Community Water Demand in Texas

as a Century is Turned

by

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Executive Summary

The central contribution of this work is to assemble necessary Texas data and use this data to statistically estimate demand functions pertaining to water use in Texas communities. These functions quantify how per capita daily water use responds to primary determinants such as climate, weather, income, and water rates. The period of analysis is the most recent five years for which data is available, 1999-2003. The targeted sample is all Texas utilities serving a population of at least 1,000 people. Of the more than 1,400 utilities satisfying initial selection criteria, slightly more than half are represented in the final dataset compiled with this study.

Except for water rates, all data used here is derived from secondary sources. Water use and population data originate from the annual reports Texas utilities make to the Texas Water Development Board, and this data is subsequently processed by TWDB analysts to improve consistency and accuracy. Water use data is monthly, so there are potentially 60 observations in this five-year period for each water utility. Weather data is provided by the National Weather Service network; data from 141 Texas weather stations are used. These records include daily observations on minimum and maximum temperature as well as precipitation for the five-year study period. Income information is developed from county-level data generated by the U.S. Bureau of Economic Analysis.

Water rate data is obtained though an original survey of the 1,406 candidate water systems. All pertinent aspects of water and wastewater rates were sought with this mailed survey. Rate elements include recurring nonvolumetric charges, block definitions, block rates, preset seasonal variations, and wastewater winter averaging. For each surveyed system, 1999-2003 rates are collected by this survey.

Once all data elements are combined and erroneous anomalies are corrected or discarded, the final dataset contains more than 39,000 observations from 730 utilities. Implicitly, this data captures the relationships between water use decisions made by average utility clients and a few important aspects of the wide array of physical and economic conditions occurring in Texas. Within this data is ample evidence that consumers respond to multiple stimuli in making their consumption conditions. In this way, water is similar to other commodities and goods selected by households. That is, households have limited incomes to spread across a broad set of products and desires, so when households choose to consume water – and choose the amount of water – they are naturally attentive to their personal circumstances. The overall goal here is to gain better understanding of how some of these conditions "drive" our communities' water use decisions. By emphasizing a formal, quantitative approach to this question, better foundations can be developed for several important kinds of project and policy analysis. Among potential uses of these results are the projection of economic benefits for projects that alleviate water supply constraints and the analysis of long-term responses to water rate modifications.

After selected elements of the dataset are individually characterized to extract general facts about the nature of community water use in Texas, regression methods are applied to quantify the intrinsic relationships maintained between water use and its drivers. Statistical models are formulated and estimated. Parameterization of a nonlinear functional form known as the generalized Cobb-Douglas (GCD) function is the emphasis of this work. The chosen dependent variable for this function is gallons per capita per day. This choice interfaces well with many types of water planning analysis that have population projections or growth rates at their disposal.

The investigated independent (driver) variables are (1) long-term rainfall (30-year monthly averages in the locale), (2) a short-term weather composite accounting for local temperature and rainfall, (3) income, (4) water price, and (5) whether or not the utility provides wastewater collection and treatment services. Using these variables, many variants of the GCD functional form are estimated using ordinary least squares. These variants pertain to alternative subsets of the 39,000-observation subsets such as only January data or only water plus wastewater utilities. The purpose of these alternative inspections is to subjectively gauge model stability and reliability.

For cross-sectional data, the overall quality of model performance is very good. All driver variables are demonstrated to have significant influences on water consumption. The only potentially disclosed weakness involves the performance of the income driver, and only in a particular data subset. Because income data is limited to county-level data, which may not match well with each utility operating within a given county, it is not surprising that this variable does not perform as well as the others.

Perhaps the most interesting finding is that water price is a strong and very consistent driver of water use within the State. As expected, when price rises (and nothing else changes), water consumption decreases. The actual quantitative linkage between price and consumption is reported as "elasticity" numbers, as is done for all other continuously valued drivers in this study. Price elasticities discovered here range from –0.4 to –0.8, depending on service type (water plus wastewater or only water), month, and data subset. Very clear and uniform results pertaining to the seasonality of price elasticity are also apparent, as households are more responsive to summer prices. Water use is also more responsive to price in the rural and urban fringe utilities which do not provide wastewater collection and treatment services.

Overall, demand responses to historical precipitation (R) are mildly negative. Hence, locales that are accustomed to drier weather tend to use more water, but not markedly more. There are additional indications that the driest communities may actually increase water use if they were to experience a shift towards permanently wetter weather. An explanation for this phenomena is that wetter weather can encourage shifts in the water-using durables held by consumers. That is, wetter weather can encourage a shift to lawns and landscapes which are more water intensive. Similarly, permanent shifts to drier weather may evoke long-term responses in the direction of reduced commitments to outdoor water use. Thus, it would seem that consumers in more arid regions make progressively greater adaptations to their climate conditions. The fact that consumers make such changes is additional evidence of the controllability of water use. It even indicates where things may progress should rising scarcity greatly increase water rates.

The study also tabulates numerous elasticity findings for the several examined exogenous variables, and the coefficients estimated for individual models are tabulated as well. To aid application of these findings, early portions of the report provide context by discussing some of the most compelling options for using this information.

As readers interpret these results, it should be acknowledged that these findings cast doubt on attempts to criticize consumers in a particular locale for their high water use or even to praise consumers in other areas for their low water use. The range of climatic conditions and water scarcities are disparate within a state as diverse as Texas, but all consumers are simply responding to their individual circumstances when they make water use decisions. Only a few indices of these conditions are incorporated in the analysis reported here, yet it is very apparent that these variables do drive water use decisions.

From a conservation policy perspective, water rates are intriguing for their role in signaling water scarcity to consumers, which is one motivation for their inclusion in this research. Indeed, a principle underlying this type of research is that regulatory efforts to standardize (or minimize) community water use are misguided. Water use generates net benefits for consumers, and preservation/maximization of these net benefits is a more compelling goal than simply reducing water use regardless of benefit and cost consequences. If water utilities throughout the state could establish water rates that incorporate the scarcity value of natural water, in addition to cost of service considerations, appropriate types of conservation activity will be promoted.

Because the data of this study is unique in its comprehensive collection of water rates, a final aspect of this study is to characterize the changing nature of these rates in Texas. The availability of a prior analysis using 1980's data makes it possible to compare 1980's data and its demand results to the data and results of this 2006 report. The results of two separate demand analyses, one using 1981-1985 data and the one reported here (1999-2003 data), are very comparable. Overall statistical results are similar. A noteworthy finding may be the rising responsiveness of demand to water and sewer rates. While the 1980's data also suggests that water demand is functionally dependent on rates, the more recent data indicates a higher degree of responsiveness. The likely cause is the rising levels of water and sewer rates. Both rate types have continued to grow at paces greater than that of inflation, thereby exacting greater impacts on household budgets. Over the 22-year period extending from 1981 to 2003, most marginal prices of water (at different consumption levels) have risen more than 2% annually after adjusting for inflation. Sewer rates have been rising at annual rates in the 4-5% range during the same period.

Acknowledgments

Many thanks are due to the utility staff throughout the State that made the important effort to respond to our rate survey and who also annually complete the TWDB water use survey. This information is a crucial element for enabling water research and advancing management.

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Chapter 1

Demand Applications and Research Overview

Despite the importance of water demand in modern water management activities, it remains misunderstood, both conceptually and empirically. The objectives of the research reported here emphasize an empirical approach to urban water demand in Texas. That is, the main tasks are to assemble recent data and to use this data to quantitatively estimate the water demands associated with households throughout the State. To establish a context for this work and thereby enable practitioners to make better use of it, the purposes of this introductory chapter are to (1) define water demand, (2) indicate some of the manners in which water demand information can be reasonably applied, and (3) describe some of the features of this report and how it is organized.

Interpreting "Water Demand"

The lay concept of "water demand" is that demand is appropriately described by a coefficient, such as 161 gallons per capita per day or 3.4 acre-feet per acre of irrigated rice annually. Unfortunately, "demand" information of this type has declining practicality in a world of growing water scarcity. Constant coefficients do not provide insight about the prospective responses of water use behavior to alternative conditions, especially rising scarcity. These coefficients typically arise from backward-looking historical conditions that are unlikely to be repeated as water scarcity intensifies. Nor do such coefficients relay usable information about the consumer-incurred costs of not meeting a targeted level of water use. This is important policy information to obtain. Supply-increasing water policies produce benefits that can be measured as the amount of costs they will alleviate for consumers[1], but only if cost measurement is based on lost benefits derived from a correct interpretation of demand.

For these reasons, water planners and managers are beginning to recognize water demand as a *function* describing the relationship between consumer behavior and demand's determining factors. In professional literature pertaining to water demand these factors are sometimes called drivers or exogenous variables. In the following equation the quantity of water is on the left-hand side and the various x terms are the drivers. W is expressed in ordinary units, such as gallons per capita per day, but it is not fixed except for its dependence on the x_i factors.

$$W = f(x_1, x_2, x_3, ...) + \mu \qquad [1.1]$$

f denotes the demand function in eq. [1.1]. The inclusion of a random error term, μ, reminds us that water use is not predictable with perfect accuracy, mainly because of many unaccounted-for determinants (omitted drivers) as well as measurement errors involving variables on both sides of this equality.

The demand function f may be linear in form, but it is typically nonlinear, inferring that linear representations are approximations at best. When demand information omits this functional

[1] Such "avoided cost" measurements should be based on lost "willingness-to-pay" as quantitatively revealed by water demand functions. Posing inefficient substitute actions or projects is an incorrect approach to benefit measurement.

relationship as the basic coefficients noted previously do (such as 161 gallons per capita per day), the resulting concept of demand is normally based on prior observations of "water use," "water consumption," or "the quantity of water demanded" that cannot be reliably expected to reoccur in the future. After all, rising water demand (upward-shifting urban demand functions) in the face of constant or declining water availability (such as groundwater depletion) implies that certain water use behaviors must be modified over time. How this behavior gets modified, or how it might be modified, can only be examined by estimating a functional portrayal of water demand, as in eq. [1.1].

Henceforth in this report and in contrast to typical state/regional planning documents, all references to "demand" are reserved for functional representations. Thus, it is not said that "water demand in 2002 across Texas communities ranged from 95 to 325 gallons per capita per day." Such statements must be phrased differently, as with "water use in 2002 across Texas communities ranged from 95 to 325 gallons per capita per day." Terms such as "use," "consumption," and the more cumbersome "quantity of water demanded" successfully indicate that the referenced quantities represent specific historical points from actual demand functions without indicating the full character of such functions.

Demand Excludes Supplyside Considerations

Another helpful distinction for understanding the notion of demand is to set aside factors that principally affect water supply. In the case of urban water demand, households are receiving treated and pressurized water for which they are commonly billed on the basis of metered water consumption. For such circumstances, water supply is what occurs on the utility's side of consumers' water meters.

Therefore, in addition to the physical availability of water – how much water is in the streams, reservoirs, and aquifers that are at a community's disposal – supplyside factors include infrastructural constraints and investments as well as the many activities a utility undertakes in transforming natural water into the retail water received by customers. In contemporary settings, supply-related determinants can also include water right holdings of various types as well as contract relationships with water wholesalers such as river authorities and water districts. All of these supplyside considerations interact to determine how much water consumers can have and how much it will cost them. Since physical and infrastructural limitations can be modified by sufficient infusions of money, this expanded portrayal of supply offers better realism than can be achieved when water supply is viewed as a purely hydrologic matter.

The economically informed notions of demand and supply offer many advantages for improving water management. By distinguishing between demand drivers and supply drivers, greater accuracy is obtained and a fuller range of management instruments is considered. The possibilities for performing policy analysis or project analysis are also enriched, as shall be noted in forthcoming sections of this chapter. Another advantage of the demand/supply delineation is to clarify the interdependent manner in which demand and supply interact to establish water use. In the majority of situations, consumers are free to consume as much water as they like as long as they pay their bills. Supplyside features are therefore signaled to consumers in the form of water rates. Urban water use scenarios are not properly construed as market situations however, given that there is a single seller that establishes rates in advance of projected consumption. Competition is necessarily absent, and rates are not resolved in a marketlike fashion.

An important contribution of the demand/supply separation is to establish an enriched thought-model for water management issues. Judging from the opinions one hears or reads in common media, the various human activities conducted in families, farms, and factories have water *needs* that must be satisfied using the water that is stored or flowing in our physical environment. One of the many problems associated with this notion is that there are many differences between the type of retail water that is consumed by people and the types of natural water that are found in waterways. These differences are quite variable across a state as diverse as Texas, and they must be bridged by utilities that make sizable expenditures to store, pump, transport, cool, clean, distribute, pressurize, and improve the reliability of naturally occurring water. However, when the notion of *need* is replaced with the notion of *demand*, many useful strategies for addressing water scarcity are realized. Similarly but not as dramatically, when exclusive emphasis upon *supply* as a physical phenomena is broadened to acknowledge the value-added transformations of producing retail water, a different and more realistic depiction of water issues and solutions is achieved.

Choosing Demand Drivers

The number of actual demand drivers (the x's of eq. [1.1]) is likely to form a very long list since there are many factors that may influence demand in great or small ways. The water demand literature recognizes that different households might differ in their water use for a wide array of reasons. Here is a partial listing for households in different locations.

number of occupants	weather
number of bathrooms	income
number and types of appliances	wealth
presence and size of swimming pool	property value
lot area	neighborhood characteristics
lawn species and condition	water and wastewater rates
manual versus automatic lawn irrigation	water quality
landscape vegetation types	traditions and culture
soil type	personal preferences

Empirical study of many of these differences requires "microdata", i.e. data that includes the water use records of different households as well as the differing driver levels of each household. For example, the effect of lot size on household water use can be studied if data on water use and lot size is available for a suitably large sample of households <u>and</u> the effect of other drivers can be controlled or is also measured for each household.

Although all of these demand factors may be interesting in specific planning settings, the extensive scale of the present study focuses on intercommunity comparisons. That is, we wish to better understand what factors distinguish communities from one another when it comes to water use. Because aggregate, community-level data is the appropriate basis for studies such as this one, it is not possible to simultaneously investigate micro-level drivers. The "short list" of demand drivers to be investigated here is advised jointly by prior literature, data availability, and the importance of uncovering certain relationships for water planning problems. Specifically, the crucial drivers include long-term and short-term weather pertaining to temperature and precipitation, income, and water and wastewater rates. Thus, this study attempts to estimate demand functions of the following generic form.

$$\frac{W}{cap} = f(\text{weather, income, rates}) + \mu \qquad [1.2]$$

where $\frac{W}{cap}$ is a community's average monthly water use per capita,

weather may be one or more temperature and precipitation measures or may be indices formed from temperature and precipitation measures,

income is average real income per capita,

rates may be one or more features of a community's procedures for assessing water bills, and

μ is accumulated unknown influences, which are presumed to equal zero on average.

Several issues immediately arise as one begins to contemplate the relationship posed by eq. [1.2]:

- Many potential demand drivers included in the prior two-column listing are omitted in eq. [1.2]. Most of the omissions stem from the inappropriateness of microdata when emphasizing intercommunity differences. Not only is it overly ambitious to acquire sufficient microdata spanning Texas, but every Texas community is populated by households that have pools or do not, have varying lot sizes, have dishwashers or not, etc. Because the tasks of this research focus on intercommunity differences, it is a good idea to inspect drivers that (1) are well acknowledged, (2) have the greatest potential to assist water planning activities, and (3) are associated with readily acquired data.
- Selecting W/cap as the dependent variable is recommended by the widespread use of this measure and the ease with which demand functions of this form can be combined with population projections to obtain water demand projections for an entire city or region. In the case of eq. [1.2], multiplication by population yields a single demand function. To then obtain a single demand point (such as 120.3 million gallons), the expected levels of demand drivers must be substituted into the function. Therefore, even though the statistical estimation of eq. [1.2] requires statewide data, application of the resulting function may only require data for a single utility.
- With the exception of rates, the elements of eq. [1.2] are not difficult to obtain even though there are important details to be respected. In the case of rates, there is no central reporting conducted for the rates used by Texas utilities, and rates are challenging to record because they are highly dimensioned. It is therefore difficult to obtain such data for a large number of

communities, particularly when older rates are needed. Still, rates are a highly desirable component of demand functions, because they open important avenues for understanding and managing the growth in water scarcity.

Additional details regarding the definition of specific exogenous variables and the details of data collection are undertaken in the forthcoming chapter.

Report Components

The big-picture details of this study are that five years (1999-2003) of monthly water production data for more than 700 Texas utilities are compiled along with their weather, income, and rate experiences to produce a dataset with more than 39,000 observations. Many more communities and data were inspected during the compilation of the final dataset, but certain requirements pertaining to conformity and accuracy resulted in the removal of some data candidates.

In Chapter 2 the origins and development of each data component are separately described. All procedures employed in the resolution of the final dataset are reviewed there. In Chapter 3 individual data elements are examined to discover fundamental information about the variety of experiences within Texas. Chapter 4 is dedicated to the statistical estimation of alternative community water demand functions, using the fully assembled data set. Noteworthy empirical findings and implications are also highlighted in Chapter 4. Chapter 5 contains a brief examination of the changes in Texas water rates found to have occurred over the past twenty years, and it also compares the findings of this study to those of prior Texas studies. Because of the content of the Executive Summary, a final "Summary" chapter is unnecessary.

In the remainder of Chapter 1, some of the more useful opportunities to apply demand functions will be presented. The purpose is to advance the general understanding of water demand concepts and to assist future water planning efforts in applying these findings.

Application Guidance

There are many end uses of water demand functions. Some require that a demand function be fully exercised, but most applications are able to use specific components or parameter subsets. For water planning purposes, the most interesting information provided by demand functions are estimates of one or more consumer responses to modified driver levels. That is, it is easy enough for planners to observe current levels of water use, but what changes can be expected to happen when population changes, economic development takes place, rates are modified, or weather diverges from its normal pattern? Other possibilities include opportunities to *value* new projects or policies with the potential to modify future water use through their impacts on either demand or water supply.

All of these inquiries are better informed when analysts know about demand responsiveness to changing conditions, regardless of whether their interests pertain to a given city, a region, a basin, or the entire State. In most of these situations, knowing an expected rate of change (slope) or a percentage rate of change corresponding to a 1% change in the driver (elasticity) is a great aid. Because linear and log-linear demand functions are statistically weaker than other functional forms in modeling water demand, it cannot be said that water demand slopes or elasticities are truly constant across the range of human experience. Yet, assuming constant rates of change is sufficiently accurate for most applications, especially when they involve small deviations from baseline conditions.

Therefore, a prime purpose of water demand estimation is to better understand slopes and/or elasticities. Using derivatives where necessary, slope (m_i) and elasticity (ε_i) for any driver x_i are defined as

$$m_i = \frac{\partial\left(\frac{W}{cap}\right)}{\partial x_i} \quad \text{and} \quad \varepsilon_i = \frac{\partial\left(\frac{W}{cap}\right)}{\partial x_i} \bullet \frac{x_i}{\frac{W}{cap}} \quad . \qquad [1.3]$$

The latter expression appears complex, but it is easily understood as the percentage change in water use per capita that is consequent to a one percent change in the driver x_i. An advantage of elasticity relative to slope is that elasticity is a unitless measure.

Putting the <u>full demand function</u> to work is conceptually straightforward. Appropriate driver values for the location and period (month/year) of interest are substituted into the function and W/cap is calculated. Because some of the demand functions identified in this report are algebraically extensive, such calculations can be aided by a spreadsheet program or other computerized approaches. However, the typical challenge is not computational but is to decide what driver levels to employ for any given inquiry. Depending on the setting, the analyst may be prepared to use local driver levels for a specific community or perhaps projections for a community. In some instances, average driver levels, or perhaps their ranges, as reported in Chapter 3 can assist analysts in making these selections.

Putting <u>individual elements of demand functions</u> to work often commences from a situation such as that depicted in Figure 1.1. Based on present conditions, the analyst can approximately know water use (w^0 on the vertical axis) corresponding to a normal or current driver level (x^0 on the horizontal axis). Because these levels are observable for the issue under examination by the analyst, there is no need to use a water demand function to obtain them. Indeed, the availability of this *point* data may offer considerable advantage in that it is well established and accurately known. Yet, the analyst may be intensely interested in how this demand point will be altered if there is a change in exogenous conditions. If the locale has never had experience with the new driver level or, more likely, its experience is confounded by other changing conditions, the availability of a slope or elasticity estimate can allow the analyst to extend his/her knowledge as lines or curves emanating from the known point. Use of fixed slopes enables linear extension of the known point. Use of fixed elasticities enables curvilinear extensions. Whether or not slopes and elasticities are positively or negatively signed will determine which direction the line/curve extends. Actual equations for the lines and curves depicted in Figure 1.1 can be readily specified using the *point-expansion method* as long as the analyst knows an (x^0, w^0) point and can obtain an external estimate of slope or elasticity (Griffin 2006, pp. 31-33, 277, 279). Elasticity measures appropriate for Texas urban demand are tabulated later in this report.

