Estimating Changes in Residential Water Demand for Voluntary and Mandatory Water-Use Restrictions Implemented during the 2002 Virginia Drought

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Abstract

Municipal water suppliers are increasingly faced with implementing programs to alleviate temporary water shortages in the United States. Having reliable estimates for the effectiveness of these programs will help in water supply planning. This dissertation estimates the reductions in residential water-use for voluntary and mandatory water-use restrictions used in Virginia during the 2002 drought. These restrictions were evaluated using both a conventional approach (single-dummy variable for each) and non-conventional approach where program intensity was accounted for. Program intensity was measured by information dissemination for voluntary restrictions, and by information dissemination and enforcement efforts for mandatory restrictions. An unbalanced panel with data from 21 municipal water suppliers was used in the analysis.

Under the conventional approach, voluntary restrictions had no significant effect on water-use and mandatory restrictions showed a small to moderate effect. However, program intensity was found to have a significant influence on the magnitude of the water-use reductions in the non-conventional approach. These reductions ranged from 0-7% for voluntary restrictions, and from 0-22% for mandatory restrictions. Moreover, these reductions followed a pattern of increasing program effectiveness with higher levels of information and enforcement. This result indicates that water supply planners need to give considerable attention to the manner in which drought management programs are implemented.

Price was also found to be an important determinant in predicting residential water-use. A moderate price increase of $3 per 1000 gallons would be expected to reduce water-use by almost 15%. Thus combining mandatory restrictions (implemented at high intensity) with a moderate to high price increase could result in water-use savings approaching 40% based on estimates from this analysis.

Other important findings included: a) consumers were responding to a mix of pure marginal price and fixed fees/previous block rates, b) apartment accounts were found to be included in most of the localities residential data and had a significant impact on water-use, and c) the income parameter was measuring more than a pure income effect.

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List of Acronyms

ADG	Average Daily Gallons
AP	Average Price
AR	Auto Regressive
CO	County
CPI	Consumer Price Index
EIS	Environmental Impact Statement
EO33	Executive Order 33
LN	Natural Log
MP	Marginal Price
MPH	Miles Per Hour
NEPA	National Environmental Policy Act
OLS	Ordinary Least Squares
VDH	Virginia Department of Health

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Chapter 1: Introduction

During the summer of 2002, Virginia (as well as most of the eastern United States) experienced a drought of unusual severity. Compounded by below average rainfall from the previous two years, municipal water supplies were stressed to some degree throughout most of the state. In many cases, local water supplies were severely depleted and emergency measures were either instituted or being contemplated. By late June, 18 municipal water suppliers had called for voluntary water-use restrictions and 4 had implemented mandatory restrictions on many forms of outdoor water-use. By late August, as the drought intensified, 39 waterworks had called for voluntary restrictions and 20 waterworks had implemented mandatory restrictions (Drought Management Report compiled by the Virginia Department of Environmental Quality, June and August reports). In addition, some localities imposed significant price increases for water in an effort to reduce demand.

By the end of August, the drought had become so serious that Governor Warner issued Executive Order 33 which imposed statewide restrictions on outdoor water-use across most of Virginia. These restrictions were targeted largely to residential customers, and to a lesser extent businesses such as golf courses. The restrictions applied to most counties and cities in the state, from the coastal plains west to the New River Valley. However, far southwest Virginia and specific areas within the Washington D.C. metro area with adequate water supplies were exempted from the executive order. Fortunately, normal rainfall returned later in the fall and most of the provisions of the statewide restrictions were lifted by mid-November

The 2002 drought has had important consequences concerning water planning in Virginia. State officials saw the drought as a warning that better procedures for dealing with water supply and demand during times of water scarcity were needed. This concern resulted in the issuance of a number of proposals by the Governor later that year and also in the State's subsequent Drought Response Plan. The Governor has directed the Department of Environmental Quality to work with local governments to develop local and regional water supply plans, with a deadline of three years for their completion, and preliminary plans due in one year. Drought management plans, which are designed to reduce water demand during periods of temporary shortages, will be an integral part of this overall process. The draft regulations are scheduled to be approved by the summer of 2005 (9 VAC 25-780).

