{aa})f_{mk}}{f_{mm}(pf_{aa} + \lambda_2 d_{aa})}\right)\dot{k}$$

$$\dot{m} = \frac{f_k}{f_{mm}} - \frac{1}{f_{mm}}\frac{c}{p} + \frac{f_m(\delta + 2\eta - \rho)}{f_{mm}} - \frac{g(\delta + 2\eta - \rho)}{pf_{mm}} + \left(\frac{f_{ak} - (pf_{aa} + \lambda_2 d_{aa})f_{mk}}{f_{mm}(pf_{aa} + \lambda_2 d_{aa})}\right)\dot{k}$$

$$\dot{m} = \frac{f_k}{f_{mm}} - \frac{1}{f_{mm}}\frac{c}{p} + \frac{f_m(\delta + 2\eta - \rho)}{f_{mm}} - \frac{g(\delta + 2\eta - \rho)}{pf_{mm}}$$

$$+ \left(\frac{f_{ak} - (pf_{aa} + \lambda_2 d_{aa})f_{mk}}{f_{mm}(pf_{aa} + \lambda_2 d_{aa})}\right)\dot{k}$$

$$\dot{m} = \frac{f_k + f_m(\delta + 2\eta - \rho)}{f_{mm}} - \frac{1}{f_{mm}}\frac{c}{p} - \frac{(\delta + 2\eta - \rho)}{f_{mm}}\frac{g}{p}$$

$$+ \left(\frac{f_{ak} - (pf_{aa} + \lambda_2 d_{aa})f_{mk}}{f_{mm}(pf_{aa} + \lambda_2 d_{aa})}\right)\dot{k}$$

$$\dot{m} = \frac{f_k + f_m(\delta + 2\eta - \rho)}{f_{mm}} - \frac{1}{f_{mm}}\frac{c}{p} - \frac{(\delta + 2\eta - \rho)}{f_{mm}}\frac{g}{p} - \frac{f_{mk}}{f_{mm}}\dot{k}$$

$$+ \left(\frac{d_a f_{ak}}{f_{mm}\big(pd_a f_{aa} + d_{aa}(s - pf_a)\big)}\right)\dot{k}$$

$$\dot{m} = \frac{f_k + f_m(\delta + 2\eta - \rho)}{f_{mm}} - \frac{1}{f_{mm}}\frac{c}{p} - \frac{(\delta + 2\eta - \rho)}{f_{mm}}\frac{g}{p} - \frac{f_{mk}}{f_{mm}}\dot{k}$$

$$+ \left(\frac{d_a f_{ak}}{f_{mm}(pd_a f_{aa} + sd_{aa} - d_{aa}pf_a)}\right)\dot{k}$$

$$\dot{m} = \frac{f_k + f_m(\delta + 2\eta - \rho)}{f_{mm}} - \frac{1}{f_{mm}}\frac{c}{p} - \frac{(\delta + 2\eta - \rho)}{f_{mm}}\frac{g}{p} - \frac{f_{mk}}{f_{mm}}\dot{k}$$

$$+ \left(\frac{d_a f_{ak}}{f_{mm}(pd_a f_{aa} - d_{aa}pf_a + sd_{aa})}\right)\dot{k}$$

$$\dot{m} = \frac{f_k + f_m(\delta + 2\eta - \rho)}{f_{mm}} - \frac{1}{f_{mm}}\frac{c}{p} - \frac{(\delta + 2\eta - \rho)}{f_{mm}}\frac{g}{p} - \frac{f_{mk}}{f_{mm}}\dot{k}$$

$$+ \left(\frac{1}{f_{mm}}\right)\frac{d_a f_{ak}}{(p(d_a f_{aa} - d_{aa}f_a) + sd_{aa})}\dot{k}$$

$$\dot{m} = \frac{f_k + f_m(\delta + 2\eta - \rho)}{f_{mm}} - \frac{(\delta + 2\eta - \rho)}{f_{mm}}\left(\frac{g}{p}\right) - \frac{f_{mk}}{f_{mm}}(\dot{k})$$

$$+ \left(\frac{1}{f_{mm}}\right)\left(\frac{d_a f_{ak}}{(p(d_a f_{aa} - d_{aa} f_a) + s d_{aa})}\dot{k} - \frac{c}{p}\right) \tag{4.38}$$