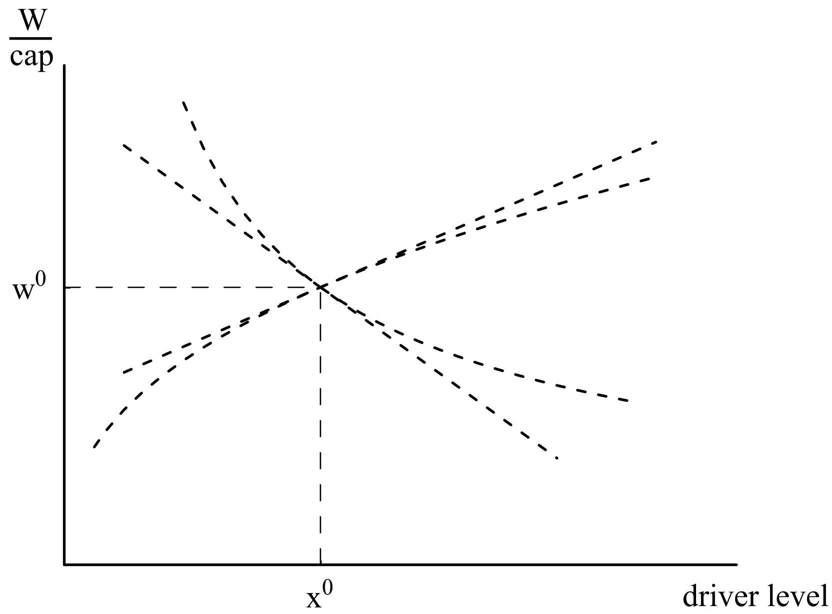

Figure 1.1 Point Expansion of Known Demand Information

Thus, as a consequence of these opportunities, the availability of slopes or elasticities endows planners with simple yet accurate analytical power while facilitating a more formal approach to various types of analysis. The formal approaches use well specified equations, either using the entirety of the demand functions given by this report or using two-dimensional point-expansion functions computed on the basis of a known point and a slope/elasticity estimate. The informal approach is to use the same fundamental results to obtain specific inferences, such as those expressed in these two examples.

1. If the average temperature in July is 1% above the norm, July water consumption will increase by __% statewide.
2. If the city raises summer water rates $0.30 per thousand gallons, summer consumption can be expected to decline by __ million gallons, implying that utility revenues will increase by __ thousand dollars.

The blanks appearing in these two statements can be readily completed when the appropriate slopes or elasticities have been acceptably determined by prior research.

Economic Applications

Inclusion of a water price driver in the research reported here enables specialized applications pertaining to water policy and project analysis. When properly used, knowledge of rate responses infers consumers' valuations of changes in the availability of retail water. Furthermore, if the costs of transforming natural water into retail water can be netted out, then the consumers' valuations of changes in the availability of natural water can be obtained. Because many policies and projects operate by modifying natural water allocations to specific uses, the demand information provided here can be a crucial element for measuring the benefits of policies or projects prior to their adoption.

To illustrate these possibilities, Figure 1.2 commences with a three-part modification of Figure 1.1. First, the axes are exchanged to correspond with the usual economic depiction of demand, although this step has no analytical significance. Second, the selected driver is no longer arbitrary – it must be retail water price. Third, W/cap has been multiplied by a population estimate to obtain total retail water demand for the area and time period in question. Suppose that a population projection for 2012 has been used. For this reason the resulting demand schedule D is labeled as 2012 demand.

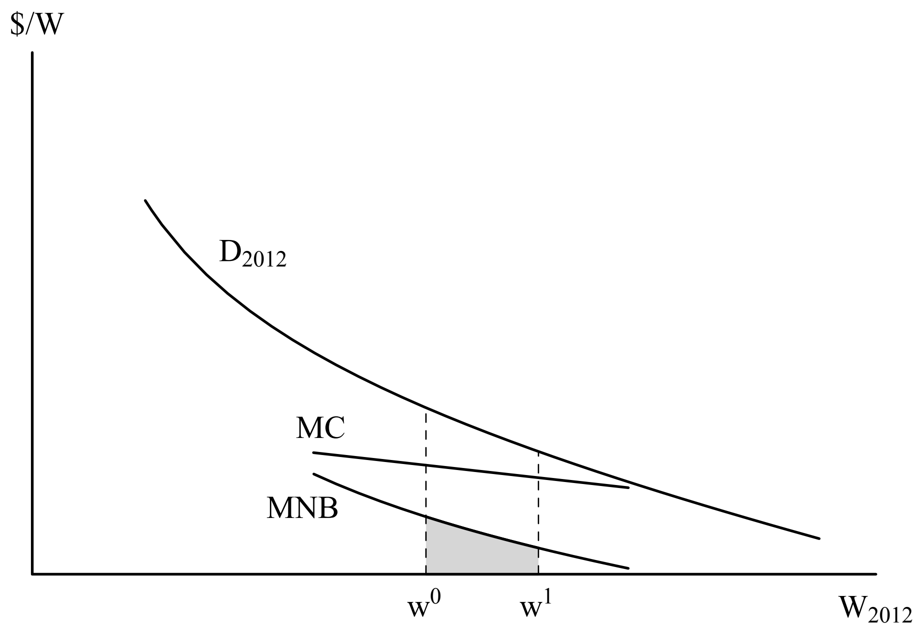

Figure 1.2 Net Benefit Measurement Using a Demand Function

Demand functions such as D_{2012} or simply D(w) can be used in rate analyses, and they can be used to value changes in the delivery of retail water. As an example of the latter, suppose that water supply is initially restricted to w^0 units of water and a public action (policy or project) promises to extend the supply to w^1. In this case the total benefits, B, of the supply increase to consumers is the area beneath the demand curve and between w^0 and w^1. That is,

$$B = \int_{w^0}^{w^1} D(w)\,dw\,. \qquad [1.4]$$

This is true because the demand function indicates the marginal benefit of each unit of water. While B is the total benefits to be received by consumers, it is not net benefits, which is the more important measure of policy/project service. To estimate net benefits, the costs of processing and delivering this added water must be subtracted. If the curve MC includes all the value-added processing costs as performed by the utility in converting natural water into retail water, then D(w) – MC(w) is the marginal net benefits (MNB) of retail water. [Other methods of netting out value-adding costs are feasible as well.] Areas beneath the MNB function specify the net benefits of enhancements and reductions in the natural water supply:

$$\mathrm{NB} = \int_{\mathrm{w}^0}^{\mathrm{w}^1} \mathrm{MNB(w)}\,dw\,. \qquad [1.5]$$

Eq. [1.5] is a critical tool for water policy analysis and the cost-benefit analysis of water projects. Such policies and projects typically have different effects in differing periods because of rising demand and variable weather. By computing NB with eq. [1.5] for every period of a forthcoming planning horizon, such as the next 20 years, and then aggregating these findings using a present value formulation, it is possible to achieve a conceptually accurate measure of a public action's benefits. None of this is possible unless water rates are an examined driver for water demand.

Having established a working basis for understanding and applying the urban water demand functions sought here, the next step is to identify the data collection procedures of this research.

Chapter 2

Data Collection Methods and Sources

The majority of water usage can be categorized as agricultural, ecological, industrial, or municipal. Methods and patterns of use vary from one of these sectors to the next, so a comprehensive picture of water demand in a region is informed by consideration of each sector. As introduced in the prior chapter, the present study confines itself to the workings of the municipal or urban sector, consisting of residences and the inseparable commercial, public, and light industrial activities of towns and cities.

In order to emphasize significant residential water user groups, the domain of this inquiry includes those water-providing systems located in Texas serving over 1000 individuals or over 400 connections in a residential capacity, for which data are available. Thus, urban demand herein is that within communities above a minimum size, excluding systems dedicated to heavy industrial and institutional uses such as mines, manufacturing plants, prisons, military bases, state and national parks, and country clubs. Of approximately 4350 systems surveyed by the Texas Water Development Board (TWDB), 1406 fit this definition, including suppliers to all major population centers.

Water Use Per Capita

The dependent variable for the models developed within this report is the volume of water used per capita,W/cap, as derived from annual reports made by utilities to the TWDB. Section 16.012 (m) of Texas House Bill 1378 (2003) requires systems to report use information solicited by the TWDB (Texas Water Development Board 2004). Information reported by the systems includes water use by the entire system, reported for each month, and population served, reported for each year and therefore constant for each month of the same year. These data were provided by the TWDB to Texas A&M University for the purposes of this study. Because the data directly reported to the TWDB by cities, towns, and districts may contain anomalies and inconsistencies of various types and severities, the original data was processed by the TWDB before it was made available for the research reported here.

2003 is the last year for which TWDB water use and population data were available for this research. In considering the latest five years of data, 1999 through 2003 inclusively, the study period can be claimed to include conditions of moderately wet and dry years. A longer study period was not adopted because of the difficulty utilities face in providing older water and wastewater rate information.

Employing this data, W/cap is calculated for each month as the total use of the system in that month divided by the population for the month, which is a linear interpolation of annual service population figures. The constructed variable, W/cap, is assumed to be well related to the quantity of water used by the typical household consumer. The calculated variable may differ from the theoretical variable in various respects, including the following.

- Water utilities record and report produced water, i.e. water pumped from wells and/or withdrawn from surface water bodies. Due to the intermediate storage facilities, such as pipes and elevated tanks, the timing of production does not exactly match that of consumption.
- As a result of leakage, spills, and evaporation, water is lost in every step of the transformation process as utilities convert natural water into the retail water that is received by customers (Texas Water Development Board 2005). The proportion and timing of these losses can be difficult to pinpoint. Rather than attempt to quantify loss, the approach here leaves it embedded in the overall modeling of use.
- Although bulk water transfers are reported annually by the systems, the timing of physical water releases can affect monthly use readings. Because these effects are expected to cancel each other out in large samples like this one, the net impact of this data error is assumed to be an increase in variance but not a change in the magnitude of estimated parameter estimates.
- Utility systems tend to accurately know how many connections or "meters "they serve, but they do not possess reliable information on the population of their service area – sometimes leading them to report population estimates from the U.S. Census that do not coincide with connection numbers. In cases of clear-cut disparities in the database, the population served is reestimated based on the reported number of connections served and the average household size of the area.
- Some communities that are primarily residential nevertheless apply significant water resources to uses other than residential. Because such uses are important components of water use in the urban sector, applications of this research will prefer to include them as though they were residential uses.[1]

Weather and Climate

When other factors are constant, high temperatures and low precipitation stimulate demand for residential water. Nevertheless, some communities with typically hot, dry weather do not use great amounts of water, presumably because consumers have adapted their water-using behaviors over their longer experience with scarcity. For this reason it is desirable to separate normal weather patterns from random fluctuations. This study considers the daily high and low temperature and precipitation frequency of each locale averaged over each month, as well as the historical annual total precipitation for the thirty-year period from 1971-2000. Other desirable weather variables can be postulated but are not supported by available data.

This data is obtained from the daily readings of active members of the National Weather Service's Cooperative Station Network, as compiled in the National Climatic Data Center of the

[1] Given that TWDB water use data is known to include various water use applications which are strictly nonresidential (e.g. government, park, and light commercial uses), the demand analysis to be conducted here is incorporating such uses in all aspects of this work. Hence, the demand analysis is not purely one of residential use, and the various drivers are best interpreted as indices of community-wide sensitivities. This is an advantage for most prospective applications of this report's findings, because findings will be combined with other data which also embeds nonresidential use.

National Oceanic and Atmospheric Administration, U.S. Department of Commerce, and available on their website (www.ncdc.noaa.gov). Data from one of 141 weather stations in this database is assigned to each water system studied, based on geographical proximity and completeness of temperature and precipitation records over the horizon of interest. Weather station names for these 141 are listed in Appendix Table A-1. In most cases, weather values assigned to a system apply to a weather station in the same county. Because temperatures and precipitation are recorded daily, values over the month are combined to produce monthly means of temperature and monthly frequencies of precipitation. Data for these stations are over 99% complete, but in the rare case of a missing datum, information is substituted from the next closest station.

Income

An increase in consumers' real income will typically increase their demand for all normal goods, including water (Dalhuisen et al. 2003). Real income is defined as average personal income adjusted for inflation. Personal income values from the U.S. Bureau of Economic Analysis are employed to calculate this measure of expenditure constraint (U.S. BEA 2005). The BEA develops personal income from data collected by the U.S. Census, the Departments of Labor, Health and Human Services, Treasury, Defense, and Veteran's Affairs, the Internal Revenue Service, and the states; and defines personal income as "the sum of wage and salary disbursements, supplements to wages and salaries, proprietors' income with inventory valuation and capital consumption adjustments, rental income of persons with capital consumption adjustment, personal dividend income, personal interest income, and current personal transfer receipts, less personal contributions for government social insurance" (U.S. BEA 2005). The BEA estimates personal income for major urban areas and all counties annually, and we derive monthly estimates by linear interpolation of these annual figures. Communities whose representative personal income is not specifically provided by the BEA are assigned the income estimate corresponding to the community's primary county.

Personal income is a nominal measure, so it should be deflated by a price index to reflect the changing value of the dollar. For this study we employ the monthly Consumer Price Index (CPI) which is defined as "a measure of the average change over time in the prices paid by urban consumers for a market basket of consumer goods and services" (U.S. Bureau of Labor Statistics). To deflate nominal income for May of 2001 (I) to January 1999 dollars, for example, one would multiply I by the appropriate ratio of two CPIs as follows:

$$\frac{CPI_{Jan99}}{CPI_{May01}} \cdot I . \qquad [2.1]$$

Nominal dollar amounts used in this study are deflated by the CPI of urban consumers in the southern U.S., using 1982-84 dollars as the baseline ($CPI_{Aug83} = 1.0$), then converted to 2003 dollars using the CPI factor of 1.7725, which is the average ratio of 2003 dollars to baseline 1982-84 dollars. The applicable monthly CPI factors are listed in Appendix Table A-2.

Rates

The periodic charges faced by residential water consumers can be separated into meter charges, which are invariant to the quantity of water used, and water prices, which are applied to the metered quantity of water used by a customer. Wastewater billing exhibits the same two-component charge structure as well as other features. (The terms wastewater and sewerage are used interchangeably here.) Griffin further discusses these components and their economic and policy significance (2006, Chapter 8).

Not only do Texas water and wastewater rates range widely in magnitudes, but there is no standard framework in place that might simplify data collection pertaining to rates. Nor is rate data centrally collected in Texas. Some organizations conduct periodic record keeping pertaining to rates in major Texas cities, but there are notable omissions in these data and they are unsuitable support for the research reported here. Therefore, original data collection is undertaken for this project.

Data collection procedures must recognize and accommodate a variety of potential rate structure types. Water and wastewater prices can either be constant or vary with the amount used over a billing cycle. In addition to uniform (constant price) rates, there are increasing block, decreasing block, seasonal, and conservation rates. In a few Texas cases, there is a low-use meter charge and a high-use meter charge. More commonly, though, higher charges are levied on greater use by dividing the range of conceivable water use into intervals, or blocks, and charging prices specific to each block. If a system imposes an increasing block rate schedule, consumers pay more per gallon as their consumption level enters higher blocks. A more subtle method with a slight resemblance to an increasing block rate is to grant a small amount of free water with the meter charge, whether the water is actually used or not, thereby establishing a zero volumetric price for the lowest levels of water use. Figure 2.1 shows the rate schedule of a hypothetical system with an increasing block rate structure. Note how the meter charge applying to each consumer is displayed; this fee must be paid whether or not the consumer uses any water.

A decreasing block rate schedule reduces the unit price of water at higher consumption volumes. Although decreasing block rates were frequently applied for urban water in Texas until the 1980's (Griffin and Chang 1989), most communities have transitioned to rate structures that do not encourage high levels of water use so overtly, and state policy now discourages decreasing block rates.

Wastewater rates may be assessed on the basis of water usage and therefore can resemble water rates by incorporating blocks and other nuances. A wastewater-specific billing practice used by many Texas utilities is winter averaging. Here, a fixed bill is assessed during nonwinter months, and this monthly charge is obtained as an average of the customer's winter sewer bills. Billing during winter months is the usual combination of a fixed fee and a volumetric fee based on metered water usage. A similar strategy used in other communities is to establish a maximum sewer bill so that wastewater charges do not increase with water usage beyond the prescribed maximum. These approaches limit sewerage fees on water used outdoors, under the presumption that water used outdoors will not require collection or subsequent processing at waste treatment facilities. An alternate formulation in some communities is to allow two meters per household,

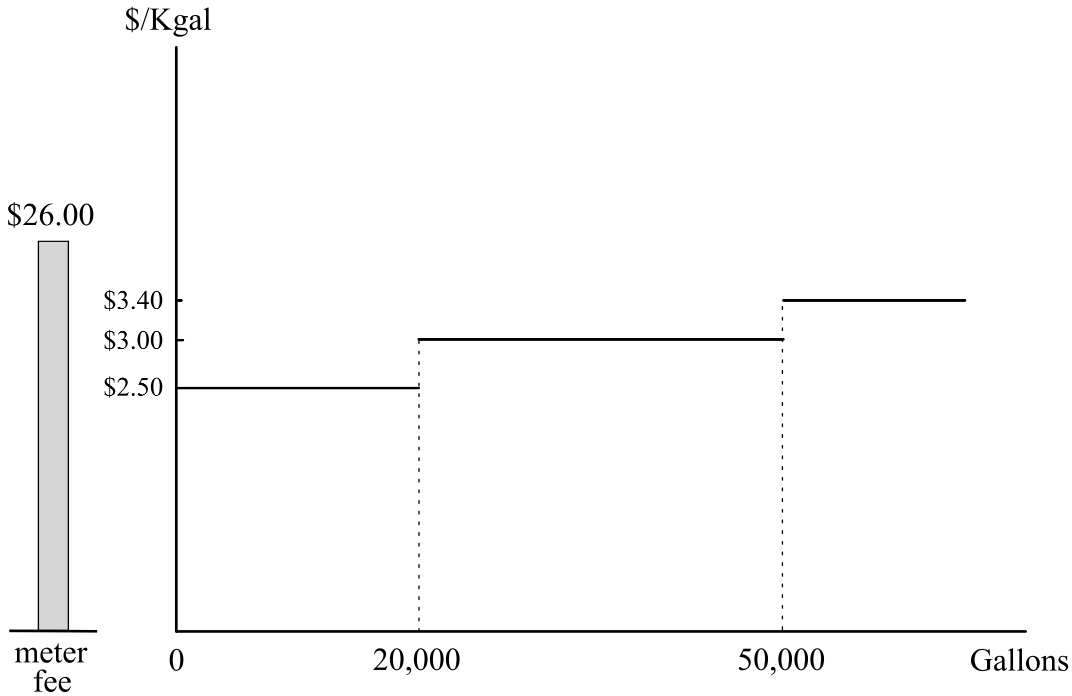

Figure 2.1 A Hypothetical Meter Fee and Increasing Block Rate

where the second meter is dedicated to irrigation and is excused from wastewater charges. Other communities do not employ either of these methods, meaning that wastewater charges rise strictly with metered water consumption.

In light of the many approaches used to assess water and wastewater charges and the fact that blocks may be variously defined, it can be difficult to acquire and accurately store or present this information for numerous communities. Other studies have addressed this problem by tabulating, for each water supplier, the total bill resulting from discrete monthly consumption gallonages (e.g. 5000, 10000, 15000, etc.). This strategy is straightforward, yet it obscures distinctive elements of a billing structure such as the meter charge and the block divisions. For this reason, the approach adopted here is to obtain and computerize the actual rates applied by each Texas water system.

The 1406 systems classified above as "urban" received a mailed survey in March 2005 asking what rates they had charged city or district residents for household water and wastewater service during the period of analysis (1999-2003). Contact information for these systems was provided by the TWDB. Respondents were invited to complete flexibly designed tables with their water and wastewater rates or to respond by returning copies of their 1999-2003 rate schedules. Although water and wastewater rates throughout Texas are arguably unprotected public information, our survey solicitations promised nonidentification of all returned rate data. A suitably large, postage-paid envelope was included in this mailing. Communities that had not responded within three weeks were reminded by postcard. Three weeks after the postcard mailing, a rephrased version of the original letter of solicitation was sent to systems that had yet to respond. Again, a form table and an envelope were included in order to ease respondents' tasks and maximize the number of responses (Mangione 1995). Systems whose mailing addresses had changed were contacted by telephone and sent repeat mailings. Appendix B replicates the first contact letter, the generic response tables included in the first and third mailings, and the postcard reminder. Unfortunately, some significant Texas cities did not elect to respond to this survey and are therefore excluded from the analysis.