The water shortages created by the 2002 drought and the responses at both the local and state-level to deal with the situation may be a precursor to long-run changes in Virginia water management. Historically, the prevalent method for dealing with water supply in Virginia has been supply-side management. Under this system, municipalities essentially have taken water demand as given and have secured sufficient water supplies to meet this demand, even under the most unfavorable circumstances. However, demographic trends and regulatory conditions increasingly limit the ability of localities to expand water supply sources at a sufficient rate to minimize or eliminate the risks of future water shortages. The mounting difficulties of Virginia municipalities in building new reservoirs, expanding reservoirs, or securing additional water withdrawal permits from rivers make future expansion of water supplies more difficult. Many of these challenges are legal in nature and reflect the increasing difficulty in expanding water supply sources in all regions due to environmental and legal constraints such as the Clean Water Act, Endangered Species Act (requirements for in-stream flows), NEPA and EIS requirements (Shabman and Cox 2004, Maddock and Hines 1995). The difficulty in expanding water supplies in conjunction with continued population growth will mean that the risk of short-term water shortages in Virginia will likely increase in the future. The new emphasis on drought management planning is one signal that the state also believes that the risks of temporary water shortages will persist.

Problem Statement

To mitigate the effects of temporary water shortages, planners need insight into what level of water-use savings can be expected with various drought management programs. The State of Virginia provided some guidelines to this question in the Drought Response Plan (2004 draft) and water supply planning regulations (9 VAC 25-780). Included in these plans are protocols for when voluntary and mandatory restrictions should be triggered. The plan states that local water supply managers should expect 5-10% reductions in water usage with voluntary restrictions, and 10-15% reductions with mandatory restrictions (9 VAC 25-780-130).

These estimates were based, in part, on analysis conducted by the Virginia Department of Health (VDH) during the fall of 2002. The VDH analysis calculated the difference between the average monthly water production across localities during the drought year and the average monthly water production during the corresponding month in the previous year (personal communication with Chris Adkins at VDH 2003). The VDH analysis has two limitations. First, the analysis did not control for intra-municipal transfers (water that was produced in one locality and sold in another), and hence there was no way to verify whether the production records were indicative of actual water-use in a given locality. Second, the analysis did not control for many other factors that affect municipal water demand such as climatic changes (variance in rainfall and temperature), price changes, and unaccounted losses (leaks in distribution system, line flushing, etc.). Essentially, these and other possible factors were implicitly assumed to have held constant and any changes in water production rates were attributed to the restrictions alone.

VDH estimates were calculated in part because few systematic studies have been conducted to identify the effectiveness of drought management programs in reducing water demand. In the expansive water demand literature, only a limited number of studies have estimated the effectiveness of drought management programs (Moncur 1987, Billings and Day 1989, Nieswiadomy 1992, Renwick and Archibald 1998, Wang et al 1999, Michelsen et al 1999, Renwick and Green 2000, Taylor et al 2004). For the most part however, the focus of these studies was on other aspects of water demand.[1]

Studies estimating the effectiveness of drought management programs have also tended to focus on the southwest region of this country. It would be expected that the water-use dynamics of this arid region would be quite unique and thus estimates from this region (even if otherwise transferable) would not necessarily be applicable to Virginia or other eastern states with different climatic and demographic conditions. For instance, in southwest cities the increase in summer usage compared to the winter months ranged from 60 – 320% with the typical increase between 100-200% (based on Michelsen et al 1999 data). In contrast, the typical increase in summer usage in Virginia in this study has been between 25-75%.