Equation (4.38) can now be converted into equation (4.43),

$$\Delta m = \beta_0 + \beta_1 \frac{g}{p} - \beta_2 \Delta k + \beta_3 \left(\widehat{\alpha_4} \Delta k - \frac{c}{p}\right) + \epsilon_2 \tag{4.43}$$

To derive the empirical model for $\dot{a}$, begin with equation (4.36.2).

$$\dot{a} = -\left(\frac{d_a(\lambda_2(2\eta - \rho) - \delta\lambda_1)}{p f_{aa} + \lambda_2 d_{aa}} + p\left[\frac{f_{ak}}{p f_{aa} + \lambda_2 d_{aa}}\right]\dot{k}\right) \tag{4.36.2}$$

$$\dot{a} = -\frac{\left(\left[d_a\left(\frac{(s - p f_a)}{d_a}(2\eta - \rho) - \delta(g - p f_m)\right)\right] + \left[p f_{ak}\dot{k}\right]\right) d_a}{p d_a f_{aa} + d_{aa}(s - p f_a)}$$

$$\dot{a} = \frac{(p f_a - s)(2\eta - \rho) d_a + {d_a}^2 \delta(g - p f_m) - d_a\left[p f_{ak}\dot{k}\right]}{p d_a f_{aa} + d_{aa}(s - p f_a)}$$

$$\dot{a} = \frac{p\left(f_a d_a(2\eta - \rho) - {d_a}^2 \delta f_m\right) - s d_a(2\eta - \rho) + g {d_a}^2 \delta - d_a\left[p f_{ak}\dot{k}\right]}{p d_a f_{aa} + d_{aa}(s - p f_a)}$$

$$\dot{a} = \frac{\left(f_a d_a(2\eta - \rho) - {d_a}^2 \delta f_m\right)}{p(d_a f_{aa} - d_{aa} f_a) + s d_{aa}} p - \frac{d_a(2\eta - \rho)}{p(d_a f_{aa} - d_{aa} f_a) + s d_{aa}} s$$

$$+ \frac{{d_a}^2 \delta}{p(d_a f_{aa} - d_{aa} f_a) + s d_{aa}} g$$

$$- \frac{d_a f_{ak}}{p(d_a f_{aa} - d_{aa} f_a) + s d_{aa}} p\dot{k}$$

$$\dot{a} = \frac{\left(f_a d_a(2\eta - \rho) - {d_a}^2 \delta f_m\right)}{p(d_a f_{aa} - d_{aa} f_a) + s d_{aa}} p - \frac{{d_a}^2 \delta f_m}{p(d_a f_{aa} - d_{aa} f_a) + s d_{aa}} p\delta$$

$$- \frac{d_a(2\eta - \rho)}{p(d_a f_{aa} - d_{aa} f_a) + s d_{aa}} s$$

$$+ \frac{{d_a}^2 \delta}{p(d_a f_{aa} - d_{aa} f_a) + s d_{aa}} g$$

$$- \frac{d_a f_{ak}}{p(d_a f_{aa} - d_{aa} f_a) + s d_{aa}} p\dot{k}$$

$$\dot{a} = \frac{\left(f_a d_a(2\eta - \rho) - {d_a}^2 \delta f_m\right)}{p(d_a f_{aa} - d_{aa} f_a) + s d_{aa}} p - \frac{d_a(2\eta - \rho)}{p(d_a f_{aa} - d_{aa} f_a) + s d_{aa}} s$$

$$+ \frac{{d_a}^2 \delta}{p(d_a f_{aa} - d_{aa} f_a) + s d_{aa}} g \qquad (4.40)$$

$$- \frac{d_a f_{ak}}{p(d_a f_{aa} - d_{aa} f_a) + s d_{aa}} p\dot{k}$$

Equation (4.40) can now be converted into equation (4.42),

$$\Delta a = \alpha_0 + \alpha_1 p - \alpha_2 s + \alpha_3 g - \alpha_4 (p\Delta k) + \epsilon_1 \qquad (4.42)$$

The $\dot{k}$ equation is simple and is given directly by equation (4.24).

$$\dot{k} = m - (\delta + \eta)k - \delta o \qquad (4.24)$$

Equation (4.24) can now be converted into equation (4.44),

$$\Delta k = \gamma_0 + \gamma_1 m - \gamma_2 k + \gamma_3 o + \epsilon_3 \qquad (4.44)$$

Chapter 5: Conclusions and Future Work

Understanding water use trends and drivers of demand is important particularly in arid locations often subject to risks related to water shortage. This is especially true in areas such has the American West that generally have increasing populations and may experience serious disruptions from climate change and extreme weather events including severe drought. While supply augmentation is one way to manage shortage, due to possible legal, technical, environmental, and financial constraints, this dissertation focused instead on understanding the demand side. Focusing on demand is particularly attractive in this context because demand-side responses may be more flexible and are likely to operate more quickly to clear a shortage than supply enhancement.