Of 1406 systems surveyed, 740 (53%) responded with at least some rate information. Median response time was eighteen days. The response rate for privately owned water suppliers tended to be poor, perhaps because they are more guarded or defensive about their rates. However, privately held water systems in Texas are required to apply to the state for permission to change their rates, and data for 42 additional investor-owned systems that did not respond were obtained from these records, available at the Austin offices of the Texas Commission on Environmental Quality. Thus, the postsurvey sample contains 782 retail water suppliers.

Responsive systems were smaller than unresponsive ones, averaging 8400 connections compared with 10,300 for the entire survey domain, using 1999 information. However, the disparity is statistically insignificant relative to the overall variance in system size across the state. The possibility that systems with higher rates were less likely to respond, although mitigated by the large sample size, cannot be discounted. Unfortunately, a publicly traded national corporation managing 150 (11%) of the surveyed systems declined to respond, and the bias engendered by this omission is unknown.

Monthly bills (sometimes bimonthly) issued to consumers by water utilities may include charges unrelated to water services, and these are not factored into the rate information assembled here. Municipal services such as solid waste disposal and street maintenance, state and local taxes, and natural gas or electricity charges, comprise this category. Water-related surcharges due to water development investments or contractual purchases from an aquifer authority, a river authority, or a water wholesaler can be billed separately to water customers or these charges may be imbedded in rates. To the extent possible, these surcharges and assessments are included in the water rate information collected for this research, but data on this facet of pricing may not have been fully reported by all communities since it was not specifically mentioned in the survey. A regulatory assessment fee of 0.5% is imposed on all water bills by the Texas Commission on Environmental Quality. Because this fee is uniform across the state, there is no advantage to adding it to the rate information collated here.

Compiling the Data

Each observation in this study consists of a month in the history of a water system. 782 systems reporting 60 months of history theoretically yields almost 47,000 observations. Some use and rate data are incomplete, so there are fewer total observations. An observation is included in this dataset only if (1) the reported water production volume is nonzero, (2) the population reported is greater than one, and (3) the system responded to the survey with rates for the month. Income and climatic data fully covers the sample and do not limit the number of available observations.

Further examination reveals that some observations fulfilling these requirements involve questionably high or low use volume values relative to the populations served. Anomalous data may, however, be accurate data. It is hard to tell. On one hand, utilities may not track monthly water use well or may be careless in reporting, or correct data may be incorrectly keyed into the TWDB database. Population changes may be inaccurately tracked in the data and may inject a false appearance of abnormally high or low water use per capita. On the other hand, water supply shortfalls or infrastructure failures may cause water use to be abnormally low for short periods. Major water line breaks can cause water use to be abnormally high.

While it is difficult and certainly subjective to edit data, a two-stage process is used here to prune and hopefully improve the dataset. The objective is to find and correct obvious errors and to exclude errant observations or observations stemming from highly unusual conditions, either of which could possibly mislead demand estimation. Given that the assembled dataset is very large, questionable data can be omitted without harming statistical degrees of freedom.

Stage 1 Corrections and Deletions

A common data error is the omission of one or more decimal places in the reported volume. The converse error of including too many zeroes is less common. Data reporting problems are addressed first by inspecting for obvious anomalies. Volume per capita is calculated and sorted to identify potential errors. Additional candidates for removal or rechecking are identified by evaluating the deviation of each observation from the annual mean for that system. Under normal conditions for a single utility, no single month's use will exceed average use by more than 200%. Observations that are suspect on the basis of these criteria are charted to test for unexpected or extreme values and randomness in the time series. Unusual values are corrected if the correct value is evident. 1,919 entries (less than 5% of the candidate data) are deleted because they indicate physically implausible volumes of water and inconsistency within their own series. Other retained entries are dubiously large or small but consistently so and do not admit ready explanation such as an identifiable magnitude error. These are preserved in the dataset. Emphasis is placed on retaining every observation that could be accurate, even if unlikely.

The resulting stage 1 dataset includes 40,289 observations involving 734 water systems reporting an average of 55 months each (4.6 years). These water suppliers are listed in Appendix Table A-3. Each system-month observation contains the set of use volume, weather, income, and price characteristics listed in Table 2.1. The difference between the mean per capita daily use in the stage 1 dataset compared with that in the central 90% of values is 8.6%. Although some portion of this difference may be attributable to data error, it is likely dominated by the asymmetry of a distribution bounded by zero on the low end (water use cannot be negative) and unbounded on the high end. The mean is unaffected by outlying values from any single system remaining in the dataset.

Table 2.1 Dataset Elements

Numeric TWDB Identifier	Days without Precipitation
Observation Year	Service Population
Observation Month	Service Connections
Water Meter Fee	Consumer Price Index
Minimum Volume	County of Service
Rate Block Minimums 1-7	Winter Average Use
Water Rates 1-8	Volume Used
Sewer Indicator	Volume per Capita
Sewer Fee	Volume per Capita per Day
Minimum Sewer Volume	Personal Income
Sewer Block Minimums 1-3	Household Size
Sewer Rates 1-4	Household Monthly Use
Winter Averaging Months	Water Bill
Historical Precipitation	Sewer Bill
Average Low Temperature	Total Bill
Average High Temperature	Average Price per 1000 Gallons

Stage 2 Deletions

The 40289-observation, first-stage dataset is employed in the following pretest-assisted procedure to examine whether extremely high or low W/cap values have destabilizing effects on water demand elasticities. Beginning with the full dataset, (1) an advanced demand function (generalized Cobb-Douglas form) is estimated; (2) elasticities for price, climate, weather, and income are computed using demand function parameters and dataset means; (3) the highest 100 W/cap and lowest 100 W/cap observations are deleted from the dataset, and (4) steps 1-3 are repeated. This process is continued until nearly one-quarter of tail data have been experimentally deleted. The various elasticity findings are plotted over a range extending from 40,289 to 31,289 observations to examine the sensitivity of results to tail data. Quite clearly, the tailmost 1000 observations have a strong and destabilizing effect on these elasticities. Further examination revealed that nine utilities have observations showing up in both 500-observation tails. That is, across all months and utilities in the first-stage dataset, certain utilities have months in both the extremely high and extremely low tails. For this to occur, a utility would have to experience months when its average client consumes at least ten times more than is consumed in other months. In most cases, the ratio is far greater than ten. The full records for these nine utilities are again reviewed to see whether the monthly water volume reports may have been blatantly concocted.

On the basis of these investigations, 1000 tail observations are dropped from the dataset. Next, the remaining observations for four utilities of the reexamined nine are entirely dropped. Three of these are because of erratic consumption volumes; one is because nearly half of its data is in the 1000 dropped observations. Finally, only 14 months of a 5th utility's data is omitted, as its most apparent data problems are confined to a single period. As a result of all these modifications, the primary dataset to be examined in forthcoming analysis contains 39,145 observations representing 730 Texas utilities.

One of the major pieces of information emerging here is the general finding of considerable noise in available data. We are confident that a great deal of this noise remains.

In the next chapter we discuss the picture of Texas water use and its potential determinants that emerges from these data. Then in chapter 4, we derive demand models for the relationships between community water use and its climatic and economic drivers.

Chapter 3

Descriptive Statistics

This chapter describes the quantitative characteristics of the primary components of the stage 1, 40,289-observation dataset. These components include service population, water use volumes, weather, income, and water and wastewater rates. All dollar denominations are adjusted to real (2003) terms. In addition to reporting noteworthy details pertaining to the elemental data, calculations exploring water/wastewater bills and implied water prices are also performed. Wherever statewide "average" conditions are reported here, the information pertains to the average water supply system in the dataset, not to the average Texan.

Represented Population

The total population reportedly served by dataset systems is 9.13 million in April 2000. The population of Texas in that month was 20.85 million (U.S. Census). The implication that 44% of Texas is directly surveyed in this report is approximate due to uncertainty in both the census and utility records. The average service population for a single system in that month is 12,985, and the median is 3152. The smallest system population in the sample is 346 people, and the largest exceeds one million.[1] The median 90% of the sample by service population ranges from 1041 to 39,869 in April 2000 with a mean of 6894, so a few large systems strongly influence the average size estimate.

Water Use

The in-sample volume of water supplied over the five-year survey period is 3.5 trillion gallons, averaging 690 billion gallons (2.1 million acre-feet) annually or 152 gallons per person per day. Median per capita daily use is 125 gallons. Figure 3.1 and Appendix Table A-4 indicate the variation in average (across all locations) daily use from month to month and year to year. Figure 3.2 compares the distribution of average use observations in the most disparate winter and summer months, January and August. Average use dropped from 157 gallons in 1999-2000 to 148 gallons in 2001-2003. The lowest average level of use is recorded in January, at 120 gallons per person per day. Median use in January is 106 gallons. The highest average use is in August, at 219 gallons per person per day, with a median use of 186 gallons. As indicated by Figure 3.2, use in the summer is more variable than in winter. The standard deviation of use in January is 78 gallons, compared with 145 gallons in August.

Water bills are based on monthly household use rather than daily personal use. Use calculated for the purpose of establishing price multiplies per capita use by the average household size for the county (U.S. Census Bureau 2002). Overall average household monthly use in the sample is 12,399 gallons, peaking at 18,202 gallons in August and dipping to 9974 gallons in January.

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[1] Populations below 1000 are present in the dataset either because of a relatively high ratio of connections per capita or because the community subsequently grew to at least 1000 by the end of the study period.

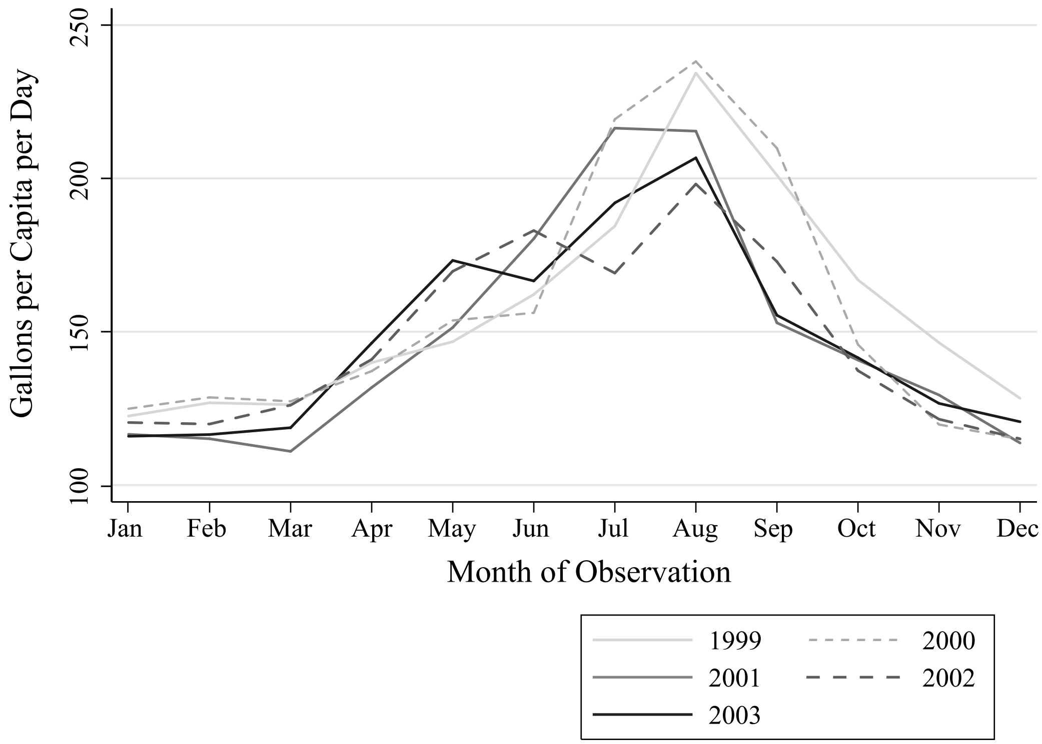


Figure 3.1 Average Water Use by Month, 1999-2003

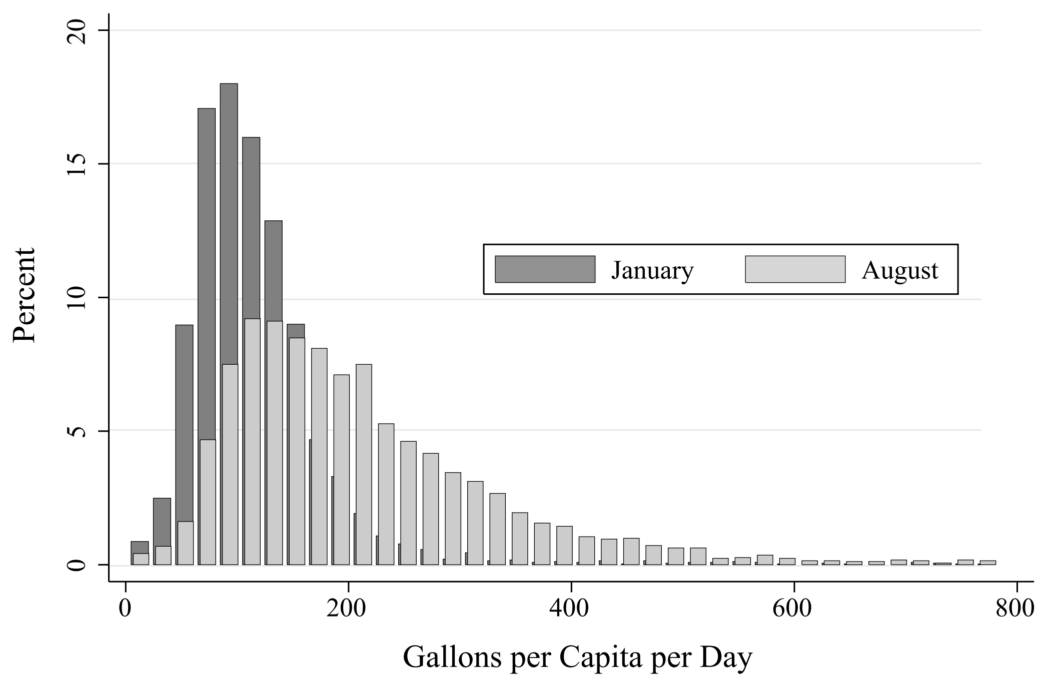


Figure 3.2 Histogram of Water Use (99.4% of Utilities and Years Shown)

Typical use in this sample increased slightly from 1999 to 2001, then declined in 2002 and 2003. For more information on water use trends in Texas, refer to the annual TWDB Water Use Survey (www.twdb.state.tx.us/wus).

Weather and Climate

The monthly average low temperature in the dataset varies from 15.6 to 79.0° F, with a mean of 55.3°F. The monthly average high temperature varies from 39.6 to 105.2°F, with a mean of 78.2°F. The highest annual average high is 80.0°F in 1999; the lowest annual average high is 76.9°F in 2002. The coldest month on average is December of 2000, and the warmest is August of 1999.

The historical 30-year average monthly rainfall over the 141 weather stations is 3.2 inches. A typical month during the survey period saw precipitation of over 0.25 inches three times per month. The rainiest year was 2001, with precipitation 3.4 days in a typical month. In 1999, precipitation was recorded in only 2.5 days of a typical month. Figure 3.3 shows the general changes in precipitation and temperature over the study period. The same information is presented numerically in Tables A-5 and A-6 of Appendix A. Whereas monthly temperature extremes are relatively predictable, the occurrence of precipitation is more random over the state as a whole. The wettest month across these Texas stations is May, historically averaging 4.5 inches over all weather stations.

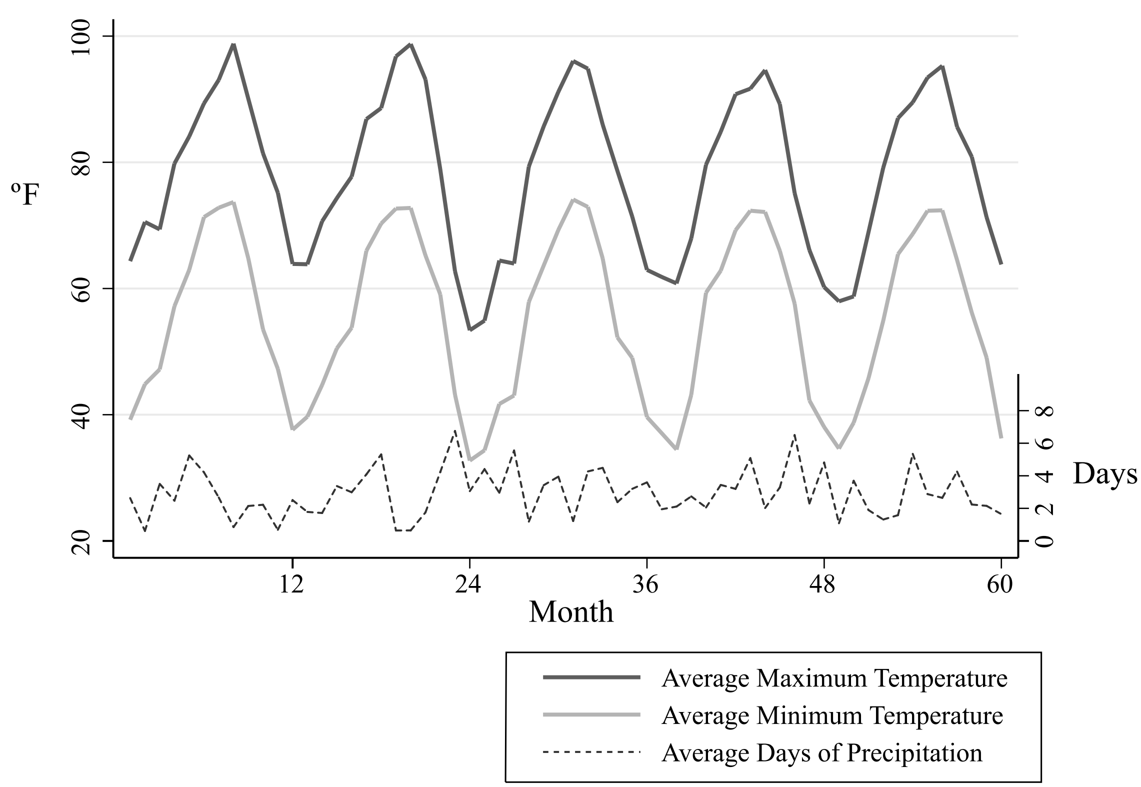


Figure 3.3 Average Monthly Weather, 1999-2003

Income

The average real (inflation-adjusted) personal income in this study is $26,310 annually, with a median of $24,548. Real income rose in every year except 2002. Due to variations in reporting, this does not imply that the income of any community declined in 2002. It is also possible that communities with lower incomes are more highly represented during that year. Overall, annual personal income averaged by community varied from $10,084 to $48,047. Figure 3.4 shows the distribution of personal income among communities. Average annual household income is $70,625, varying between $37,211 and $128,766. The monthly water bill represents an average 0.98% of monthly income. This proportion is unchanged over the horizon of study; in other words, water bills have kept pace with income growth even though the amount of water purchased per capita is declining.