Furthermore, previous studies have not evaluated the intensity in which various drought management programs were implemented.[2] Intensity is defined in this study as information used to promote awareness and understanding of the program provisions as well as enforcement efforts used to ensure compliance. Other studies treated all similar programs identically in that no distinction was made for variation within a program-type such as intensity that could lead to differences in water-use. For example, mandatory restrictions that levied fines for non-compliance were treated the same as ones that had no enforcement provisions. Voluntary programs with a high-level of information dissemination were treated the same as programs with a cursory level of effort. The effectiveness in reducing water demand in either case might depend on the level of effort expended by the locality in the implementation of the program. This potential variation in the intensity of drought management programs is expected to influence water-use behavior, although no empirical evidence appears to exist in addressing this hypothesis.

Overall, there appears to be a lack of empirical estimates which measure the effectiveness of drought management programs that have the ability to meet the needs of water planning practitioners. This is especially true in Virginia and elsewhere in the eastern U.S. where few empirical studies have been conducted. This limited knowledge base makes planning for future drought situations difficult and uncertain.

Objectives

The objectives of this analysis are to:

1. Estimate the reduction in residential water-use due to voluntary and mandatory restrictions used in Virginia during the 2002 drought.
2. Estimate the influence that program intensity has on the level of water-use reductions for voluntary and mandatory restrictions. For mandatory restrictions, intensity includes both information level (to promote the program) and enforcement effort (to ensure compliance). For voluntary restrictions, information level is the sole determinant of program intensity.

[1] Exceptions being Renwick and Archibald (1998), Renwick and Green (2000), and Michelsen et al (1999).
[2] An exception is Billings and Day (1989) that used a proxy for information level.

Procedures

In fulfilling these primary objectives, this analysis will specify and estimate a statistical water demand model that will test whether drought management program intensity influences residential water-use. The model will also account for and estimate other factors that influence residential water-use such as the price of water, climatic influences, and various demographic variables. The paper will focus on residential water-use as the 2002 restrictions in Virginia were largely aimed at this user group. Residential users also typically consume the largest proportion of water in metropolitan areas (Baumann et al 1998).

The following chapter (Chapter 2) will provide an overview of the various policy options for reducing water demand during times of drought. The discussion will describe the general activities involved in implementing these policies, as well as a conceptual discussion of how information and enforcement levels will influence the behavior of individual water users.

Chapter 3 describes the empirical approaches used to model water demand, the variables typically included in water demand models, and provides estimates from previous studies on the effectiveness of drought management programs in reducing water-use. The chapter will also discuss how previous studies dealt with various modeling issues, and provide the general empirical water demand model used in this study.

Chapter 4 will present the data used in this analysis. It will discuss how municipal water suppliers were selected for inclusion in the study and describe the approaches taken by these localities to reduce residential water-use during the drought. Details of the survey instrument used to identify the intensity in which voluntary and mandatory programs were implemented are described. This chapter also discusses and summarizes the other forms of data used in this analysis such as pricing, demographic, and climatic data.

Chapter 5 presents the formal specification of the water demand model used in this analysis. This will include a discussion on how the final model was formulated and the hypothesized effects that model variables are expected to take. Chapter 6 presents the results of the model as well as a discussion of these results. Chapter 7 covers the conclusions, policy implications, and directions for future research related to this analysis.

Chapter 2: Drought Management Program Intensity

Drought management programs are used by localities to reduce water-use during times of water supply scarcity. Voluntary restrictions, mandatory restrictions, emergency pricing programs, rationing programs, and public awareness campaigns are all used to reduce short-term water-use.[3] Drought management programs can be divided into two groupings based on the general way in which they function. Voluntary restrictions, mandatory restrictions, and public awareness campaigns are demand shifters, where the water demand for a given price is less than before the drought management program went into effect. These three programs are considered non-price drought management programs. In contrast, emergency pricing and rationing programs are considered price-based drought management programs and result in an upward movement along a single demand curve.