Furthermore, the analysis presented in this dissertation provides qualitative and quantitative estimates of demand behavior via both utility action and exogenous stimuli. Results may be leveraged for planning purposes by a city or municipality. In any event, this dissertation argued that it is paramount to acquire a better understating of the drivers of demand to ensure that water resources are effectively managed.

While it is true that demand estimation has been undertaken many times, largely ignored in the literature are small cities and municipalities, so this dissertation made a concerted effort to focus on the small city experience; without additional evidence, it is unclear that demand estimation from large cities should be used as a proxy for the experience of small cities. Therefore, relatively small New Mexico cites such as Clovis, Rio Rancho, and Edgewood are highlighted (along with the large city Albuquerque) in Chapter 2, with specific attention to Clovis in Chapters 2 and 3. The analysis was broadened from the small city context to the non-specific context in Chapter 4 as the general optimizing behavior of a private utility engaging in a rebate program for water saving technology was investigated.

5.1 Key Results and General Conclusions

This dissertation demonstrated not only that demand is declining in the small set of New Mexico municipalities examined, but that key drivers of declining demand are price (rate increases)[27] and water-saving rebate programs. Specifically, Chapter 2 identified declining demand in all New Mexico municipalities studied (Albuquerque, Rio Rancho, Clovis, and Edgewood); this pattern is generally true for high and low volume users on a per premises basis, and perhaps more significantly, in terms of aggregate water use.

Aggregate declines may present two interrelated management challenges: first, most projections for aggregate demand call for increasing demand over the next few decades – despite generally declining demand over the last decade (or longer). However, if demand stays flat or continues to fall, the assumption of increasing demand may call for unnecessary costly overinvestment in infrastructure and supply enhancement. Second, all else equal, declining aggregate demand will lead to reduced revenues which will constrain a utility's financial ability to make necessary infrastructure investments and repairs. Due to these vulnerabilities, it is critical to develop a better qualitative understanding of the factors contributing to demand as well a better quantitative estimates of responsiveness to utility and non-utility stimuli (including rate changes, climate, etc.).

[27] However, it is important to reiterate the fact that the price-inelastic nature of municipal water dictates that price changes only have a modest impact on water use. In addition, elasticity heterogeneity with regard to group (e.g. low versus high water users, rebate program participants, etc.) highlights the value of deeper investigation into the various population cross-sections examined in this type of analysis.

Also found in this analysis were statistically significant breaks in trend, which were uncovered for the cities of Clovis for all users, and Rio Rancho for high volume users. Despite the generally declining trend in water demand in the city of Clovis, upward breaks appear to relate to severe drought conditions. This is interesting because, despite the fact that all municipalities experienced drought over their respective series, no other municipality exhibited sufficient climate sensitivity to induce a break in trend. The break observed in the Rio Rancho series is likely associated with the large rate increases experienced in the municipality and the associated reduction in demand from industrial users.

Focusing specifically on Clovis, an econometric model of demand was developed at the spatial scale of the entire city and compared against results from premises-level and US Census block group spatial scale estimations. That analysis confirmed that price and weather responses were not dissimilar to more disaggregated analysis. However, the estimation also uncovered estimation limitations at this spatial scale; in particular, premises-level inferences are at the very least imprecise, and at most impossible, when using highly aggregated data.

Due to the limitations discussed in Chapter 2 related to trying to understand premises-level response with city-level data, Chapter 3 investigated factors contributing to declining water demand in Clovis, New Mexico at the premises level. This approach allows for a detailed understanding of the effects of various demand-side factors. Key results indicate that rebate programs for landscaping changes and for the installation of water saving technology successfully reduce premises-level water use. Overall, after controlling for confounding factors such as temperature and precipitation, the installation of a rebated toilet reduced water use by an average of nearly 32 gallons per day, installation of a water saving washing machine reduced water use by an average of about 38 gallons per day, and an average household receiving a landscaping rebate saved 19 gallons per day. While it might be surprising that landscaping rebates save so little water, it is likely due to the fact that irrigation only takes place in part of the year; washing machines and toilets, on the other hand, are used year-round.