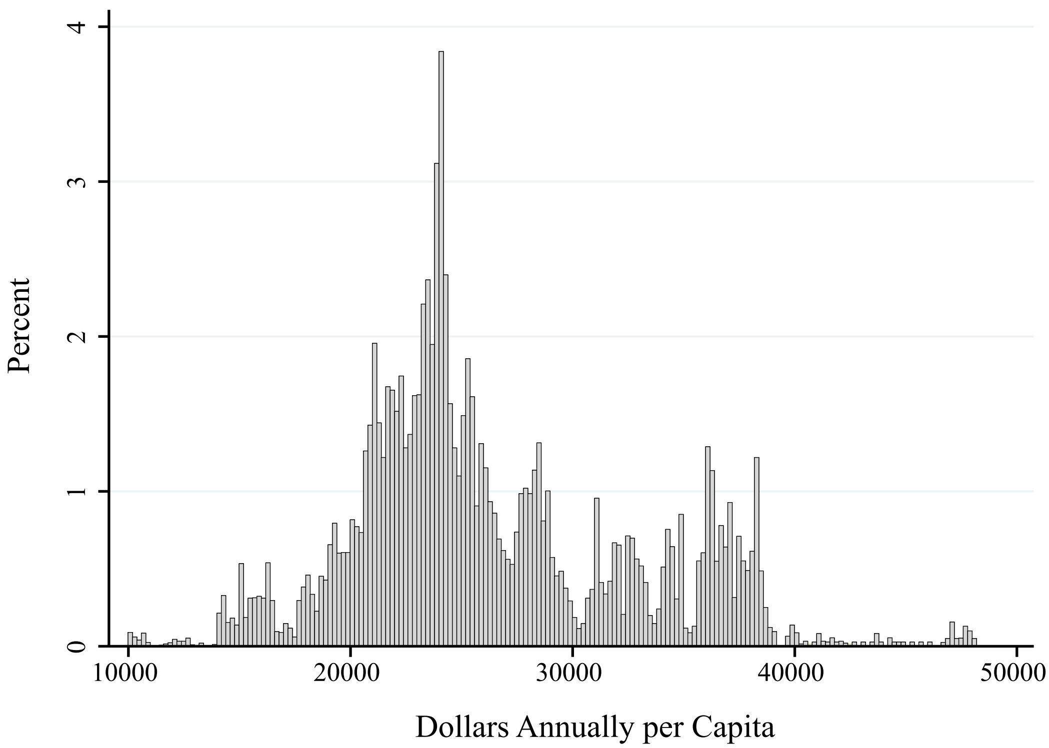


Figure 3.4 Histogram of Personal Income

Water and Sewer Rates

Water

The rates charged for water consumption vary considerably across the State during the study period. The fixed fee for water service varied from $0.00 to $59.13 per month, averaging $14.35 with a median of $13.20. Ten systems (1.4%) did not meter water use, implying that a zero price is applied to each unit of water use. These systems tend to be small, having an average service population of 2819. For systems that did price water volumetrically, rates for the first 1000 gallons of metered use ranged from \$0.08 to \$17.54, averaging \$2.41 and with a median of \$2.25. Over half (51.4%) of the sample employed a uniform rate; 44.3% employed increasing block rates; 3.5% employed decreasing block rates; and 0.8% employed decreasing then increasing block rates. Some systems changed their rate regimes during the period of study. By December of 2003, 343 of the systems studied were utilizing increasing block rates, compared with only 281 systems in December 1999. Figure 3.5 shows how water rates in the sample, aggregated by year, vary with volume. As is true for the other descriptive information appearing in this chapter, the calculations underlying Figure 3.5 employ a unweighted average across communities, meaning utilities with more clients are not weighted more highly. The figure illustrates a general stability in the shape of the average structure over time and a general rise in real water rates – inferring that water rate increases are outpacing inflation. The figure also indicates the dominant effect of increasing block rates given that there are also uniform rates and decreasing block rates in the sample. The pattern of increasing block rates is also indicated by Table 3.1, which is aggregated over the sample.

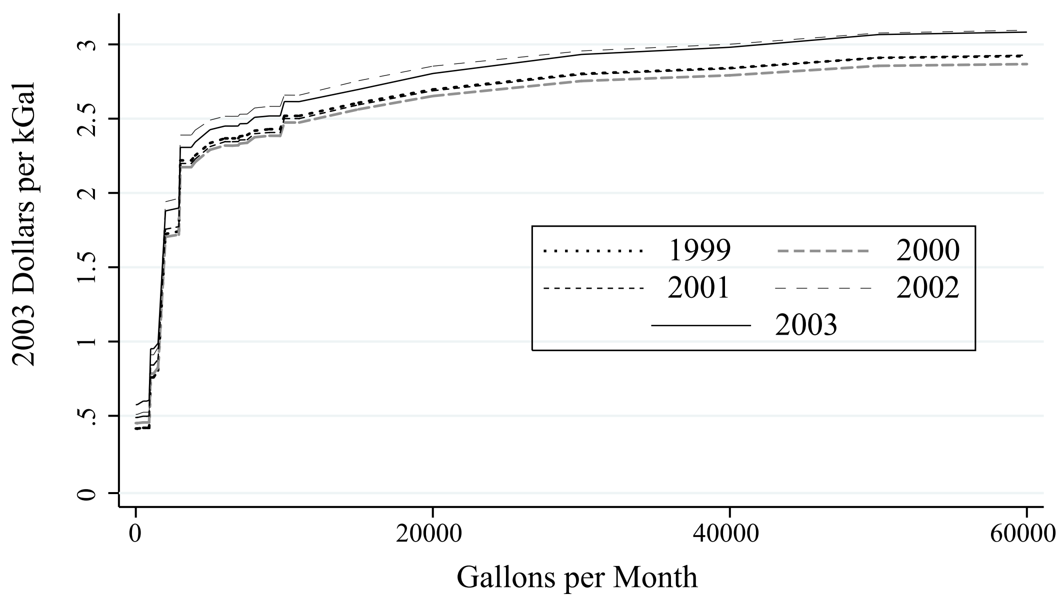


Figure 3.5 Mean Marginal Water Prices

Table 3.1 Summary of Real Price for Water Service by Block

Block	Rate *(dollars per 1000 gallons)* Minimum	Maximum	Mean	Standard Deviation	Number of Observations
Meter Fee	0.00	59.13	14.35	6.66	40289
First	0.08	17.54	2.41	1.18	39732
Second	0.12	17.74	2.72	1.35	19400
Third	0.85	8.64	3.17	1.50	14378
Fourth	0.84	11.09	3.51	1.67	8811
Fifth	0.80	12.19	4.23	2.20	4195
Sixth	0.75	14.98	4.56	2.41	1618
Seventh	1.63	10.85	4.94	2.31	771
Eighth	1.66	9.98	5.37	2.76	478

<u>Sewer</u>

Sewer services were offered by the water systems in 63% of cases, including a small number who instituted sewer service during the study period. The monthly fee for sewerage varied from \$0 to \$77.60, averaging \$11.57. Of those offering sewer service, 74% employed only one volumetric rate, 7% employed increasing block rates, and 19% employed decreasing block rates, including structures limiting the maximum monthly bill. The initial volumetric rate for sewer service cost ranged between \$0.06 and \$14 per thousand gallons, averaging \$1.75 for metered months. Figure 3.6 shows aggregate sewer rates by volume, indicating the tendency of sewer

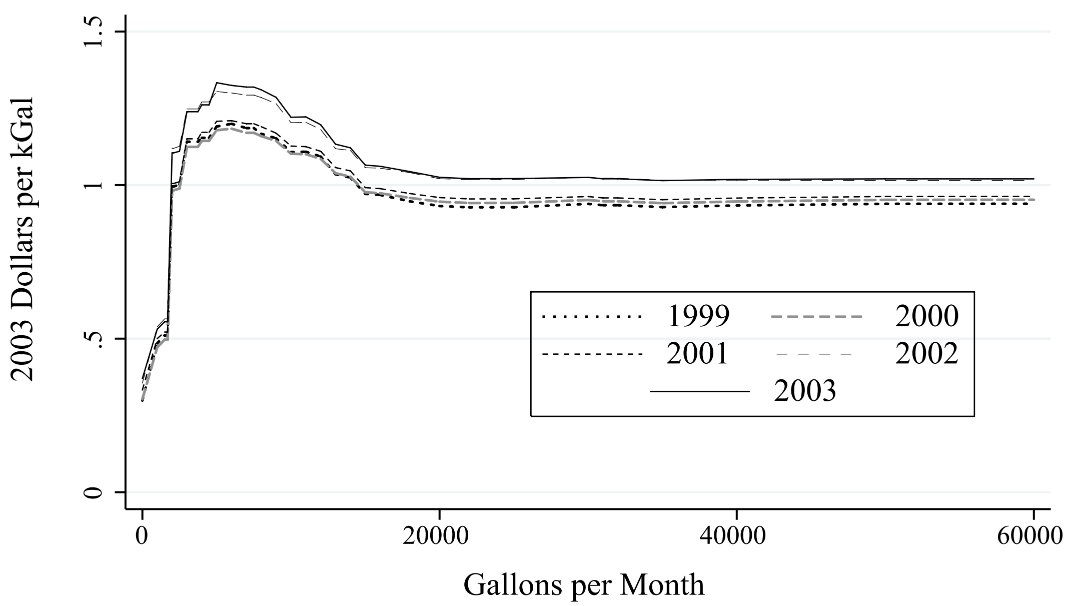


Figure 3.6 Mean Marginal Sewer Prices

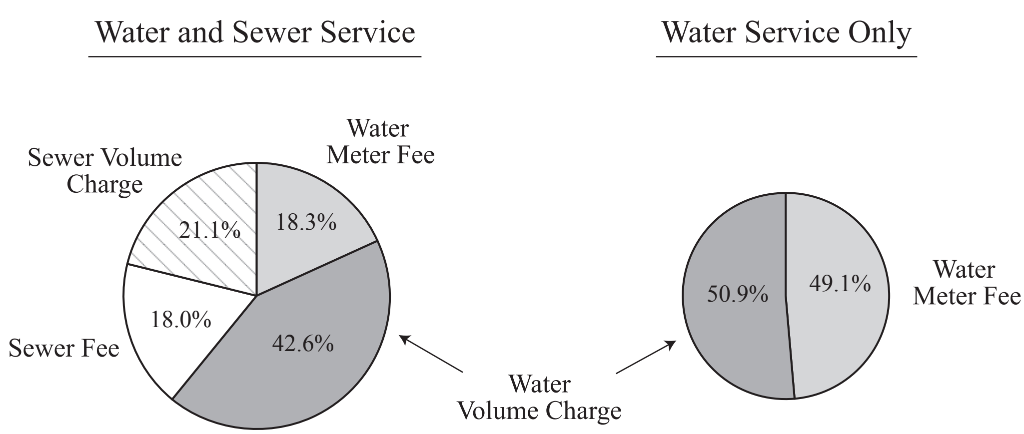
rates to decline at high volumes. 45% of observations with sewer service included a ceiling on sewer charges including instances of winter averaging. Table 3.2 describes the range of fixed sewer fees and nonzero sewer block rates, suggesting an association between more blocks and higher block rates.

Table 3.2 Summary of Real Price for Sewer Service by Block

Block	Rate *(dollars per 1000 gallons)* Minimum	Maximum	Mean	Standard Deviation	Number of Observations
Sewer Fee	0.00	77.60	11.57	6.04	25351
First	0.06	14.17	1.82	1.07	18424
Second	0.25	5.27	1.78	1.11	2622
Third	0.45	5.44	1.95	1.12	1291
Fourth	0.67	5.52	1.86	1.18	442

<u>*Average Prices*</u>

For each observation, applicable components of the typical water/wastewater bill are estimated as a hypothetical household consuming at the mean consumption level for that utility and month. Volumetric water charges averaged $24.40 per month with a median of $18.95. Volumetric sewer charges averaged $13.56 per month for systems that offered sewerage services, with a



$64.18	Average Bill (2003 $)	$38.23
+0.9%	Annual Rate of Real Price Increase	+1.2%
25,350	Number of Observations	14,939

Figure 3.7 Bill Composition by Service Type

median of $9.36. Fixed and variable charges for water and wastewater service average $54.56 per month across the dataset. The average is $38.23 for customers using no sewerage, and $64.18 for those paying for both water and sewerage. Figure 3.7 shows mean proportions of the four components of the water bill for systems with and without wastewater service.

The average price of service faced by consumers is computed as the sum of fixed and volumetric water charges plus fixed and volumetric sewerage charges, divided by average use. Variable water charges per 1000 gallons fluctuate between $1.85 in January and $2.12 in August. The average price of water service per 1000 gallons (variable and fixed) averaged $3.78 with median $3.32. Average price of water rose from $3.67 in 1999 to $3.88 in 2003, for an average annual increase of 1.41%. Recall that all of these values are CPI-adjusted, so inflation has been removed. Consequently, rises in water prices are shown to outpace inflation here. The average price for water and sewerage is $5.12 per 1000 gallons, with a median of $4.69 (Table 3.3).

Variation in the real price of water results from differences across systems, periodic changes in rate policy, and seasonal shifts in demand to different rate blocks. Relative variability arising from these three effects is captured by the variance (which is the square of standard deviation) of the price variable measured in each dimension. The variance of fixed fees across systems is $43. The variance in variable charges is $416. In contrast, the variance across years is $0.0266 for fixed fees, and $0.518 for variable charges. Variances across months are $0.0026 and $43.61, respectively. Fixed fees do not generally change within a fiscal year. As expected, these statistics indicate that price is much more stable in a given community over time than across communities.

Winter Averaging of Sewer Charges

The sewer bill charged in nonwinter months under winter averaging is approximated by the cost of sewerage service for use observed during winter months of the same year. For example, if the sewer bill for May 2002, is based on the use in December 2001, this quantity is represented by the average use in December 2002, because of the incomplete availability of data in multiple years.

The average price per 1000 gallons consumed ($5.12) is the same for water alone and for water and sewerage. The primary explanation for this anomaly is the discounted water consumed during nonwinter months by households subject to winter averaging. Due to the practice of winter averaging, only 59% of monthly sewer bills reflected the quantity consumed in the billed month. Consequently, the average variable sewerage price per 1000 gallons of water consumption drops from $1.01 in January to $0.86 in August. If fixed, variable, and averaged costs are considered, the average wastewater price per 1000 gallons is $2.41 in January and $1.71 in August. The practice of winter averaging can counteract the demand effects of block rate pricing because water and wastewater charges are experienced by the consumer as a single bill.

Table 3.3 Summary Statistics, n=40289

Variable	Units	Mean	Median	Standard Deviation	Minimum	Maximum
Population	#	13761	3287	61825	318	1144646
Use (month)	kGal	85713	12590	728860	62	4.30 E+07
Personal Daily Use	gallons	152	125	109	1.99	1974
Personal Income	dollars	26310	24548	6302	10084	48047
Total Bill	dollars	54.56	46.03	40.85	7.37	1543.05
Average Price	$/kGal	5.12	4.69	3.39	0.26	168.33
Marginal Price	$/kGal	3.18	2.88	1.76	0	17.55
Low Temperature	ºF	55.3	56.5	14.2	15.6	79.0
High Temperature	ºF	78.2	79.5	13.3	39.6	105.2
Days with Rain	days	2.9	3	2.2	0.0	13.0
Mean Monthly Precipitation	inches	3.2	3.1	1.3	0.14	7.8

Summary Information

Table 3.3 contains descriptive statistics for the major variables assembled into the completed dataset. A correlation matrix showing the extent of linear relationship between each pair of variables is provided by Table 3.4. The magnitude of the largest correlation shown in this table is 0.95, indicating a very close relationship between high and low temperature. Although these two variables are expected to be well correlated, regression analysis such as that conducted in the forthcoming chapter should not include exogenous variables that are so highly correlated. Doing so causes particular parameter estimates to exhibit unnecessarily high variance without contributing to the explanatory power of models. For this and other reasons, a composite weather variable is used in the statistical analysis of the forthcoming chapter.

Table 3.4 Correlation Matrix

	Pop	Use	Income	Price	Low	High	Rain
Population	1.00						
Personal Daily Use	0.11	1					
Personal Income	0.07	0.04	1				
Price	– 0.02	– 0.28	-0.01	1			
Low Temperature	0.00	0.23	0.02	– 0.10	1		
High Temperature	0.01	0.29	– 0.04	– 0.14	0.95	1	
Days with Rain	– 0.03	– 0.12	0.12	0.07	0.05	– 0.10	1

It is a perhaps counterintuitive that frequency of rain is unrelated to temperature in the aggregate, but this data characteristic makes it meaningful to consider both kinds of weather elements as demand drivers. The next highest correlations in Table 3.4 are the positive correlation of 0.29 between high temperature and water use and the negative relationship of −0.33 between price and water use. High correlations here are not problematic because they involve the dependent variables of the demand function. Indeed, the negative relation between water use and water price highlights a major principle underlying demand estimation. Elsewhere in Table 3.4 the generally low correlation coefficients provide confidence that all variables may have separate contributions to make as demand-side drivers and that statistically obtained parameter estimates may be relatively stable.

The next chapter applies the data assembled here to an empirical formulation of the theoretical model developed in Chapter 1. The result will be a set of quantitative relationships between personal use and the explanatory variables, ultimately presented as elasticities of demand with their standard errors. Whereas Stage 1 data has been summarized thus far, forthcoming analysis relies on Stage 2 data so as to limit the influence of the most suspect data.

Chapter 4

Econometric Demand Analyses

Using Stage 2 data (pp. 17-18) this chapter explores the mathematical relationships between personal daily demand for water service and climatic, income, and price factors. The contemporary theoretical background and issues of water demand analysis are briefly reviewed, and then the theoretical model of Chapter 1 is further developed into an empirical form and estimated. The primary data summarized in Chapter 3 are transformed to improve simplicity and flexibility, and the transformed variables are subjected to a multivariate linear regression to produce parameter estimates and related statistical information. These parameter estimates in turn produce elasticity estimates which are the principal result of this chapter. Readers who are mainly interested in the elasticity findings may wish to advance to p. 37.

Background

Although no prior studies of this type have assembled as many observations as are present in this dataset, the methodologies and findings of earlier research guide the present work by indicating how such data is best applied in demand estimation. That is, certain approaches are recommended or discouraged by the available body of urban water demand literature, which has grown voluminous over the past 25 years. In this section some of the more relevant suggestions of this literature are considered. Ultimately, all of these components are combined when water demand is estimated – inferring that each of the forthcoming subsections is important to the results which are ultimately obtained.

Functional Form

In Chapter 1 the general form of the water demand function was given as

$$\frac{W}{cap} = f(\ldots) + \mu \qquad [1.2]$$

and it was indicated that the functional form of the relation f is likely to be nonlinear. To estimate f we must now select one or more candidate functional forms. The "best" functional form is unknowable, but certain available principles illuminate the decision.

- Statistical results are improved by preserving "degrees of freedom", defined as the number of observations minus the number of estimated parameters, which tend to be consumed by more complex functional forms. In this study, however, the availability of a large dataset renders this issue irrelevant.
- "Simple" functional forms have the unfortunate consequence of imposing considerable structure upon the estimated model. More "flexible" functional forms are less restrictive, thereby allowing the data to be more influential in producing results. Other things being equal, greater flexibility is desirable. Some of the structure imposed by inflexible forms may even be regarded as inappropriate for the setting under study. For example, a linear function

imposes at least two disputable properties on a water demand function: (1) a $0.25 per kGal increase in the price of water has the same impact on consumption regardless of whether the price is initially $1 or $10 per kGal and (2) at some level there is a "choke" price (a price above which there will be no water demanded). Imposed properties such as these may constrain the ability of data to identify demand. While all conceivable functional forms are associated with some structural impositions, less structure is better. Functional forms with fewer parameters tend to be less flexible.

- A popular, yet inflexible functional form in the water demand literature is the double log model. Its popularity stems from convenience in use rather than its accuracy in estimation. The coefficients of the double log model are elasticities, so further computing of elasticities is unnecessary. Therefore, one of the rigidities imposed by the double log model is that the elasticity of each exogenous variable is constant across all possible values of all variables. General results from available water demand literature are not supportive of constant elasticity models when they are contrasted to more flexible forms. For example, Dalhuisen et al.'s investigation (2003) over many previous studies indicates that elasticity estimates are not constant in general, but vary with income, and that price elasticity in particular will be reduced at some income level. Findings such as these cast doubt on the appropriateness of the double-log form.
- Most published examples of urban water demand estimation report estimates for multiple functional forms. Linear and double log models are normally among those reported. In some situations, use of these two functional forms is necessary because the dataset contains a limited number of observations, and the desire to preserve degrees of freedom urges the adoption of simplistic functions. In other cases, reporting of linear and double log models occurs as a research tradition, in spite of the inflexibility of these two forms.
- Other functional forms sometimes employed in the urban water demand literature include log-linear, linear-log, translog, generalized Cobb-Douglas, Stone-Geary, and augmented Fourier forms (Arbués, García-Valiñas, and Martínez-Espiñeira 2003; Griffin and Chang 1991; Renzetti 2002).

Consideration of these matters leads us to favor a flexible functional form for the central model of this research. Therefore, a slightly modified version of the generalized Cobb-Douglas (GCD) functional form is selected here. This form is relatively flexible, yet not too cumbersome for application. It performed well in prior Texas work in that it best matched the results of the extremely flexible yet difficult to apply augmented Fourier form (Griffin and Chang 1991). The GCD form "nests" the double-log model as a special case, so it is necessarily more flexible than the double-log form. Prior experience with the translog form using 1980's data caused it to be rejected, because it did not exhibit the seasonality of price elasticity accurately.

Data Levels

Urban water demand estimation can be pursued using either microdata or aggregate data, as noted in Chapter 1. Microdata involves observations on individual households while each observation in aggregate data identifies summary data for a group of households – usually an entire community of households served by a single water utility. Explanatory variables such as lot size, number of bathrooms, and appliance ownership are conceivable for microdata, whereas aggregate data calls for more broadly based variables such as those applied in this study.