Voluntary and mandatory restrictions are common programs enacted to reduce water-use during times of drought. Mandatory restrictions prohibit specific water-use activities, generally certain forms of outdoor water-use. Lawn and garden watering are popular activities targeted by mandatory restrictions as are the filling of swimming pools, washing cars, and washing driveways. Mandatory restrictions are backed by the threat of penalties for non-compliance.

Voluntary restrictions generally cover similar types of outdoor water-use activities as mandatory restrictions. The distinction between the two is that voluntary restrictions are merely suggested, and compliance is not officially required. Furthermore, voluntary restrictions are not backed up by either warnings or citations. Thus voluntary restrictions are essentially pleas by the local government to reduce water-use for specific activities through the goodwill of the citizens. By its very nature, voluntary restrictions would generally be expected to have less of an impact in reducing water-use than mandatory restrictions.

Emergency pricing programs are where localities raise the price of water significantly in order to encourage water conservation during times of drought. A distinction for an emergency pricing program from a general price increase is that the former will be temporary in nature. After the water supply situation improves, the price of water will decrease.

Rationing programs are typically implemented by "restricting" water-use for all residential users to the same level, or by restricting water-use to a percentage of individual user's base level (e.g. 100% of average winter month's usage). Contrary to

[3] Two other programs, retrofit programs and building code changes, are often mentioned in the literature as general demand-side management programs. Retrofit programs encourage the adoption of water efficient appliances such as low-flow toilets and showerheads by distributing them freely or by subsidizing a portion of their cost. Building codes also typically target more efficient toilets and showerheads but require that these water fixtures be installed, generally for new houses or renovations. With both types of programs, the aggregate water-use reduction stemming from these programs will occur gradually. Both retrofits and building codes are used more for long-term water conservation and thus are not considered here as drought management programs.

popular belief, water-use is almost never shut off after this base level has been reached due to political, legal, and sanitary reasons (Renwick and Green 2000). Instead, customers are generally charged a higher rate for the excess water used. In this light, most rationing programs could be considered as emergency water pricing programs. The main practical distinction between the two possibly being that the word "rationing" connotes a dire, emergency situation, and thus citizens might be more responsive to reducing water-use under this pretext.

Public awareness campaigns are probably the most often used technique in times of drought. The general goal of public awareness campaigns is to educate citizens as to the seriousness of the water supply situation. In this way, public awareness campaigns are typically used in conjunction with other programs such as voluntary and mandatory restrictions in order to inform the public why they should take the restrictions seriously, and to better understand what the restrictions entail. A secondary goal of public awareness campaigns is to inform the public of additional ways in which they can most easily reduce water-use during their daily activities (e.g. taking quicker showers, running full loads of laundry, and fixing leaks.) not covered or prohibited by official restrictions.

Implementation/Intensity of Drought management Programs

Although there are important distinctions between the various drought management programs, there are also important distinctions in the way specific programs are carried out. For instance, two rationing programs may have different base-usage levels that are not supposed to be exceeded. Two public awareness campaigns could disseminate different amounts of information to consumers. Mandatory restrictions in one locality may be strictly enforced, while mandatory restrictions in another locality may not be enforced at all. This concept will be referred to throughout this study as the intensity or the implementation of drought management programs.

Thus intensity or implementation of drought management programs is hypothesized to fall into three categories:

1. Program content
2. Information dissemination
3. Enforcement (for applicable programs)

Program content refers to the actual provisions enacted by the program and is a measure of the rough potential of the programs success. Increasing the scope of outdoor water-use restrictions from lawn irrigation to all outdoor uses would be expected to increase the reductions in water-use, as would lowering the base water-use level for a rationing program from 100% of average winter usage to 75% of average winter usage. However, by itself, program content may do little to reduce water-use if citizens do not know about and/or understand the provisions of the program (through information efforts), or if localities are not serious about ensuring compliance with the provisions (through enforcement efforts).