In addition, this analysis found that water demand is price inelastic at current prices in Clovis; however, elasticity varies depending on which data are studied, with data subsets based on rebate type experiencing different levels of (in)elasticity. Elasticity for the entire dataset, as well as those households that did not receive a rebate was estimated to be around -0.50. When the data is subset to only include premises that received toilet or washing machine rebates, price becomes relatively more inelastic; however, premises that received landscaping rebates, while still price inelastic, were much less so, indicating the relative ease at which premises can reduce their outdoor water consumption in the face of price increases.

Additionally, in an analysis of low, medium, and high water users, results suggest that low water users are both more price and income elastic than high water users (though still inelastic). Given the relatively higher income elasticity, it is likely the case that low volume water users have relatively lower incomes; however, that in concert with their increased price sensitivity possibly raises equity concerns that call for increased investigation by the utility and regulator prior to a new rate increase.

This analysis also confirmed that weather and climate plays an important role in influencing water demand at the premises level; as the temperature increases water use increases and as precipitation increases, water use declines. This result provides useful evidence of the relationship between climate and water use, which can be brought to bear in times of high temperature or low precipitation, such as the period from 2011 to 2014 when Clovis experienced prolonged drought. In addition, income variables show that water is a normal good – as income increases, water demand increases.

Although the cost to the utility of the washing machine rebate and the toilet rebate is the same (USD 150), toilet rebates are the most cost-effective rebate program of the three programs because of the relatively longer expected useful life of a new toilet compared to a new washing machine (25 years versus 12 years). This implies that toilet rebates should generally be prioritized before washing machine rebates and both should be prioritized before landscaping rebates. However, it is important to note that it is not uncommon for premises that received landscaping rebates to have already participated in other rebate programs. So if a water user has a relatively high propensity to participate in rebate programs and they have already received a toilet or washing machine rebate, the landscaping rebate program may be the only way to significantly reduce that user's actual demand.

In addition, although data on the year each structure was built is not available, two separate analyses provided evidence that relatively newer construction used more water than older construction – this result was unexpected. In particular, the coefficient on the building permit variable in the underlying econometric estimation, which was used to proxy for new construction, was positive and statistically significant, indicating that as permits for new construction increases, water use also increased. This was confirmed by a subset analysis, which compared water use for premises that were on the utility's rolls in January 2006 with premises that entered the rolls during or after January 2009. In that case, estimated mean water use for the relatively new construction was higher than the old construction. However, estimated median use for the new construction was relatively lower than the old construction, implying the existence of outliers that operated to inflate the mean.

Given that rebates for water-saving technology effectively reduced demand in Clovis, Chapter 4 turned to investigating optimal investment by a water utility in the context of advertising (by the utility) for the installation of water-saving technology. While advertising is typically done for the purpose of encouraging the purchase of the product or service that the entity sells, and effectively shifting the demand curve rightward, utility-level advertising for water-saving technology does the opposite: it reduces the demand for the product that it sells. The fact that this activity increases an element of a utility's cost and reduces demand for the product it sells, operates to make the rationale for the activity unclear at least on the surface. To investigate a possible justification for this behavior, a capital accumulation framework is utilized.

A key result from this analysis is that the optimal path for each investment type (e.g. advertising investment and infrastructure investment) depends on the other and both impact the optimal repair behavior – in other words, the path of infrastructure investment depends on the path of advertising investment and vice-versa. Therefore, in order to ensure that the optimal paths are reached, it is critical to not only consider how investment compares against the benefits associate with repairs, but also how one investment type impacts the other. While the analytical model and qualitative results provide some insight into when a utility should invest in infrastructure or advertising, they provide no assistance with regard to determining whether the model accurately describes the utility decision. Therefore, empirical models are developed which, assuming the availability of appropriate data, can be compared against expected outcomes. While the empirical methodology will likely require estimation by a system or a similar method, the inclusion of various controls, and the testing of various model specifications, the necessary data are not yet available.

5.2 Discussion of Methodologies and Analytical Tools

This dissertation highlighted several analytical techniques that can be leveraged to better understand factors affecting water demand. Because the many techniques and empirical approaches are diverse, this section is designed to demonstrate how the various pieces may be used in concert to more broadly describe demand.