In addition, data may be cross-sectional, meaning that it spans households in the case of microdata or communities in the case of aggregate data, or data may be time-series. Purely cross-sectional data has no time series dimension to it; that is, all observations are for a single period, such as a single year. If the cross section is large – meaning that a large number of households/communities are included, the data may be able to support a relatively deep examination of water demand. When different households or communities operate under disparate conditions and have the latitude to adjust their behaviors to the particularized conditions they face, data from these experiences can reveal much about the nature of water demand. By taking advantage of these widely ranging conditions, the water demand functions that underlie all of these households/communities is illuminated.

Pure time series data has no cross-sectional dimension. All observations are then for a single household (microdata) or a single community (aggregate data). By itself, time series data has a weak ability to disclose important aspects of water demand (Arbués, García-Valiñas, and Martínez-Espiñeira 2003, p. 89), because many exogenous (driver) variables may change very little or only steadily over time, thereby providing a limited picture of potential consumer responsiveness. On the other hand, time series data tends to improve the variety of weather conditions that are present in a dataset. Thus, time series data is appropriate when a purpose of demand estimation is to discover responsiveness to weather conditions.

Data employed in this study has both cross-sectional and time series dimensions. Such data is known as pooled data or panel data. Pooled data from the widest practical cross-section is pursued in this research for the reasons just acknowledged. A time-series dimension is also pursued to examine the seasonality of water demand, as well as to help disentangle the effects of weather-related determinants from the other exogenous variables. Appendix D presents an advanced use of panel data to increase the precision of estimated parameters[1].

Cross-sectional data presents the best opportunity to discover the long-run impact of changes in nonweather drivers. As the scarcity of water increases, new conditions will encourage people to change not only their water use but also the water-using durables they possess in their households. These durables include modifiable items such as appliances, pools, lawns, and landscaping (Griffin and Mjelde 2000). Because these types of goods are slowly altered in response to rising water scarcity and because it is the variety of situations arising in cross-sectional data that may allow these differences to be witnessed, it is appropriate to rely on cross-sectional data to acquire a longer run analysis of demand.

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[1] Use of formal panel methods require advanced econometric methods (not ordinary least squares) and, more importantly, a balanced sample – meaning that all cross sections must have equivalent time series. Accomplishing this balance disqualifies a sizeable portion (47%) of this study's dataset because missing data means that some utilities have less than 60 months of observations. Since the panel model results of Appendix D result in small modifications to the OLS results developed here, the improvements made available by panel methods here are slight relative to the disadvantages (complex technique and data loss).

Price Specification

The water demand literature's most discussed issue is the selection of a specification for water price. Given that water pricing is sometimes complex, involving both flat and volumetric components and often block rate elements too, any single water price variable has to be regarded as a proxy or index of the true pricing policy. A further complication is that households tend to possess imperfect knowledge about the rate structure they face. They generally do not know rates, block divisions, or even their own consumption level as it is occurring. Furthermore, in the case of aggregate data such as that employed here, it should be acknowledged that the data pertains to an average or "representative" consumer when the actual situation may be one of different households facing different rates because their consumption amounts place them in different blocks.

The two prime candidates for a price variable are average price (AP) and marginal price (MP). Whereas AP is a household's total bill divided by the number of thousand gallons consumed, MP is the cost of an additional thousand gallons at the prevailing level of consumption. The specification used in this study is AP. The MP specification is clearly appropriate in many kinds of nonwater demand models and conforms to economic theory if restrictions such as full information are achieved. However, water service is not purchased under full information (Gaudin 2005; Carter and Milon 2005). Whereas most consumer goods are labeled with prices at the time of sale, water faucets and other appliances do not display water price or meter information as they are operated. Even when an after-the-fact water bill arrives, its components are not transparent to all consumers, and bills are often not large enough to inspire further investigation or price discovery by consumers. Because of the relative remoteness of the consumer from MP, we believe AP is a more accurate representation of the price experienced. AP also embeds meter fees and block rates, neither of which is reflected in MP. Thus, AP is the proxy employed here. This specification incorporates both water and wastewater bills as recommended by available literature.

Other studies have employed discrete-continuous price or an income-adjusted price. It is also possible to use multiple price variables in the same model, usually for the purpose of statistically verifying the preferred price specification. Such research is well reviewed by Renzetti (2002, pp. 22-25) and Arbués, García-Valiñas, and Martínez-Espiñeira (2003, pp. 84-85). When a multiple price approach was performed using 1980's Texas data, AP was determined to be the statistically preferred specification (Griffin and Chang 1990).

Weather Specification

Urban water demand studies have addressed weather dependencies in various ways. These methods include the division of datasets into like-weather periods (e.g. two seasons or twelve months) and the incorporation of weather variables such as temperature and rainfall. More elaborate variables have also been created in attempts to model the greater sensitivity of outdoor water use occurring during summer months. Some of these efforts have introduced new variables defined as "effective rainfall," "moisture deficit," or "sprinkler need" (Renzetti 2002).

Recognizing prior findings and suggestions, a long-term and a short-term weather variable are utilized here. The long-term variable is the 30-year average monthly rainfall experienced by the community. This variable represents an explicit accounting for the range of expected weather conditions across Texas. Communities that habitually experience wetter weather are likely to have conditioned their water-use behavior to conform to this situation. For example, the selection of landscape plantings and irrigated lawn area are affected by long-term weather expectations. Similarly, the households of typically arid communities are more likely to have made adjustments favoring low water use possessions and behavior.

Even though households can be expected to adjust their water use practices and durable possessions to normal long-term climate expectations, deviations from these conditions can have a large impact on water use, especially during summer months. For this reason, inclusion of a short-term weather variable is also desirable. Because data here is monthly, this weather variable must likewise be monthly. Many possibilities are imaginable, but few are supported by available data since widely available monthly data are limited to temperature maximums and minimums and precipitation information. The variable used here is a weather composite labeled as C. Rather than utilize precipitation amounts, we incorporate "number of days in which a significant rainfall did not occur" where a significant rainfall is defined as 0.25 inches. This formulation models the "mainly psychological" response that can appear in the water use behavior of households (Arbués, García-Valiñas, and Martínez-Espiñeira 2003, p. 87) and it controls for the different lengths of months. For example, March is 6.9% or 10.7% longer than February depending on whether it is a leap year. We multiply days without rainfall by the average daily temperature occurring for the community/month in question. This particular weather composite has not been applied in research outside of Texas, but it was the most statistically significant driver when 1980's data was originally investigated (Griffin and Chang 1989).

Estimation Methods

Although many urban water demand studies have used ordinary least squares (OLS) regression techniques, a good deal of this research has employed more advanced methods. The more advanced approaches are commended by the peculiarities that often arise for this sort of data. The primary concern is that OLS employs an assumptive base that includes elements such as (1) the endogenous variable (W/cap) being dependent on the exogenous variables but not vice-versa and (2) the degree of randomness being constant throughout the data.

In block rate structures and average price specifications, assumption (1) is unsatisfied, thereby raising issues of "simultaneity" or "endogeneity" (Renzetti 2002). The result may be that bias is introduced in coefficients estimated via OLS procedures. If this issue is suspected to occur in the dataset of interest, then regression techniques such as instrumental variables (including two-stage procedures) may be applied (Kennedy 2003). A pretest utilizing the double log specification failed to reject the hypothesis that the price elasticity of demand for uniform rates is identical to that for block rates in the present sample. That is, a high degree of simultaneity bias was not detected in the data.

If the random error of each observation is not of the same magnitude, a condition known as heteroskedasticity, the standard error of OLS estimates may be overstated. A multi-stage generalization of OLS is one way to address this sort of imprecision. The parameters themselves will not be biased by heteroskedasticity; thus it is a less serious issue than simultaneity. OLS is adopted in the analysis below, and the precision gains sought from more generalized estimation procedures are derived instead from the flexible GCD form and the breadth of primary data. The previously mentioned panel technique of Appendix D uses an alternative to multi-stage estimation to investigate whether there are disadvantages to OLS estimation using the data assembled in this study.

Variable Specifics

R

Weather is sufficiently important to advise a two-variable strategy, as noted above. The long-run variable is R, defined as average inches of precipitation for the 30-year period 1971-2000. Monthly averages are used, so for any given community this variable changes from month to month but not year to year, meaning that it takes on twelve values for each utility's 60 (or fewer) observations.

C

The short-run weather variable is a composite called C, and it embeds average daily temperature, rainfall occurrences, and month length. It is defined as follows.

$$C = \frac{Temp_{max} + Temp_{min}}{2} \bullet \frac{\text{days without precipitation}}{1000} \qquad [4.1]$$

Division by 1000 was not applied in the prior Texas research, but it scales this variable to a range similar to the other variables here.

I

Income, denoted I here, is real personal income in $10,000 units.

P

As noted above, the average price (P) specification is used here. If the utility also provides wastewater services, then sewer bills are included in the P specification. P is the real average price paid per 1000 gallons.

S

To further differentiate the absence or presence of wastewater collection/treatment, an indicator variable S (for sewer) is introduced. S=0 for those systems offering water service only, and S=1 for systems offering water and wastewater service. The purpose of this binary variable is to investigate whether there may be a statewide difference in demand behavior, depending on whether sewerage services are available. Since locales without community sewerage are different in many ways from areas possessing sewerage, any inferences from demand analysis using this variable should be carefully stated.

Together with the formative elements of Chapters 2 and 3, the above descriptions and definitions fully define the completed dataset to be used in the immediately following econometric analyses. This dataset is downloadable at http://waterecon.tamu.edu/udemand.html.

Estimation Results

The generalized Cobb-Douglas (GCD) functional form is nonlinear in parameters, so a logarithmic transformation is required to perform OLS. Once the variables described above are substituted and a logarithm is taken of both sides, the following function results.[2]

$$\begin{aligned}\ln\left(\frac{W}{cap}\right) = {} & ß_0 + ß_1 \bullet \ln C + ß_2 \bullet \ln R + ß_3 \bullet \ln I + ß_4 \bullet \ln P + ß_5 \bullet S + ß_6 \bullet \ln(C+R) \\ & + ß_7 \bullet \ln(C+I) + ß_8 \bullet \ln(C+P) + ß_9 \bullet S \bullet \ln C + ß_{10} \bullet \ln(R+I) + ß_{11} \bullet \ln(R+P) \\ & + ß_{12} \bullet S \bullet \ln R + ß_{13} \bullet \ln(I+P) + ß_{14} \bullet S \bullet \ln I + ß_{15} \bullet S \bullet \ln P + \nu \qquad [4.2]\end{aligned}$$

There are 15 beta (ß) coefficients to be estimated for this model. Table 4.1 shows the correlations of the log-transformed independent variables and the interactions incorporated in eq. [4.2]. Some of these correlations are higher than the simple correlations given for untransformed data in Table 3.4, meaning that some imprecision will occur for OLS-obtained parameters of the estimated equation. This condition is anticipated since the interaction terms are combinations of other variables. While this sort of correlation is reason for some caution, its consequence – misestimation of individual ß's – is not likely to bias slope or elasticity estimates [3] because results such as these are combinations of parameter estimates from eq. [4.2].

Coefficient estimates and general statistics for the GCD "full-data" model (eq. [4.2]) are given by Table 4.2. For interested readers, linear and double-log functions are estimated and the resulting models are reported in appendix Table C-1, but they will not be further discussed here except to observe that the adjusted R^2 and mean squared error statistics of model fit confirm the expected preference for the GCD model. All 39,145 observations are employed to obtain the models summarized in Tables 4.2 and C-1, so they are referred to as full-data models in this report. Each parameter of the GCD model is at least 99% significant.

Twelve "monthly-data "GCD models have also been estimated by using data from each single month (e.g. January) to obtain alternative sets of parameter estimates. These models are not tabulated in this report, but they are used in some of the forthcoming calculations to investigate the stability of results.

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2 Because the logarithm of zero is undefined, the binary S variable is introduced multiplicably in this function and it is not transformed by logarithm.

3 Errors of collinearity within families of regressors tend to "even out" at the slope or elasticity level, inferring that collinearity has greatly reduced consequences for applications that employ combinations of ß's such as slopes and elasticities.

Table 4.1 Full Correlation Matrix (n=39145)

	In C	In R	In I	In P	S	In(C+R)	In(C+I)	In(C+P)	SIn C	In(R+I)	In(R+P)	SIn R	In(I+P)	SIn I	SIn P
In C	1.00														
In R	0.11	1.00													
In I	-0.12	0.28	1.00												
In P	-0.16	0.15	0.01	1.00											
S	0.00	-0.07	0.13	0.00	1.00										
In(C+R)	0.39	0.94	0.21	0.06	-0.06	1.00									
In(C+I)	0.49	0.30	0.78	-0.11	0.13	0.42	1.00								
In(C+P)	0.06	0.18	-0.01	0.97	0.01	0.15	0.01	1.00							
SIn C	0.52	0.02	0.03	-0.08	0.77	0.17	0.32	0.04	1.00						
In(R+I)	0.02	0.91	0.61	0.11	0.00	0.85	0.53	0.12	0.02	1.00					
In(R+P)	-0.08	0.64	0.18	0.83	-0.02	0.55	0.08	0.83	-0.04	0.59	1.00				
SIn R	0.08	0.50	0.30	0.09	0.76	0.48	0.32	0.12	0.65	0.51	0.34	1.00			
In(I+P)	-0.18	0.23	0.33	0.94	0.05	0.13	0.15	0.91	-0.05	0.31	0.85	0.19	1.00		
SIn I	-0.04	0.06	0.46	0.01	0.92	0.04	0.38	0.01	0.67	0.23	0.06	0.79	0.16	1.00	
SIn P	-0.05	0.00	0.12	0.38	0.89	-0.02	0.08	0.37	0.65	0.04	0.30	0.72	0.40	0.82	1.00

Table 4.2 Parameter Estimates for the GCD Regression (n=39145)

Parameter	Coefficient*	Standard Error
ln C	0.189	0.0264
ln R	0.339	0.0233
ln I	0.541	0.0624
ln P	-0.448	0.0331
S	0.393	0.0252
ln (C+R)	-0.219	0.0487
ln (C+I)	0.316	0.0699
ln (C+P)	0.909	0.0597
S • ln C	-0.0699	0.0156
ln (R+I)	-0.260	0.0550
ln (R+P)	-0.526	0.0416
S • lnR	0.0903	0.00861
ln (I+P)	-0.800	0.0637
S • ln I	-0.268	0.0185
S • ln P	0.144	0.00915
Constant	5.58	0.0674
Adjusted R^2	0.49	
(Mean Squared Error)$^{0.5}$	0.36	

*All parameter estimates significant at 99% confidence level.

Based on the statistical evidence of Table 4.2, the GCD model demonstrates a strong correspondence between water use per capita and the selected set of exogenous variables. The adjusted R^2 statistic is relatively high for cross-sectionally dominated data and provides confidence regarding the overall merits of the model. The high statistical significance of the parameter estimates infers that Texans do make different choices about how much water to consume based upon the climates they live with (R), the weather they experience (C), average income in their counties (I), the pricing signals they face (P), and whether or not their locale is similar to areas that receive wastewater services from their water provider (S). These distinctions begin to indicate that water use is likely to be determined by many varying conditions across the State.

Elasticity Results

Recall that an elasticity is unitless as well as simple to understand. An elasticity of –0.5 means that a 1% rise in the level of the driver will decrease water use per capita by 0.5%. In the remainder of this chapter, discussion of various elasticities is the main avenue for exploring and demonstrating the estimated model of Table 4.2. Because individual model coefficients are not readily interpretable, we use the elasticity definition (eq. [1.3]) to compute elasticity functions for each of the continuously valued drivers (R, C, I, and P). Because of the flexibility of the GCD functional form, each of the relevant elasticities is functionally dependent on the coefficients reported in Table 4.2. Also, because each elasticity is not constant across the data range, complete computation of a numeric elasticity cannot be performed until a level is selected for all drivers (R, C, I, P, and S). Except when noted below, mean values from the dataset are used for the tabulated elasticities that follow.

Table 4.3 exhibits basic annual elasticity estimates derived from the full-data GCD model as well as S=0 and S=1 partitions of the data. These include computations made at mean values for each

Table 4.3 Demand Elasticities

			Elasticity Evaluated at Variable's		
Variable	Mean	Standard Deviation	Mean – S.D.	Mean	Mean + S.D.
			For S = 0.628		
C	1.82	0.43	0.38	0.43	0.48
Rainfall	2.95	2.23	0.21	-0.07	-0.21
Income	2.63	0.63	0.20	0.16	0.12
Price	4.96	2.24	-0.47	-0.55	-0.59
			For S = 0 (Water Service Only)		
C	1.81	0.43	0.48	0.46	0.44
Rainfall	3.03	2.24	0.20	-0.17	-0.33
Income	2.51	0.52	0.44	0.33	0.24
Price	4.89	1.97	-0.58	-0.65	-0.70
			For S = 1 (Water & Wastewater Service)		
C	1.82	0.43	0.36	0.43	0.49
Rainfall	2.90	2.22	0.23	-0.03	-0.15
Income	2.71	0.68	0.08	0.06	0.04
Price	5.01	2.38	-0.41	-0.48	-0.53

of the four exogenous variables as well as computations towards the edges of data ranges.

The uppermost section of Table 4.3 is obtained using the GCD model of Table 4.2. Elasticities are presented for each driver except S. Elasticity values are computed for mean values of all variables including S (even though S only takes on 0 or 1 values in the data). To gain perspective on the range of sensitivities to demand drivers, elasticities are also computed for one standard deviation on either side of the variable means. These "off-mean" evaluation points use mean values for variables other than the variable of focus. For the most part, the "mean +/-1 standard deviation" provides a reasonable approach, with the possible exception of the rainfall variable. The standard deviation of rainfall is large in comparison to its mean (because rainfall is not normally distributed about its mean). Consequently, rainfall's mean minus its standard deviation is a very small value (less than 9 inches per year) that is not characteristic of many Texas utilities.

The lower sections of Table 4.3 repeat these elasticity computations using alternative population sets. The full-data, 39,145-observation dataset is separated into its S=0 and S=1 subsets (14,548 and 24,597 observations respectively). New GCD models are estimated for each (reported in appendix Table C-2), and new means and standard deviations are obtained to generate alternative outlooks on demand determination. Thus, differences among the three groups of results reported in Table 4.3 arise both from the use of different model coefficients and different means and standard deviations. Note that population means and standard deviations are not markedly different and that elasticity signs and magnitudes are generally alike. The largest discrepancy pertains calculated income elasticities. Further observations emerging from Table 4.3 will be discussed in the subsections to follow.

Table 4.4 reports complete sets of monthly elasticity estimates using two alternative modeling options. In the upper portion of the table, monthly means are substituted into the overall GCD model (Table 4.2) to obtain elasticity estimates for each month. In the lower half of the table, monthly means are substituted into twelve monthly GCD models[4] to obtain comparable results. Throughout this table, elasticities are computed for the fictitious average utility (S=0.628).

A binary variable does not properly have an elasticity, but the effects of "sewerage presence" can be seen in Table 4.5. Table 4.5 uses different monthly GCD models to examine the differing demand responsiveness for the two types of utilities present in the data sample. Monthly elasticities are computed for those utilities engaged only in water service as well as for those engaged in both water and wastewater service. Water-only means and models are on the left side of Table 4.5. The upper half of Table 4.5 employs the same GCD models (12) for both left (S=0) and right (S=1) sides, and it uses separate subsample means (for water-service-only and water/wastewater partitions) in making the elasticity calculations. The lower half of Table 4.5 uses 24 distinct GCD models[5] by splitting the dataset along both service (water, water/wastewater) and month delineations.

Regarding the left versus right sides of Table 4.5, interpretation of these differences should acknowledge the many differing characteristics of locales that do/do not possess centralized wastewater collection and treatment. Because water-service-only utilities tend to serve rural and

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[4] These twelve monthly models result from regression upon data only for a given month and therefore are based on a division of the 39,145 observations into twelve separate datasets. Regression statistics for these models are not tabulated in this report.

[5] Regression statistics are not reported for these 24 models.