Information dissemination refers to the manner in which programs are advertised to the public and can be thought of as having four general effects: 1) emphasize the seriousness of the water supply situation, 2) specify which activities are covered by the restrictions, 3) specify penalties for non-compliance (when applicable) and 4) promote additional ways to reduce water-use that might not be covered by the restrictions. De Loe et al (2001) lists the most common forms of information dissemination used by municipal waterworks as print media (newspapers, magazines, etc.), information packets from the locality, education in schools, information included with the water bill, and radio/TV.

Enforcement refers to how localities ensure that provisions of the program are being followed by its citizens. The two basic components to enforcement are monitoring and penalization. Monitoring generally occurs through having a physical presence in residential neighborhoods (public works department or police), having hotlines where residents can call in to report violations, or possibly even by requiring citizens to sign affidavits as reported by Renwick and Archibald (1998). Penalization generally occurs by issuing warnings to violators and by issuing fines to violators.[4] Overall, enforcement acts as a measure of the seriousness, or resolve that a locality has in ensuring compliance of the drought management program.

These three components of program intensity: program content, information efforts, and enforcement efforts, have varying degrees of importance and relevance with the five drought management programs previously discussed. With voluntary restrictions, the major focus is with information dissemination. With mandatory restrictions, all three components are applicable. With emergency pricing programs and rationing, both program content (the base water-use level and/or price) and information efforts are important, while enforcement efforts are essentially ensured through the billing system. With public awareness campaigns (if used as a stand-by program) information efforts are the main focus.

Citizen Response (Compliance)

How citizens actually respond to restrictions will of course determine the ultimate success of the program. Compliance refers to the degree in which citizens are following these provisions. In order to predict the degree of compliance for a program, some general principles from consumer theory are useful. Consumer theory would suggest that the compliance for non-price programs will be based on the costs and benefits expected from adhering to the program provisions (Becker 1968). If the costs of adherence are greater than the expected benefits from following the provisions, then the consumer would rationally choose to not comply with the provisions. Conversely, if the costs of adherence are less than the expected benefits from following the provisions, then the consumer would rationally choose to comply with the provisions. However, there is also the possibility that the consumer would choose to partially abide by the restrictions. In

[4] In some extreme cases repeat violator's water connections have been shut off as described by Bruce Boyer, Water Conservation Officer with Spotsylvania County (Personal Communication 2004).

order to help understand this case, a more general model of compliance is presented below.

There are two basic factors that determine the level of compliance for non-price program provisions: 1) Gain in utility realized from violating the provision, and 2) Loss in utility realized by the imposition of penalties for non-compliance. The gain in utility from violating program provisions occurs when program restrictions are preventing an activity that a water consumer would otherwise undertake. For instance, if a program prohibits all outdoor water-use, then consumers could gain utility through violation of the provisions by watering a dried-up lawn or vegetable garden, filling a low swimming pool, or washing a dirty driveway. As seen in these examples, the gain does not have to be purely monetary.

However, the consumer must balance this gain in utility with the possibility of realizing a loss of utility through the imposition of penalties if caught violating the program provisions. Penalties do not necessarily have to be actual monetary fines but could also be warnings issued by the locality. The warnings may cause embarrassment to violators, either because they have been formally scolded, or because their neighbors may have seen the warning being issued and/or the large red warning tag hung from the front door. This same reasoning can also apply to citations. The actual fine may be quite low compared to the embarrassment it causes. This is an important point: It is the total potential negative utility from being caught that is considered by consumers and not necessarily just the possible monetary fine. Thus even voluntary restrictions where no formal penalties are issued by localities can still carry a penalty deterrent from the standpoint of the water consumers. People may believe their neighbors will think unfavorably of them for not following the recommended practices.

The perceived penalty is itself a function of the probability of being detected times the magnitude of the penalty. A high possibility of being caught combined with a low penalty may be perceived as identical by a consumer to a situation with a low probability of being caught combined with a high penalty. Again, the penalty does not necessarily have to be monetary.