Chapter 2 utilized seasonal trend and breakpoint analysis which can help inform water demand analysis by stripping away seasonal noise in an effort to uncover trends in demand as well as systematic series breaks. Given the relatively light data requirements, these analyses can be useful in quickly identifying patterns or trends that can be qualitatively compared against known events. It is important to note that seasonal trend and breakpoint analysis provides only a preliminary approach to understanding demand; however, trends and qualitative analysis may be leveraged in the development of economic models and further econometric estimation. Also developed was a simple instrumental variable demand model (2SLS) that controlled for water price and weather conditions and produced estimation results for those variables that were not dissimilar to results from more disaggregated analysis.

However, the benefit of large scale estimation is limited; while it is possible to make some useful inferences regarding general water use, it is nearly impossible to develop more fine-tuned inferences. Therefore, Chapter 3 used premises-level data to investigate demand using a fixed effects instrumental variable model (FEIV). Analysis at a more refined geographic scale allows for estimation of effects at the premises-level, such as uptake in water-saving rebated technologies or landscaping changes. Results, such as elasticity estimates, responsiveness to weather or climate conditions, behavioral response to rebate programs, and the like, can be directly useful for setting more targeted policy. In addition, estimation results can be further leveraged to gain additional useful insight. For example estimated marginal effects of the rebate variables can be used to estimate relative cost effectiveness of rebate programs per volumes of water conserved using techniques such as levelized cost analysis.

Both intuition and diagnostic testing suggested that water use may have spatial characteristics that require empirical correction; therefore, spatial panel econometric estimation was undertaken in Appendix 3.3. In particular, spatial lag and spatial error models were employed. Although spatial lag models appear to fit well, there may be little theoretical justification for spatial lag estimation in this context. This is especially true where premises are subject to similar exogenous factors such as climate and pricing. Furthermore, due to data constraints such as incomplete panels and high computational requirements in spatial panel estimation, the benefits may not outweigh the costs of losing the additional detail from a more fine-grained premises-level analysis. Nevertheless, if data are only available at relatively large geographic scales, testing and controlling for spatial effects, and particularly accounting for spatial error, is prudent.

Both Appendix 2.2 and Appendix 3.4 discussed in-sample and out-of-sample prediction using straightforward ordinary least squares (OLS) regression techniques. In the case of Appendix 2.2, the focus was on city-level econometric estimation using monthly price and climate data; that estimation offered a significant improvement over simple trend models. Appendix 3.4 focused on peak-day estimation. From the perspective of a water utility, ensuring adequate water supply each day is paramount; this includes the day of highest (or peak) demand during the year. While it is unclear from year to year what day the peak will occur, this appendix showed how it may be possible to predict the peak volume using lagged temperature and precipitation data, which is readily available to the water manager. Both of these appendices demonstrate that the inclusion of simple information and/or a few variables (e.g. price, temperature, precipitation, PDSI), it is possible to produce reasonably accurate predictions of water use.

Finally, an optimal control model was used in Chapter 4 that investigated optimal investment by a water utility. This technique is useful for first identifying the key elements of the utility's decision: this includes identifying what the utility is optimizing, what the utility is choosing, and quantifying additional key parameters. Uncovered are the various tradeoffs that are faced when the utility is attempting to make the optimal decision and it allows the analyst to infer whether a particular course of action is likely to place the utility on the optimal path. While the outcomes presented in the chapter are generally qualitative in nature, also developed is an econometric model along with expected signs for the parameters to be estimated. With appropriate data, this system may be estimated and coefficients can be compared to expected signs, which will provide evidence about whether a utility is behaving optimally.

5.3 Limitations and Future Work

It is important to note the limitations in this dissertation – some of which may be investigated in future work. As has already been discussed in the text, although it is possible to conduct rapid ad hoc analyses, the primary disadvantages of the seasonal trend and breakpoint analysis presented in Chapter 2 is that the model is both atheoretical and does not quantitatively tie the breaks and trends to exogenous events; in other words, it does not explicitly capture behavioral responses. Nevertheless, it does provide some information regarding the direction of the trend and timing of breaks, both of which can be leveraged when attempting to fit an econometric model. Additionally, the large spatial scales used (entire city) in the seasonal trend analysis as well as the econometric model in Chapter 2 do not allow for an accurate estimation of premises-level responses; rather, they provide a more general understanding of demand behavior for variables that are likely impacting all premises in a similar fashion. Therefore, Chapter 3 focused on the spatial scale of the individual premises (main text) and the US Census block group (Appendix 3.3).