Table 4.4 Monthly Demand Elasticities (at S=0.628 and monthly means)

	C	R	Income	Price
	Using the All-data GCD Model			
Jan	0.360	-0.030	0.178	-0.531
Feb	0.353	-0.011	0.179	-0.544
Mar	0.404	-0.109	0.192	-0.510
Apr	0.417	0.023	0.136	-0.600
May	0.476	-0.118	0.157	-0.538
Jun	0.486	-0.173	0.170	-0.506
Jul	0.502	-0.022	0.108	-0.611
Aug	0.508	0.002	0.093	-0.626
Sep	0.476	-0.095	0.145	-0.550
Oct	0.446	-0.108	0.168	-0.529
Nov	0.393	-0.082	0.185	-0.519
Dec	0.368	-0.088	0.197	-0.501
Average Annual	0.442	-0.067	0.153	-0.552
	Using 12 Separate Monthly GCD Models			
Jan	-0.230	-0.096	-0.059	-0.531
Feb	-0.153	-0.070	-0.091	-0.550
Mar	-0.097	-0.147	-0.030	-0.509
Apr	-0.057	0.007	-0.178	-0.659
May	0.150	0.026	-0.123	-0.688
Jun	0.235	-0.413	0.124	-0.568
Jul	0.634	-0.237	0.377	-0.621
Aug	0.249	-0.236	0.400	-0.695
Sep	0.684	-0.146	0.317	-0.617
Oct	-0.118	-0.153	0.083	-0.611
Nov	-0.019	-0.129	0.044	-0.542
Dec	-0.109	-0.152	-0.136	-0.508
Average Annual	0.143	-0.155	0.093	-0.601

Table 4.5 Separate Monthly Demand Elasticities for W and W/WW Utilities

	C	R	Income	Price	C	R	Income	Price
	Water Service Only Utilities (S=0)				Water & Wastewater Service Utilities (S=1)			
	From the 12 All-data Monthly GCD Models:				From the 12 All-data Monthly GCD Models:			
Jan	-0.189	-0.177	0.098	-0.621	-0.255	-0.047	-0.153	-0.477
Feb	-0.001	-0.194	0.094	-0.621	-0.244	0.005	-0.200	-0.507
Mar	0.127	-0.263	0.225	-0.585	-0.230	-0.078	-0.181	-0.465
Apr	0.151	-0.108	0.037	-0.770	-0.181	0.075	-0.305	-0.594
May	0.387	-0.172	0.152	-0.775	0.010	0.145	-0.287	-0.637
Jun	0.228	-0.416	0.233	-0.711	0.239	-0.410	0.059	-0.483
Jul	0.473	-0.163	0.432	-0.713	0.729	-0.279	0.345	-0.567
Aug	0.128	-0.159	0.520	-0.807	0.319	-0.279	0.330	-0.628
Sep	0.715	-0.172	0.304	-0.728	0.666	-0.130	0.325	-0.552
Oct	-0.013	-0.287	0.227	-0.733	-0.180	-0.073	-0.001	-0.539
Nov	0.056	-0.215	0.180	-0.640	-0.064	-0.078	-0.036	-0.484
Dec	0.067	-0.259	0.093	-0.596	-0.214	-0.088	-0.272	-0.456
Average Annual	0.204	-0.213	0.242	-0.703	0.105	-0.120	0.006	-0.541
	From the 12 W-data Monthly GCD Models:				From the 12 WW-data Monthly GCD Models:			
Jan	-0.170	-0.161	0.128	-0.626	-0.270	-0.055	-0.158	-0.478
Feb	-0.022	-0.266	0.050	-0.641	-0.216	0.028	-0.181	-0.502
Mar	0.157	-0.382	0.133	-0.589	-0.225	-0.019	-0.168	-0.464
Apr	-0.021	-0.216	0.109	-0.781	-0.137	0.115	-0.294	-0.604
May	0.274	-0.384	0.192	-0.774	0.066	0.215	-0.261	-0.655
Jun	0.177	-0.430	0.327	-0.716	0.264	-0.400	0.023	-0.481
Jul	0.494	-0.091	0.391	-0.710	0.740	-0.302	0.348	-0.573
Aug	0.117	-0.132	0.430	-0.762	0.324	-0.294	0.376	-0.639
Sep	0.777	-0.143	0.308	-0.752	0.647	-0.139	0.332	-0.541
Oct	-0.010	-0.363	0.124	-0.748	-0.171	-0.041	0.033	-0.530
Nov	0.023	-0.240	0.174	-0.659	-0.041	-0.069	-0.037	-0.474
Dec	0.069	-0.282	0.088	-0.613	-0.220	-0.075	-0.260	-0.446
Average Annual	0.184	-0.248	0.228	-0.706	0.119	-0.105	0.017	-0.541

possibly urban fringe communities, which differ in a variety of ways from urban and town environments, there are many factors distinguishing these two groups.

Taken together, Tables 4.4 and 4.5 shed light on the alternative structural assumptions and their effects as well as the stability of results in the face of alternative modeling selections.

Weather and Climate

From Table 4.3, annual demand elasticities with respect to C are positive, inferring that periods of higher temperature and less frequent precipitation encourage increased consumption of water. These results conform to theoretical expectations about the influence of the weather on water use. For W-only utilities (S=0), demand response to C is generally even across the range of C levels, but W/WW utilities (S=1) tend to experience greater demand responses to C as C increases.

From the monthly results of Table 4.4, the all-data model differs from the month-specific models in estimating the seasonality of C elasticities. Because it pools all data and thereby forces some homogeneity upon demand responses, the all-data model indicates a flowing reaction to C, peaking in the summer. There is less structure (and much less data) in the individual monthly GCD models, so seasonal C responses are not smoothly changing from month-to-month, and C elasticity is sometimes slight or even negative in winter months. Peak responses to C are seen in the summer under all model options. Table 4.5 confirms these patterns within both W-only and W/WW partitions. As a result of these analyzes, we feel that the true pattern of responses to C are reasonably depicted by the monthly models (Table 4.5 and lower half of Table 4.4), but these responses are too erratic to be applied without first smoothing them in some formal fashion (which is not pursued here).

Throughout most of the modeling approaches reported in Tables 4.3-4.5, the demand response to historical precipitation (R) is mildly negative. Hence, locales that are accustomed to drier weather tend to use more water, but not markedly more. This result tends to be exhibited by both annual and monthly models. One interesting exception is displayed in the "Mean–S.D." column of Table 4.3. The indication here is that the driest communities may actually increase water use if they were to experience a shift towards permanently wetter weather. A reasonable explanation for this phenomena is that wetter weather can encourage shifts in the water-using durables held by consumers. For example, wetter weather can encourage a shift to lawns and landscapes which are more water intensive. Similarly, permanent shifts to drier weather may evoke long-term responses in the direction of reduced commitments to outdoor water use. To the extent this may be true, it would seem that consumers in more arid regions make progressively greater adaptations to their climate conditions. The fact that consumers make such changes is additional evidence of the controllability of water use. It even indicates where things may progress should rising scarcity greatly increase water rates.

Income

If one examines only the annual results of Table 4.3, it appears that water demand is weakly responsive to personal income. Income elasticity has the expected positive sign here, but it is small, especially for utilities offering both water and wastewater services. Recall that income data is specified at the county level. Hence, utilities operating in the same county are treated as having the same income, even though any given county is likely to contain both high- and low-income households. To the extent that like-income households may congregate in the same communities, different utilities in the same county may be serving differing client groups (in terms of income). This issue is more problematic for large-population counties where communities may be very diverse and multiple utilities may be operating. Affluent households may compose a smaller proportion of one utility's customer base than another's, yet a county-level income variable cannot capture the difference. Given this general weakness of income data, a weaker than actual performance might be expected for the income driver, especially for S=1 utilities (which are more likely to lie in urban counties where other utilities are also operating).

Examination of the monthly results – contained in the lower half of Table 4.4 and all of Table 4.5 – reveals two additional outcomes. First, in the cooler six months of the year, income elasticities may be near zero or even negative. Second, income elasticity in summer months well exceeds that of other months.

With regard to the first of these two observations, negative elasticities arise only for the S=1 utilities for which income data may be more poorly indicative of a utility's actual personal income level. Although we have not calculated confidence intervals for any of these elasticity estimates, some of these S=1 monthly income elasticities may be insignificantly different from zero.[6]

For the second observation pertaining to heightened summer income elasticity, such a finding is theoretically consistent with the idea that much of summer water use is more discretionary than it is during the remainder of the year. Given data weaknesses, it is suspected that the summer income elasticities determined from the monthly models may even be understated.

Price

All three tabulations of price elasticities indicate that demand responses to price are consistent and of the anticipated sign. Across all service partitions and monthly delineations, elasticities range from approximately –0.48 to –0.8 when evaluated at data means.

With respect to service partitions, water-service-only utilities encounter higher magnitude price elasticities, at about –0.7 annually, than do water and wastewater utilities (Table 4.5). Price elasticities for water and wastewater utilities are about –0.54 on an average annual basis.

Seasonality in price elasticity is very evident. As expected, the greater discretionary flexibility of summertime water use gives rise to more pronounced demand responses to price. Across both service partitions, summer price elasticity is higher in magnitude by about 0.15 over winter price elasticity.

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[6] For the S=1 annual model, Table C-2 shows that two of the four income-using parameters are statistically insignificant from zero, whereas all parameters are significant for the S=0 model.

In most ways, the price-related results of these demand models are more definitive than those emerging from weather, climate, and income drivers. Clearly, community water demand is price responsive. We believe the performance of the price variable is assisted by its data origins. Both the water consumption information and water rate information of this study come directly from surveys of water utilities. Other data used in this analysis comes from area sources that may not match well with the individual water utilities. Weather data comes from nearby weather stations, of which there are only 141 with sufficiently complete records. Income data pertains to the county in which the utility primarily operates. Thus, although average water price is a proxy for the complete rate system actually faced by consumers, the price variable is well matched to the individual utilities.

Given the demand functions that were theoretically diagrammed in Chapter 1, it is potentially reaffirming to graph actual demand curves emerging from the empirical results obtained here. Lots of possibilities are available, because of the many model variants examined for Tables 4.3 - 4.5. However, in order to concretely juxtapose the range of experiences disclosed in these results, we can select January and August demands for both water-service-only and water/ wastewater utilities. Figure 4.1 precisely illustrates these four separate demand functions using the same mean variable values and regression coefficients that produce the upper portion of Table 4.5.

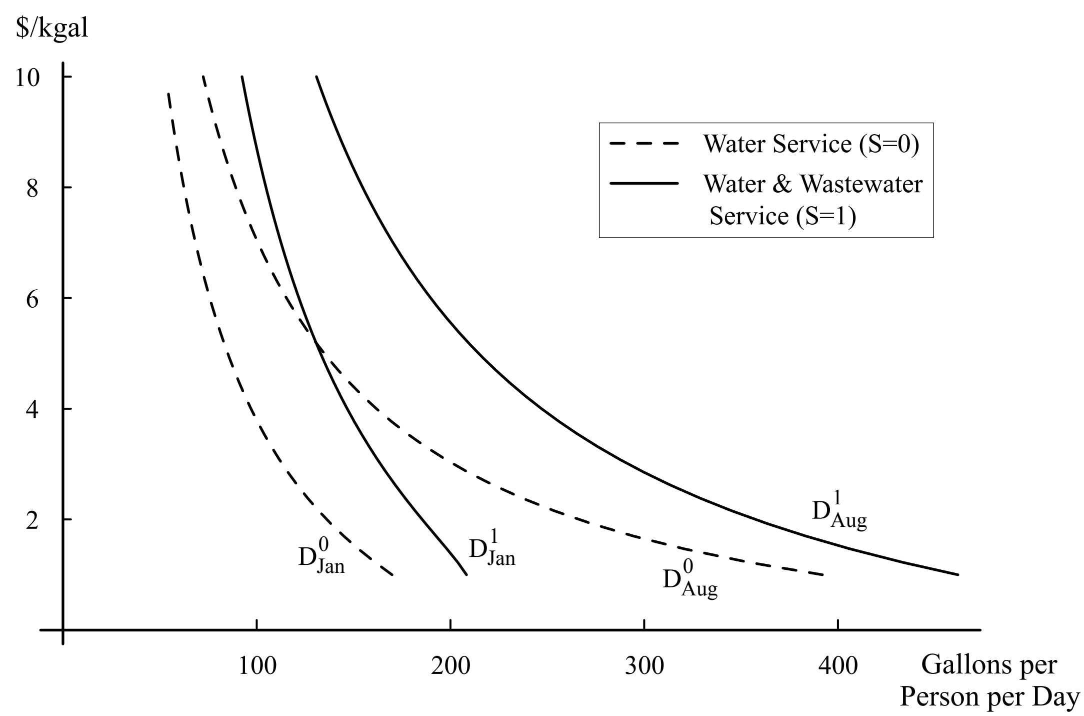

Figure 4.1 Texas Community Water Demand Functions

Figure 4.1 clearly exhibits the anticipated shape and negative slope of all four demand functions. August demands are rightward of January demands, as expected. August demands appear to be more price responsive than January demands when compared at equivalent prices. Water demand in S=0 utilities is less than that of S=1 utilities. Note also that as prices increase for either utility type, August demands appear to be converging in the direction of January demands – indicating that consumers are better able to reduce summer water use as water costs rise. Yet, it is quite evident that even January demands are price responsive.

Chapter 5

Concluding Comparisons

Rather than summarize findings at this point, we conclude with a few reflections pertaining to the changes that have occurred in Texas over the last twenty years. Readers wishing to obtain an overview of this report can rely on the Executive Summary commencing on p. ii. Also, keep in mind that methodological guidance for some water planning applications of Chapter 4 results is overviewed in Chapter 1.

The 1981-85 Texas Study

In the late 1980's the Texas Agricultural Experiment Station sponsored a study similar to the one reported here. This earlier project was documented by a report and two consequent articles (Griffin and Chang 1989, 1990, 1991), all of which are downloadable[1]. The current study parallels the 1989 one relatively well, enabling some insights about the changing nature of urban water demand and water pricing in Texas. The most notable comparisons are reported below.

The 1980's study compiled very similar data to that of this 2006 report. Monthly data from 1981-85 were used, so a 60-month record was established. Data were similarly collected, including the use of TWDB water use data and a mailed survey to obtain rate information. The eventual dataset included 221 Texas water systems, yielding a 12050-observation dataset.

The most interesting comparisons of these two studies may lie in the areas of water use, water rates, and estimated demand elasticities. Yet, one must be mindful that the two studies involve different (though overlapping) cross sections, not just different time periods. Therefore, not all of the distinctions between the results of these studies stem from modified consumer behavior and increased water scarcity.

Comparing Consumption and Rates

Figure 5.1 is primarily a replica of Figure 3.1 with the years 1981-85 added. Here, the Stage 2 dataset is employed, and utilities are weighted by population.[2] All of the dashed lines represent 1981-85 years with no attempt to identify the individual years. There are 10 individual years displayed as well as average (bold) water use for each of the two periods. Observe that water use during the more recent five-year study period is lower. However, the more exhaustive coverage of this study means that more communities are included and average community size is lower. Whereas the average system-month of the 1980's study involved water service to 23,600 people,

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[1] A later study employing more contemporary econometric techniques, but also using the 1980's data, was published in 2001 (Gaudin, Griffin, and Sickles). Whereas the methods of the 2001 study are somewhat different than the earlier work, the data is unchanged except for the omission of data which did not meet the requirements of new econometric procedures. The issue addressed by the 2001 work is also considered in the present study (Appendix D).

[2] Each of the ten base years shown here indicate population-weighted monthly water use, so as to accurately portray water use statewide. That is, since the metric of interest is daily water use by the average Texan, communities with greater population are more significant. Figure 3.1 provides unweighted results.

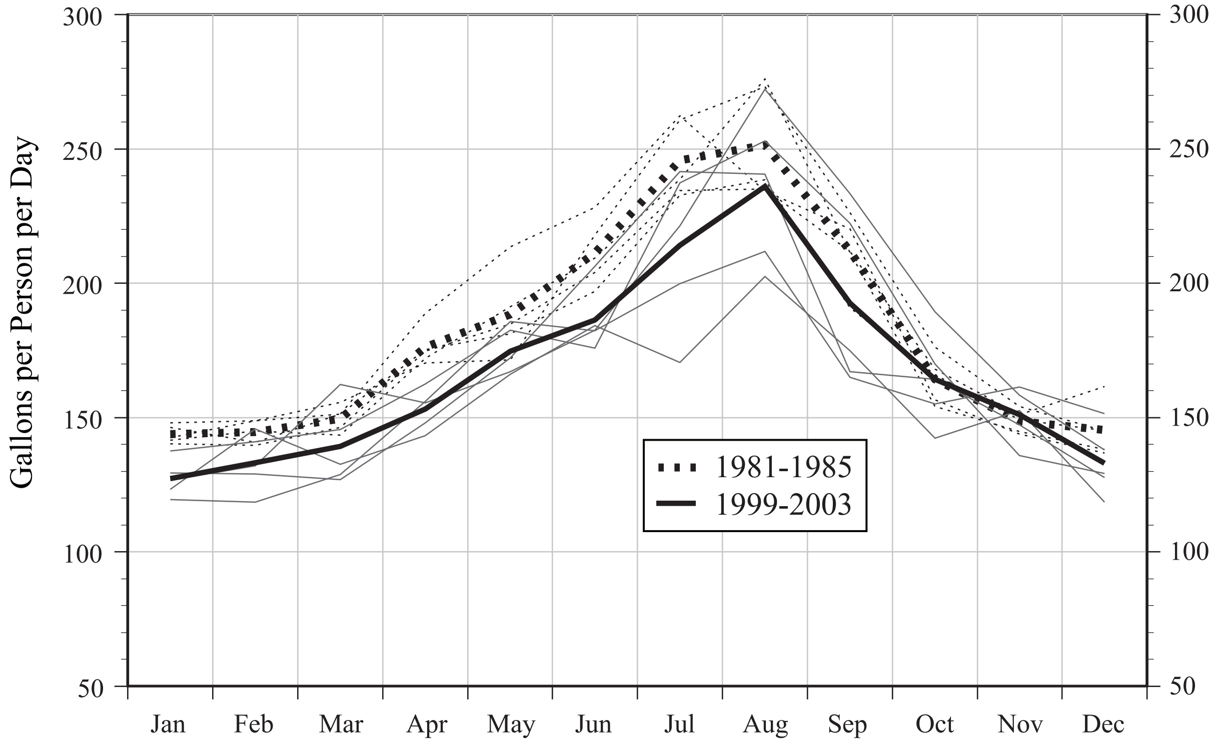

Figure 5.1 Comparing Average Water Use in the Two Periods

that average is 13,200 in the present study (Stage 2 data). This difference makes it difficult to assign great significance to the water consumption "changes" displayed in Figure 5.1. Yet, the fact that the series appearing in this figure are population-weighted implies that a partial accounting for population differences has been accomplished here.

Figures 5.2 and 5.3 display average water and sewer marginal prices for the ten years, similarly to Figures 3.5 and 3.6 previously in this report. To present this meaningfully, the 1981-85 prices have been CPI-adjusted to the same base month (June/July 2003) as that employed in the present analysis. Stage 2 data and population weighting are employed. Several observations are readily obtained here, either directly from these figures or the underlying data.

- For water rates, the early 1980's was the era during which the average Texan experienced a switch from decreasing block rates. Across the ten-period record displayed in Figure 5.2, the increasing nature of block rates has steadily advanced. More detailed examination discussed previously indicates that many of the rate structures embedded here are uniform rates, yet increasing block rates are clearly dominant for the average Texan.
- Water rate increases over these 22 years can be measured at different levels. Here, average annual increases are listed for meter fees (not displayed in Figures 5.2-5.3) and two levels of marginal price. Again, inflation has been netted out, so the nominal increases have been

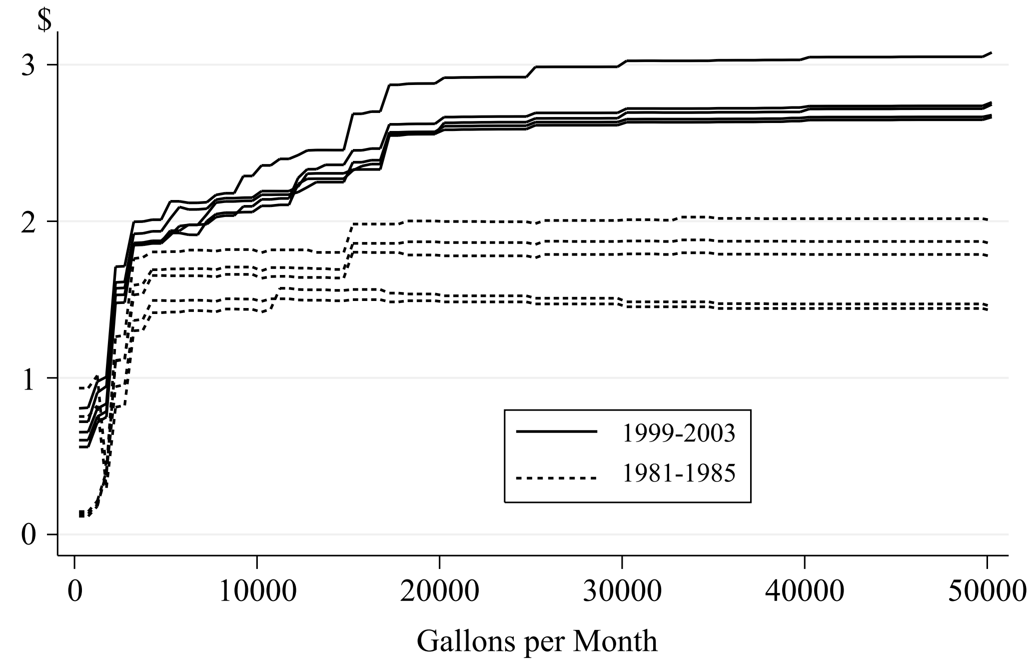

Figure 5.2 Comparing Mean Marginal Water Prices

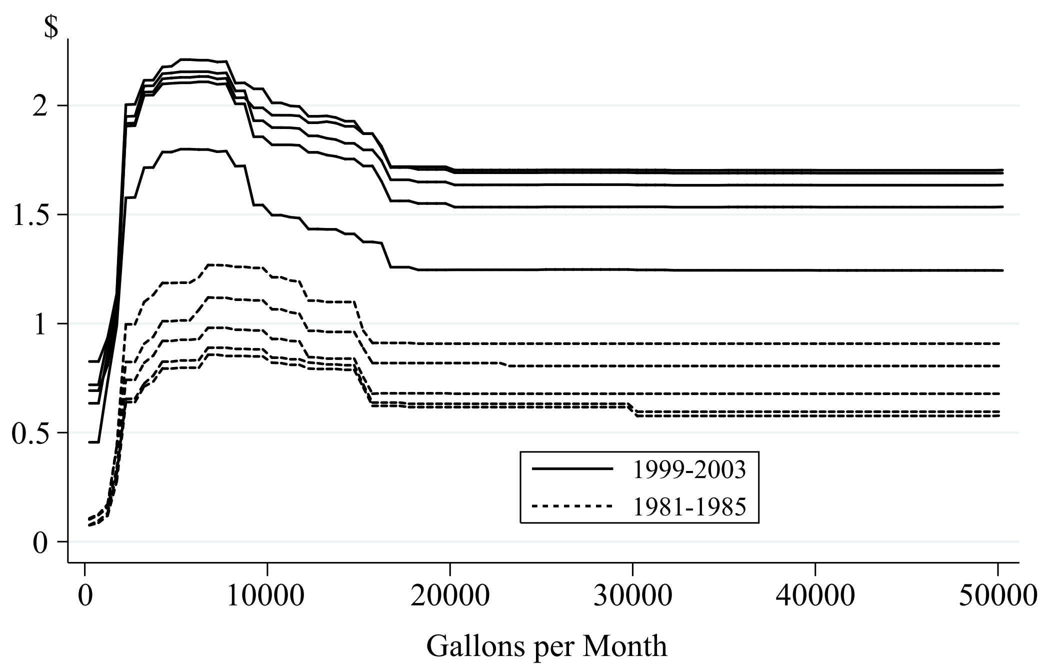

Figure 5.3 Comparing Mean Marginal Sewer Prices

much higher.

Meter Fee: +1.25%/yr. 5,250 gal.: +1.85% /yr. 20,250 gal.: +2.99% /yr.

At all consumption levels higher than 12,000 gallons, the increase has been at least 2% annually.

- For sewer rates, various elements of rate structures combine to maintain a decreasing block rate appearance for most of the displayed water use range in all years. As compared to water rates faced by the average Texan, sewer rates have increased sharply over time, even at low consumption levels.

- Sewer rate increases (average annual) over this 22-year period are as follows once inflation components are removed.

Meter Fee: +0.82% /yr. 5,250 gal.: +4.74% /yr. 20,250 gal.: +4.69% /yr.

At nearly all consumption levels, the increase has been 4-5% annually.

Comparing Results

We now turn to the comparisons between the 1980's and 2000-era econometric results, principally those pertaining to the response of water demand to its drivers. Noteworthy differences between the earlier work and the research reported here bear upon the available comparisons, so they are identified as follows. First, the earlier work included an additional exogenous variable and omitted another used in the present study. The additional 1980's variable (percent Hispanic population) was somewhat negatively collinear (–0.49) with the 30-year average rainfall variable (R), making it difficult to compare the two studies with respect to the rainfall driver. Moreover, the prior study included sewer rates as well as systems that do and do not provide sewerage service, but it did not examine the distinction between the two system types with a binary variable (S) as performed here. Second, the prior study explored more functional forms. Fortunately, the generalized Cobb-Douglas function is among the forms evaluated in the earlier study. Third, the earlier study was very focused on price as a potential demand driver, because Texas planning presumptions prevalent at the time tended to deny the relevance of water price. Consequently, the 1980's publications included nonprice exogenous variables, but elasticity results were not tabulated for nonprice variables. The Gaudin-led reexamination (2001) of the 1980's data did report nonprice elasticities, so some added comparisons can be obtained there.

With these distinctions in mind:

- General goodness-of-fit measures are slightly better for the 2000-era data when estimating a generalized Cobb-Douglas function (2006 Table 4.2 and 1989 Table D-4). Given this small advantage, there seems to be little difference in the overall explanatory powers of these models in the two periods.

- Price elasticity – the responsiveness of water demand to price – has increased during the past twenty years. The earlier work found that price elasticity generally lies around –0.36 when evaluated at overall variable means, (1991 Table 4, 2001 Table 3). Comparable computations from the 2000-era data find price elasticity to be in the vicinity of –0.55 (Table 4.3). This may be an important change. If this finding is not just an anomaly of 1999-2003 period, it has noteworthy implications for future conservation-oriented policy as well as project analyses.

- Both sets of data are supportive of "higher" summer price elasticities. Depending on which model formulation is assumed and which evaluation points are used, both data periods show summer price elasticities to be 0.1 to 0.2 higher (in magnitude) than they are in the winter. Thus, whereas mid-winter price elasticity may be around –0.50 in the 2000-era data, this elasticity appears to –0.60 to –0.70 in July/August. Regardless of which evaluation basis (water service only, water/wastewater, etc.), the 0.1 to 0.2 increase appears to hold (2006 Tables 4.4, 4.5). The 1980's analyses indicated a similar swing (1991 Table 4). It is therefore important for planners to realize that higher summer elasticities together with the higher levels of summer use make seasonal pricing a valuable policy instrument. This finding dovetails well with the typical situation where summer water is more costly to provide and the opportunity cost of natural water supplies is elevated too.
- For the remaining comparable exogenous variables (C, Rainfall, and Income) the two study periods yield elasticities of the same overall signs and of like magnitudes (column 1 of 2001 Table 3, S=0.628 group of 2006 Table 4.3). This finding indicates that these drivers have relatively stable influences on community water use.

Other Texas Studies

Although there may be others, we are only aware of two Texas-focused studies with similarities to the research reported here. Both of these studies are consultant reports sponsored partially or wholly by the Texas Water Development Board. Unfortunately, the differing emphases and/or methods of these works, as contrasted to the present study, limit some of the comparisons that can be drawn.

The 1991 study conducted by Holloway and Ball uses data which is similar to that reported here. Eleven years of monthly data was assembled for 72 Texas cities. This information included water use per capita, water price, and income. Temperature and "number of dry days" information was also included. Hence, there are strong data similarities with our work here.

In their efforts to generate well-fitting statistical models as opposed to emphasizing driver effects, Holloway and Ball estimate separate models for different Texas regions (nine). Different functional forms are reported for different regions, as statistical fit was allowed to determine a preferred function for each region. Moreover, within each of these models, intercept-shifting dummy variables were used to separate the individual cities within each region. As a consequence of these methods, which strongly tend to construct city-specific analyses, the study dismisses most of the data's cross-sectional variability. It is this variability which is useful in analyzing drivers like price and income. Consequently, it is not surprising that Holloway and Ball's reported price and income elasticities are widely variant across cities, since such findings are primarily determined by time-series elements of the data within their analysis (Holloway and Ball 1991, pp. 37-38). Although one might argue that this approach can successfully identify short-run elasticities, given the reliance on time-series data, monthly data for an average household in a single city is not very informative in examining responses to nonweather variables. Because drivers like price and income change slowly within a given utility, data variability for these drivers is weak for time-series dominated data. In any case, it is difficult to draw meaningful comparisons between the results of the Holloway and Ball and those of the present study because of the differences in methods.

The second report was led by John Whitcomb of Stratus Consulting (1999). This 1999 study uses household-level microdata (defined above in Chapter 1) from the Cities of Austin, Corpus Christi, and San Antonio. A mailed survey sent to 7500 households was used to acquire microdata pertaining to elements such as housing size and value, installed appliances, income, and attitudinal perspectives. Monthly water use and price data for 1990-1997 was provided by the cities. The analysis is primarily descriptive, and no regression work is performed. Due to the microdata dimensions of the analysis, there are limited grounds for comparison with the present study. However, sections of the Stratus report do attempt to address price elasticity measurement. The reported elasticities of this study cannot be confidently accepted because they come from a simple comparison of Austin and San Antonio circumstances. No attempt to control for other exogenous variables is made, and the two-system cross section represents a highly limited basis for examining price elasticity. Not surprisingly, the tabulated findings are wide ranging (Stratus Consulting Inc. 1999, p. 4-3).

Therefore, while these two studies may offer insights which are useful in certain Texas planning contexts, they do not reveal much information against which results of the present study can be benchmarked.

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Appendix A

Supporting Tabulations Pertaining to Data Collection and Description

Table A-1. The 141 Weather Stations

Anahuac	Crosbyton	Jacksonville	Paris
Archer City	Crystal City	Joe Pool Lake	Pearsall
Aspermont	Daingerfield 9 S	Junction 4 SSW	Penwell
Athens	Dalhart 6 SW	Kaufman 3 SE	Putnam
Bakersfield	Danevang 1 W	Kerrville 3 NNE	Rio Grande City 1 SE
Ballinger 2 NW	Del Rio 2 NW	La Grange	Robstown
Bardwell Dam	Dell City 5 SSW	La Joya	Rockport
Bay City Waterworks	Denton 2 SE	Lake Alan Henry	Roscoe
Beaumont Research Center	Denver City	Lake Fork Reservoir	Rotan
Benbrook Dam	Dimmitt 2 N	Lake Kemp	Sam Rayburn Dam
Blanco	Eagle Pass	Lake Palo Pinto	San Antonio 8 NNE
Boerne	Eastland	Lake Tawakoni	San Marcos
Boys Ranch	Elgin	Lamesa 1 SSE	Sanderson
Brady	Fairfield 3 W	Laredo 2	Seminole
Breckenridge	Floresville	Levelland	Shamrock 2
Brenham	Floydada	Lexington	Silverton
Bridgeport	Fort Davis	Lipscomb	Sinton
Brownfield 2	Fowlerton	Littlefield	Sonora
Brownwood	Fredericksburg	Livingston 2 NNE	Spur
Burnet	Freeport 2 NW	Llano	Stamford 1
Cameron	Freer	Longview	Stephenville 1 N
Camp Wood	Gatesville 4 SSE	Lufkin 11 NW	Stillhouse Hollow Dam
Candelaria	Georgetown Lake	Marshall	Sulphur Springs
Canyon	Gilmer 4 WNW	Memphis	Tahoka
Carrizo Springs	Goldthwaite 1 WSW	Miami	Texarkana
Centerville	Goliad	Midland 4 ENE	Tilden 4 SSE
Charlotte 5 NNW	Gonzales 1 N	Morton	Town Bluff Dam
Childress 2	Graham	Mount Pleasant	Tulia
Clarendon	Greenville KGVL Radio	Mount Vernon	Vernon
Clarksville 2 NE	Hallettsville 2 N	Muleshoe NTL WLR	Waco
Cleburne	Harlingen	Nacogdoches	Water Valley
Cleveland	Haskell	Orange 9 N	Weatherford
Coleman	Henderson	Ozona 1 SSW	Wellington
Columbus	Henrietta	Jacksonville	
Concho Pk Ivie Rsrvr	Hillsboro	Paducah 15 S	
Corsicana	Hondo	Panhandle	

Table A-2. Monthly Consumer Price Index for 1999-2003, Urban U.S. South*

Month	1999	2000	2001	2002	2003**
Jan	159.9	164.1	169.3	170.6	175.1
Feb	160.0	164.8	170.2	171.0	176.4
Mar	160.6	166.5	170.6	172.1	177.5
Apr	161.5	166.7	171.4	173.1	177.4
May	161.6	166.7	171.7	173.2	176.8
Jun	161.7	167.5	172.2	173.5	177.2
Jul	162.2	168.0	171.6	173.6	177.3
Aug	162.6	168.0	171.5	173.8	177.9
Sep	163.2	168.5	172.2	174.2	178.3
Oct	163.6	168.5	171.7	174.9	178.1
Nov	163.5	168.6	171.0	174.9	177.5
Dec	163.6	168.4	170.3	174.6	177.5

* Source: U.S. Bureau of Labor Statistics. Index based on average for 1982-1984 = 100.0 .

** 2003 average = 177.25

Table A-3. The 734 Communities and Systems Represented in the Study*

439 WSC	Boerne	Childress
Abernathy	Bois D'Arc MUD	China Springs Water Company
Acton MUD	Bold Springs WSC	Chisholm Trail SUD
Addicks UD	Bolivar Peninsula SUD	Cibolo
Afton Grove WSC	Bolivar WSC	Cimarron Park Water Co., Inc.
Alamo Heights	Borger	Cisco
Alice	Bovina	Clarendon
Allen	Bowie	Clarksville
Alto	Boyd	Claude
Alvarado	Brandon-Irene WSC	Clay Road MUD
Alvord	Brazoria	Cleburne
Amarillo	Breckenridge	Clifton
Anderson County Cedar Cr	Bremond	Clyde
Andrews	Brenham	Coahoma
Angelina WSC	Bright Star-Salem WSC	Cockrell Hill
Angleton	Brookshire MWD	Coleman
Archer City	Brownfield	Coleman County WSC
Argyle WSC	Brownsville	College Mound WSC
Arledge Ridge WSC	Brownwood	College Station
Arlington	Bruceville-Eddy	Collinsville
Armstrong WSC	Brushy Creek WSC	Colorado City
Arp	Buena Vista-Bethel SUD	Columbus
Arrowhead Lakes	Bunker Hill	Comanche
Arrowhead Shores	Burkeville WSC	Comanche Harbor
Aubrey	Burns Redbank WSC	Combine WSC
Austin	Caddo Basin SUD	Commerce
Bacliff MUD	Caldwell	Community WSC
Baffin Bay WSC	Calhoun County Rural WS	Concho Rural Water Corp.
Ballinger	Callender Lake	Conroe
Bandera County FWSD 1	Callisburg	Converse
Bangs	Calvert	Copeville WSC
Barton Creek West WSC	Canadian	Country Terrace Subdiv.
Bastrop	Caney Creek MUD	County Line WSC
Batesville WSC	Canton	Craft-Turney WSC
B-C-Y WSC	Canyon	Crandall
Bell County WCID 3	Canyon Lake MH Estates	Crane
Bells	Canyon Lake WSC	Creedmoor-Maha WSC
Belton	Cape Royale UD	Crescent Heights WSC
Ben Wheeler WSC	Carrollton	Crockett
Benbrook	Carthage	Crockett County WCID #1
Berryville	Cash WSC	Crosby MUD
Bertram	Castle Hills	Crowley
Bethany WSC	Castroville	Crystal Clear WSC
Bethel Ash WSC	Centerville	Crystal Springs Water Co
Bethesda WSC	Central Washington Cty WSC	Cypress Springs SUD
Bexar County WCID #10	Chalk Hill SUD	Damascus-Stryker WSC
Bi County WSC	Chandler	Dawson
Bilma PUD	Chatfield WSC	Dayton
Birnam Woods	Cherokee Shores	De Soto
Bloomington	Chester WSC	Dean Dale WSC
Blue Bell Manor Utility Co.	Chico	Decker Hills

(continued on next page)

* We are deeply indebted to each water system that responded to our survey. Some communities responding to the rate survey may have been dropped from the dataset through no fault of their own; see Chapter 2 for data development explanations.

Table A-3. (continued)

Denton	Fate	Gunter Rural WSC
Denton Cnty Freshwater SD	Fayette WSC	Hallettsville
Desert WSC	Ferris	Hallsville
Diana SUD	Flo Community WSC	Haltom City
Diboll	Florence	Hamby WSC
Dimmitt	Floresville	Hardin WSC
Dobbins-Plantersville WSC #1	Forest Glade Water System 2	Harleton WSC
Dobbins-Plantersville WSC #2	Forest Hill	Harlingen
Dodge-Oakhurst WSC	Fort Belknapp WSC	Harris County FWSD 27
Donna	Fort Bend County WCID #2	Harris County FWSD 47
Dowdell PUD	Fort Clark Spring MUD	Harris County FWSD 61
Dripping Springs WSC	Fort Gates WSC	Harris County MUD #1
Dumas	Fountainview Subdivision	Harris County MUD #180
Duncanville	Four Way WSC	Harris County MUD #189
Eagle Pass	Frankston	Harris County MUD #24
Early	Frankston Rural WSC	Harris County MUD #365/#364
Earth	Freeport	Harris County MUD #368
East Bernard	Freer WCID	Harris County WCID 1
East Cedar Creek	Friendswood	Harris County WCID 99
East Central WSC	Friona	Harris County WCID 113
East Fork SUD	Fruitvale WSC	Harris County WCID 133
East Garrett WSC	Gainesville	Hart
East Marion County WSC	Galena Park	Haskell
East Medina County SUD	Galveston County MUD #12	Haslet
East Mountain	Galveston County WCID #12	Hazy Hollow East Estates
East Plantation UD	Galveston County WCID 8	Hearne
East Rio Hondo WSC	Garden Ridge	Hemphill
East Tawakoni	Garland	Henrietta
Eden	Garrett System	Hi Texas Water Company
Edna	Garrison	Hickory Creek SUD
El Paso	Gaston WSC	Hidalgo
El Paso County	Gastonia-Scurry WSC	Highland Park, Town of
El Paso County Tornillo Wid	Gholson WSC	Highland Village
El Paso County WCID 4	Giddings	Highsaw
El Paso WCID-Westway	Gilmer	Hill Country
El Tanque WSC	Glenwood WSC	Hill County WSC
Elderville WSC	Golden WSC	Hilltop Lakes WSC
Eldorado	Goldthwaite	Holiday Beach WSC
Electra	Goliad	Holliday
Elgin	Gonzales County WSC	Homestead MUD
Elk-Oak Lake WSC	Gorman	Hondo
Elm Creek WSC	Grand Saline	Honey Grove
Elmo WSC	Grandview	Howe
Emory	Granite Shoals	Hudson WSC
Ennis	Grant Road PUD	Humble
Euless	Grapeland	Huntsville
Eustace	Grapevine	Hurst
Everman	Greenville	Hutto
Fair Oaks Ranch	Greenwood Village	Huxley
Fairfield	Grimes County System	Indian Springs Estates
Falfurrias	Groesbeck	Inverness Crossing
Farmers Branch	Groveton	Iowa Park
Farmersville	Gruver	Irving
Farwell	Gum Springs WSC 1	Itasca

(continued on next page)

Table A-3. (continued)