In addition, the issue of declining demand discussed principally in Chapters 2 and 3 do not fully tackle certain aspects of premises characteristics including new construction and renovation. Although Chapter 3 attempts to model, or at least proxy for, new construction, the fact that new construction uses more water than old construction (on average) is puzzling and calls for a better understanding of individual building and premises characteristics for both existing and new premises. With more accurate information about property and building characteristics (such as property size, number of bathrooms, and the like), water use estimates can almost certainly be tightened.

Similarly, more fine-grained data regarding household characteristics could be employed to better control for inter-household differences. While Chapter 2 described demographic data generally and Chapter 3 used household income and household size as explanatory variables, the fact that a county-level spatial scale was employed in estimations make the results less robust. Better information about the residents of the households at a premises-level (or at least at a scale smaller than the county) can provide necessary variation required to produce stronger estimates. This, along with acquiring additional premises information, will likely require surveying and direct communication with occupants.

In addition, building upgrades, such as expansion (e.g. increase in the number of bathrooms), or such as pipe and plumbing replacement and new efficient building practices also likely play a role in reducing water demand, but were not estimated in this analysis. Having this information would be extremely useful as the fixed effects methodology used in Chapter 3 essentially assumes that building characteristics remain static throughout the analysis. And while the fixed effects treatment may be valid in general, it is almost certainly true that characteristics of at least some premises changed throughout the ten year timeframe. Similarly, although rebated technology certainly reduced water use, there are likely to be numerous premises that switched to low flow toilets and washing machines, and maybe even engaged in landscaping changes, but did not avail themselves of the benefits of the rebate program. Therefore the signals corresponding to installation of a low flow device or landscaping change may be somewhat muted.

Controlling for other factors such as vegetation and drought indices appears (in this case) to only provide marginal analytic benefit – at least in terms of the premises-level analysis presented in Chapter 3 (although drought indices provided a tighter model fit in the simple estimations in Appendix 2.2). The marginal benefit is not surprising given that those variables were correlated with the more straightforward temperature and precipitation variables. Also, the vegetation variable presented in Chapter 3, suffered from a relatively shorter time series (8 years versus 10 years) and also because the data were annual in nature. Nevertheless, I do not believe that this conclusion is the end of the investigation with regard to trying to understand vegetation and water demand; a longer time series in concert with more frequent readings (and perhaps even finer spatial scale) could help to better explain water use going forward.

Also with regard to the issue of spatial scale is the spatial analysis conducted in Appendix 3.3. In that section, spatial panel econometric techniques were employed at the spatial scale of the US Census block group. The major conclusion was that premises-level data and analysis are likely preferable if they are available due to estimation challenges and the current requirement of balanced panels – even despite the likely presence of spatial effects (and in particular spatial error). However, it is likely that the frontier for this type of estimation will move forward and allow for more robust techniques taking advantage of the spatial dependencies apparently inherent in water demand.

Changes to preferences, or an increasing desire of the population to conserve, may also play a role in declining demand. Future work could include an assessment of some of those factors. For example, panel or repeated cross section surveying methods may be used to uncover true household-level responses. In addition, improved accuracy with regard to spatial scale, especially with regard to vegetation, could better pinpoint landscaping changes and its impact on water use.

Finally, and with specific regard to Chapter 4, an element that is not included in the optimal control model of utility investment is utility payment for qualifying rebated technology. Rather, the model assumes that the utility engages in advertising but it does not subsidize the purchase of low flow technologies. In other words, that analysis assumed that the cost to the utility was zero; however, because the utility subsidizes the purchase, the cost to the utility should be included. This assumption was incorporated for simplicity as adding another element to the model significantly increases its complexity and reduces its ability to be easily understood. A natural addition to the model would be to include the cost to the utility for subsidizing the purchase of new technology. In addition, although econometric models were developed in that chapter and expected signs were hypothesized, actual estimation was not undertaken. Therefore, this chapter could be pushed ahead through data collection and model estimation. An alternative approach would be to develop model simulations or phase diagrams based on the solved time paths which could be leveraged to better understand the dynamic nature of utility choice and response.

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