Jacksonville	Live Oak PUD	Montgomery County MUD #47
Jarrell-Schwertner WSC	Lockney	Montgomery County MUD #60
Jasper	Log Cabin	Montgomery County MUD #67
Jefferson	Lometa	Montgomery County WCID 1
Jewett	Longhorn Town UD	Montgomery Gardens
Jim Wells County FWSD #1	Longview	Mooney Heights
Johnson County FWSD 1	Lorenzo	Morton
Jonah Water	Los Fresnos	Moscow WSC
Jones WSC	Lost Creek MUD	Moulton
Katy	Louetta Road UD	Mount Vernon
Kaufman	Luella WSC	Mountain Springs WSC
Kemp	Luling	New Boston
Kempner WSC	Lumberton MUD	New Braunfels
Kendall County Utility Co.	Lyford	New Caney MUD
Kendall County WCID 1	Lytle	New Hope WSC
Kenedy	M&M WSC	New London
Kerens	Mabank	New Prospect WSC
Kermit	Mac Bee WSC	New Waverly
Kerrville	Madisonville	Nocona
Kerrville South Water Co.	Malakoff	North Bosque WSC
Kingsland WSC	Manor	North Cherokee WSC
Kiowa Homeowners WSC	Mansfield	North Forest MUD
Knox City	Marfa	North Hopkins WSC
Kountze	Markham MUD	North Hunt WSC
Kyle	Marlin	North Richland Hills
La Grange	Mary Francis/Bertrand	North Runnels WSC
La Joya WSC	Mason	North Rural WSC
La Porte	Mason Creek UD	North Zulch MUD
Lacy-Lakeview	McAllen	Northampton MUD
Lago Vista	Mclean	Northeast
Lake Cities	McClelland WSC	Northwest
Lake Medina Shores	MClennan Co. WCID 2	Northwest Grayson WCID #1
Lake Palo Pinto Area WSC	Meadowlakes MUD #1	Northwest Harris Cty MUD 22
Lake Ransom Canyon, Town of	Meeker MWD	Northwest Harris Cty MUD 23
Lake Tanglewood, Inc.	Melissa	Northwest Harris Cty MUD 24
Lakeway Harbor	Memorial Villages	Nueces County WCID 4
Lakeway MUD	Memphis	Nueces WSC
Lamesa	Men WSC	Oak Hills WSC
Lancaster	Mesquite	Oak Trail Shores
Lavernia	Mexia	Oakridge North
Lavon WSC	Midlothian	Odem
Leon Valley	Milano WSC	Odessa
Leonard	Military Highway WSC	Odem
Levelland	Millersview-Doole WSC	Odonnell
Lewisville	Milligan WSC	Omaha
Liberty	Millsap WSC	Onalaska Water Supply Corp.
Liberty City WSC	Mineral Wells	One-Five-O WSC
Liberty Hill WSC	Mitchell County	Orange Co. WCID #2
Lilly Grove SUD	Moffat WSC	Orange County WCID #1
Lindale	Montgomery County MUD #6	Orange Grove
Lindale Rural WSC	Montgomery County MUD #7	Ore City
Little Elm	Montgomery County MUD #36	Ovilla
Little River-Academy	Montgomery County MUD #40	Oyster Creek
Littlefield	Montgomery County MUD #46	Paducah

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Table A-3. (continued)

Palestine	River Acres WSC	Shoreacres
Palm Valley Estates	Riverside WSC	Sinton
Panhandle	Robertson County WSC	Smithville
Panola-Bethany WSC	Robinson	South Sabine WSC
Pantego, Town of	Roby	South Tawakoni WSC
Parker County WSC	Rockdale	Southeast WSC
Parker WSC	Rockett SUD	Southern Montgomery MUD
Pasadena	Rocksprings	Southern Utilities Company
Pearland	River Acres WSC	Southside
Pearsall	Rockwall	Southwest Fannin SUD
Pendleton WSC	Rolling Hills	Southwest Milam WSC
Perryton	Rosenberg	Spearman
Pflugerville	Round Rock	Splendora WSC
Pharr	Rowlett	Spring Creek Forest PUD
Pine Harbor	Royse City	Spring Creek UD-Fox Run
Pink Hill WSC	Rural WSC	Spring Valley WSC
Pioneer Valley Water Co.	Rusk	Springs Hill WSC
Pittsburg	Sabinal	Staff WSC
Plains	Sachse	Stanley Lake MUD
Plainview	Salado WSC	Star Mountain WSC
Plano	San Angelo	Starr County WCID #2
Plum Creek	San Antonio	Starr WSC
Poetry WSC	San Augustine Rural WSC	Stephens County Rural WSC
Point Comfort	San Juan	Stephenville
Polonia WSC	San Marcos	Stinnett
Ponder	San Saba	Sturdivant-Progress WSC
Port Arthur	Sanderson	Sudan
Port Lavaca	Santa Rosa	Sugar Land
Port Mansfield	Schertz	Sulphur Springs
Port Neches	Schulenburg	Sundown
Post	Seabrook	Sunray
Postwood MUD	Seagoville	Sweetwater
Poteet	Sealy	Talty WSC
Poth	Sebastian MUD	Tarkington SUD
Potosi WSC	Selma	Tatum
Pottsboro	Seminole	Taylor
Preston Shores	Seymour	TCW Supply, Inc.
Pritchett WSC	Shady Grove WSC	Temple
Quail Creek MUD #5	Snyder	Terrell
Quanah	Somerville	Texarkana
Queen City	Sonora	The Colony
Quitman	Sour Lake	The Oaks WSC
Ramey WSC	South Grayson WSC	Thorndale
Ranger	South Houston	Three Rivers
Rankin Road West MUD	South Jasper WSC	Timber Lane UD
R-C-H WSC	South Limestone County WSC	Timberwood
Red Oak	Shady Hollow MUD	Tomball
Red River County WSC	Sharon WSC	Travis County WCID #10
Redwater	Sharyland WSC	Tri County SUD
Reno	Shasla PUD	Thorndale
Ricardo WSC	Shenandoah	Tri WSC
Richland Hills	Sherwood Shores	Trinidad
Ridgecrest	Shiner	Trinity Rural WSC
Rio Hondo	Shirley WSC	Trophy Club MUD #1

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Table A-3. (continued)

Troup	Webster	Wheeler
Troy	Weimar	White Deer
Twin Creek WSC	Wellington	White Shed WSC
Two Way WSC	Weslaco	Whitehouse
Universal City	West	Whitesboro
University Park	West Bell County WSC	Whitney
Upper Jasper Cty Water Auth 1	West Cedar Creek MUD	Wichita Falls
Valley Mills	West Columbia	Wichita Valley WSC
Van Horn	West End WSC	Wildwood Resort City
Van Vleck	West Gregg SUD	Willis
Vega	West Hardin WSC	Wills Point
Venus	West Harris County MUD #10	Wilmer
Vernon	West Harris County MUD #11	Windthorst WSC
Victoria	West Harris County MUD #17	Winnsboro
View-Caps WSC	West Harris County MUD #9	Winters
Village Jamaica Beach	West Harrison WSC	Woodbine WSC
Virginia Hill WSC	West Jefferson County	Woodbranch Village
Waco	West Park MUD	Woodcreek MUD
Waller County System	West University Place	Woodrow-Osceola WSC
Wallis	West Wise Rural WSC	Woodsboro
Walnut Cove Subdivision	Westador MUD	Woodville
Walnut Creek SUD	Western Hills Harbor	Wright City WSC
Walnut Grove	Western Hills WS	Wylie
Warren WSC	Western Lake Estates	Wylie Northeast WSC
Waskom	Westminster WSC	Yoakum
Waxahachie	Westwood Beach\Wildewood	Zavalla
Weatherford	Westworth Village	
Webb County Water Utility	Wharton Co. WCID 1	

Table A-4. Average Daily Use per Person

Month	1999	2000	2001	2002	2003
			(gallons per capita per day)		
Jan	122.5	124.9	116.6	120.4	115.9
Feb	126.8	128.6	115.1	119.9	116.5
Mar	126.2	127.3	111.0	126.1	118.7
Apr	139.9	137.1	131.8	141.0	146.3
May	146.7	153.7	151.4	169.7	173.3
Jun	162.1	156.2	180.3	183.0	166.6
Jul	184.4	219.3	216.4	169.1	192.0
Aug	234.3	238.1	215.4	198.2	206.7
Sep	201.0	209.9	152.9	172.9	155.4
Oct	166.9	145.8	140.8	137.3	141.5
Nov	146.4	119.7	129.4	121.5	126.6
Dec	128.3	115.0	113.7	115.1	120.6

Table A-5. Monthly Climatic Means For 141 Texas Weather Stations

Year	Month	Temperature (degrees F)		Percentage of days with precipitation over 0.25 inch
		Low	High	
1999	Jan	35.6	63.9	6.1
	Feb	41.3	70.8	1.3
	Mar	44.6	69.0	10.7
	Apr	54.0	79.6	7.4
	May	60.8	84.2	14.7
	Jun	69.1	89.6	13.0
	Jul	71.1	93.6	6.9
	Aug	71.5	98.6	3.8
	Sep	62.8	89.5	5.6
	Oct	50.8	81.1	5.7
	Nov	44.2	75.0	1.2
	Dec	34.5	62.7	5.6
2000	Jan	36.3	63.7	4.2
	Feb	41.6	70.7	5.2
	Mar	47.5	74.2	9.1
	Apr	52.0	78.8	7.9
	May	64.2	88.6	10.2
	Jun	68.8	88.5	18.0
	Jul	71.3	97.2	2.5
	Aug	71.0	98.7	1.8
	Sep	63.1	93.5	4.2
	Oct	56.9	77.6	14.2
	Nov	40.4	61.4	18.4
	Dec	30.6	52.6	7.6
2001	Jan	32.4	53.9	11.3
	Feb	39.2	63.1	8.5
	Mar	41.5	63.1	14.5
	Apr	55.2	79.5	3.4
	May	61.6	96.1	11.7
	Jun	68.2	92.8	8.0
	Jul	72.9	97.7	3.2
	Aug	71.3	95.3	11.5
	Sep	62.9	86.7	12.7
	Oct	50.8	79.1	5.5
	Nov	47.4	70.3	10.4
	Dec	36.8	61.6	8.2
2002	Jan	34.7	61.4	4.8
	Feb	32.7	60.6	6.3
	Mar	40.6	68.3	7.7
	Apr	57.2	79.9	5.9
	May	61.0	86.0	8.3
	Jun	68.4	91.9	9.2
	Jul	70.8	91.4	15.3
	Aug	71.0	95.0	6.2
	Sep	64.0	88.8	9.9
	Oct	55.5	74.3	19.4
	Nov	40.3	65.1	6.0
	Dec	35.7	59.4	12.3
2003	Jan	32.6	58.1	2.9
	Feb	36.3	58.5	10.2
	Mar	43.4	69.4	5.4
	Apr	52.5	79.9	3.9
	May	63.2	87.8	5.7
	Jun	66.9	89.7	17.7
	Jul	70.8	94.1	7.6
	Aug	70.8	95.7	7.9
	Sep	62.9	85.2	11.9
	Oct	54.5	80.5	7.1
	Nov	46.1	69.6	5.0
	Dec	33.7	63.5	3.1

Table A-6. Average Precipitation for 141 Texas Weather Stations (1971-2000)

Month	Precipitation (Inches per Month)			Standard Deviation
	Minimum	Maximum	Mean	
Jan	0.32	5.94	1.78	1.32
Feb	0.28	4.55	1.89	1.07
Mar	0.20	5.29	2.12	1.21
Apr	0.14	4.59	2.39	1.04
May	0.44	5.94	3.89	1.17
Jun	0.87	6.95	3.61	0.99
Jul	1.08	4.86	2.25	0.75
Aug	1.27	5.87	2.58	0.60
Sep	0.93	7.80	3.28	0.99
Oct	0.82	5.34	3.21	1.20
Nov	0.40	5.88	2.32	1.49
Dec	0.46	6.12	2.11	1.46

Appendix B

Water and Wastewater Rate Survey Documents

TEXAS A&M UNIVERSITY
Urban Water Demand Project

January 31, 2005

Dear Water System Manager:

Texas A&M University and the Texas Water Development Board are investigating water demand factors throughout Texas. The success of this study depends upon 100% participation by water systems and districts. If you include contact information below, we will provide you with access to a downloadable version of our 2005 report.

Your part is easy. Please send copies of water and wastewater rates that were in effect from January, 1999, to December, 2003 (spanning 6 fiscal years), and complete the short questionnaire at the bottom of this page. We know that complicated rate schedules can entail several pages: if sending copies is inconvenient for you, you can report the information instead by completing the form on the back of this page. Please include the rates applicable to residential connections (such as for 3/4" meters), and details such as seasonal rates and winter averaging for wastewater charges.

An addressed, stamped envelope is provided for your response. Just return this page and the appropriate rate schedules, or this page completed front and back. Your participation will contribute to the understanding of water use patterns in Texas, although your data will not be used to identify your system individually. Thank you for taking the time to help us in this matter. Feel free to contact us if you have any questions, at the telephone number or e-mail address below.

Sincerely,

Dr. Ron Griffin

Dr. Ron Griffin
Texas A&M University

Urban Water Demand Project Assistant David Bell: (979)845-1992 or belldr@tamu.edu.

Water Provider Questionnaire

Your identifying information will be held confidentially by Texas A&M University.

1. Name and position of person completing the survey:____________________/__________________________.
2. Your telephone number during office hours: (   ) __________-_______________.
3. Would you like a free copy of the final report made available to you? Yes__ No__.

   If so, do you have an e-mail address to which we can send the report?_____________@_____________._____.
4. When does your fiscal year start (mm/dd)? ________/_______.
5. IMPORTANT: To the best of your recollection, list any months between January, 1999, and December, 2003, that your system was unable to meet demand due to supply shortfalls or infrastructural failure:

   ____.
6. Please check one:

   _____I have enclosed with this survey a copy of each residential water and wastewater schedule for 1999-2003.

   _____I have completed the back of this survey with rate schedules for 1999-2003.

Thank you for your cooperation.

Units used in this chart (100cu.ft., 1000gal., etc.):______________________

Record of residential **water** rates from January 1999 to December 2003

Some systems use a Summer rate that is different from the Winter rate. If your system does this, please indicate in the first column the months to which each listed rate applies.

Seasonal Rate?	Effective Date	Basic Service		First Block	Second Block	Third Block	Fourth Block	Fifth Block
sample			Starting quantity:	*3000 gallons*	*10000*			
October-April	*10/1/98*	*$21.50*	Rate per unit: $	*2.35/1000*	*2.55/1000*			
sample			Starting quantity:	*3000*	*10000*			
May-September	*10/1/98*	*$21.50*	Rate per unit: $	*2.65/1000*	*2.95/1000*			
			Starting quantity:					
		$	Rate per unit: $					
			Starting quantity:					
		$	Rate per unit: $					
			Starting quantity:					
		$	Rate per unit: $					
			Starting quantity:					
		$	Rate per unit: $					
			Starting quantity:					
		$	Rate per unit: $					
			Starting quantity:					
		$	Rate per unit: $					

ADDITIONAL NOTES OR EXPLANATIONS HERE:

Record of residential **wastewater** rates from January 1999 to December 2003

If your system calculates wastewater charges based on water consumption in selected (i.e., Winter) months, please indicate which months in the first column.

Winter average months?	Effective Date	Basic Service		First Block	Second Block	Third Block
sample			Starting quantity:	*0 gallons*		
Dec., Jan., and Feb.	*10/1/98*	*$11.50*	Rate per unit: $	*1.05/ 1000*		
			Starting quantity:			
		$	Rate per unit: $			
			Starting quantity:			
		$	Rate per unit: $			
			Starting quantity:			
		$	Rate per unit: $			
			Starting quantity:			
		$	Rate per unit: $			
			Starting quantity:			
		$	Rate per unit: $			
			Starting quantity:			
		$	Rate per unit: $			

TEXAS A&M UNIVERSITY
Urban Water Demand Project

Did you receive our survey?

Everyone benefits when we share our water management experiences and data.

Your 1999-2003 water and wastewater rates contain vital data with the power to illuminate an important aspect of community water demand in Texas. We are combining this information with many other relevant data to improve knowledge in this area.

Please respond to the short survey and allow us to identify your water system among the hundreds of cooperators in our forthcoming report on Urban Water Demand in Texas. [Cooperators will be provided with free access to the report and will be notified when it is published.]

If you did not receive the Urban Water Demand Survey, or cannot locate it, please call or e-mail us (979-845-1992, belldr@tamu.edu). We will mail another. If you leave voice-mail when calling, please provide your name so we can send the survey directly to you.

Most sincerely,

David Bell	Ron Griffin
Urban Water Project Leader	Professor of Water Resource Economics

Appendix C

Supporting Tabulations Pertaining to Econometric Results

Table C-1. Parameter Estimates for the Double Log and Linear Regressions

Variable	Log-Log (ln Q = ...)	Variable	Linear (Q = ...)
	(standard errors are in parentheses)		
ln C	0.442 (0.00717)	C	52.3 (0.777)
ln R	-0.0384 (0.00402)	R	-5.43 (0.268)
ln I	0.101 (0.00847)	I	0.000717 (0.000055)
ln P	-0.508 (0.00429)	P	-13.1 (0.15)
S	0.418 (0.00396)	S	56.3 (0.690)
Intercept	5.04 (0.0115)	Intercept	78.6 (2.32)
Adjusted R^2	0.46		0.36
(Mean Squared Error)$^{0.5}$	0.37		64.93
n	39145		39145

Table C-2. GCD Parameter Estimates for W-only and W/WW Service Partitions

	Water Service Only (S=0)		Water & Wastewater Service	
Parameter	Coefficient	Standard Error	Coefficient	Standard Error
ln C	0.667	0.0522	0.0329*	0.0240
ln R	0.475	0.0366	0.375	0.0277
ln I	1.23	0.110	0.0657*	0.0750
ln P	-0.389	0.0523	-0.332	0.0412
ln (C+R)	-0.360	0.0861	-0.222	0.0604
ln (C+I)	-0.706	0.134	0.554	0.0845
ln (C+P)	0.817	0.107	0.968	0.0733
ln (R+I)	-0.432	0.0989	-0.121*	0.0676
ln (R+P)	-0.466	0.0696	-0.554	0.0524
ln (I+P)	-0.867	0.113	-0.786	0.0783
Constant	6.64	0.120	5.65	0.0821
n	14548		24597	
Adjusted R^2	0.49		0.33	
(Mean Squared Error)$^{0.5}$	0.33		0.38	

*These parameter estimates are insignificantly different from zero at the 99% confidence level.

Appendix D

A Panel Model

An econometric approach that has been increasingly advocated in water demand analysis is panel data analysis (Arbués, Barberán, and Villanúa 2004). Panel data analysis includes a variety of techniques that take advantage of the structure of cross-sectional time series, such as the dataset used in this report, to refine parameter estimates and reduce error. Unfortunately, a panel is only effective when each community's time record is complete. Of the 730 communities whose data are usable in the primary, pooled analysis, complete records are only available for 385 (53%) communities. In comparing panel analysis to the OLS approach as exercised in this research, a primary concern is whether the sample is substantively altered by the exclusion of almost half of the data. This concern may be allayed by Table D-1, which compares the variables of analysis in this subsample to those of the sample at large. Based on mean variable values, the panel subsample appears to be quite representative of the full sample in every dimension.

Table D-2 presents the results of a panel regression of the same GCD form used in Chapter 4. By identifying the data as a being cross-sectional time series in nature, the regression package is able to assign a unique error parameter to each community, rather than a common error variance throughout the data. A comparison of Tables D-2 and 4.2 reveals some differences in coefficient estimates and a remarkable similarity in the confidence interval of each parameter. Table D-3 shows the elasticities derived from this estimation, analogous to the first rows of Table 4.3. Thus, the panel model provides equivalent precision with only one half of the observations. Elasticities calculated at the sample means from coefficients of the panel model agree with those derived from the OLS model to a great extent. Some divergence between the two models away from the means is due to the sensitive balance of the interactive minor terms of the Generalized Cobb-Douglas form. In the end, preference must be given to the larger sample size of the Chapter 4 regression.

The primary function of Table D-3 within the context of this report is to illustrate the insensitivity of elasticity estimates to alternate procedures. The results of the panel analysis add little qualitative substance to the analysis of Chapter 4.

Table D-1. Comparison of Summary Statistics

Variable	Units	OLS Mean	Panel Mean
Population	#	13232	14643
Use (month)	kGal	67600	69800
Personal Daily Use	gallons	145	143
Personal Income	dollars	26321	25897
Total Bill	dollars	52.72	52.68
Price	$/kGal	4.96	4.94
Low Temperature	ºF	55.3	55.4
High Temperature	ºF	78.2	78.2
Days with Rain	days	2.9	3.0
Mean Annual Precipitation	inches	3.2	3.2

Table D-2. Parameter Estimates for GCD Panel Regression (n=23100)

Parameter	Coefficient	Standard Error
ln C	-0.106	0.0267
ln R	0.216	0.0222
ln I	0.781	0.0633
ln P	-0.442	0.0348
S	0.391	0.0243
ln (C+R)	0.092 *	0.0475
ln (C+I)	0.497	0.0702
ln (C+P)	1.519	0.0591
S • ln C	-0.037	0.0129
ln (R+I)	-0.417	0.0533
ln (R+P)	-0.338	0.0406
S • lnR	0.040	0.0074
ln (I+P)	-1.612	0.0686
S • ln I	-0.251	0.0183
S • ln P	0.124	0.0083
Constant	5.28	0.0688
Log Likelihood	-2427	

* All parameter estimates except this one are significant at the 99% level.

Table D-3. Panel Demand Elasticities

Variable	Mean	Standard Deviation	Elasticity Evaluated at Variable's Mean – S.D.	Mean	Mean + S.D.
			S = 0.649		
C	1.82	0.43	0.57	0.52	0.51
Rainfall	3.23	1.26	-0.07	-0.06	-0.05
Income	2.59	0.60	-0.01	0.17	0.29
Price	4.94	1.96	-0.53	-0.51	-0.49