It is also possible to have an optimal level of non-compliance. For instance, the perceived gain from watering a dry lawn may be greater than the perceived penalty for the first hour of irrigation. Hence the consumer would choose to disregard the restriction and water the lawn at this point. However, the perceived gain in utility for the next hour of irrigation may fall below the perceived penalty, and the consumer would rationally decide to stop irrigation at this point. Thus the optimal level of noncompliance for a consumer occurs when the increased marginal utility from violating program provisions equals the decreased marginal utility in perceived penalties for violating program provisions.

Information is also an important determinant of compliance levels and is generally used in two ways. First, information can be used to better inform consumers of the program provisions. In the case of non-price programs, this includes specifying the activities covered by the restrictions and the penalties for non-compliance. For emergency price and rationing programs, this would mainly involve helping consumers understand how the new pricing structure works. In both cases, the main goal is to get the consumer to better understand the drought management program.

From the consumer's perspective, information can be costly to obtain. In most situations, it would not be economically expedient for consumers to check the price of water every day or every week, as water price increases are generally infrequent and also small in magnitude. Most consumers probably find out about general price increases after the prices have already gone into effect through subsequent bills. Thus for an emergency pricing or rationing program, part of the success of the program will depend on how well the locality informs its citizens of the change. This needs to be done in a way that is both convenient for its citizens, as well as being noticeable.

The same is true for non-price drought management programs. If for example, there are multiple outdoor water-use activities prohibited by a program, consumers may not remember which activities are prohibited if they heard them quickly listed on the radio. However, if they have a listing that was distributed directly to their household and is posted on the refrigerator, the cost of obtaining this information will be relatively low. Obviously, if consumers do not know what the provisions of a mandatory restriction program are, or if they don't understand an emergency price schedule, then compliance levels may suffer.

The second way in which information can be used to encourage compliance is by changing the preferences of the individual. Examples of this method include discussing the seriousness of the water supply situation and promoting a sense of civic responsibility. The focus here is to shift the concern of the individual from just the penalty function to one where they also want to do what is good for the community. In other words, this use of information tries to diminish the marginal benefit from violating provisions of the drought management program. For some consumers, this sense of civic responsibility may be important enough so that no penalty is even needed to ensure compliance. Voluntary restriction programs rely heavily on this information-type.

Thus overall, there is considerable variation in how citizens might respond to a drought management program depending on the level of program intensity. Possibly the most effective way to summarize the overall process is with an analogy of a very common form of municipal regulation, speed limits. Consider a locality that initiates a program to reduce driving speeds on a stretch of road where repairs are being made. The program content (potential) in this example would be the actual speed-limit set for this stretch of road. The lower the limit, the higher will be the potential of reducing the actual driving speeds.

Information efforts would be an important determinant for program success. Information dissemination would include the direct provisions of the new regulation by informing citizens about the new speed limits. This might consist of speed limit signs, signs indicating fine levels for violations, and possibly even news of the change in local media outlets. Information dissemination may also include efforts to shift preferences, such as with “My Daddy Works Here” signs that try to directly appeal to our civic responsibility. In effect, their purpose is to diminish the marginal utility gained from speeding by inducing guilt.

Enforcement efforts might consist of additional police presence in the area and issuing tickets for speeding, both of which are designed to increase the perception that violators will be penalized. Compliance would also be a function of the actual fine levels. The higher the fine levels, the greater will be the deterrence for breaking the speed limit.

For some drivers, just the knowledge of the program change (e.g. speed limit signs) will be enough to change their behavior and ensure their compliance. For these individuals, civic responsibility has an important bearing on their utility. For others, it might take the physical presence of police cars checking speeds from the roadside and issuing tickets to prevent them from speeding. For these people, the actual speed reduction would be largely dependent on the perceived chance of being caught as well as the penalty levels. Moreover, if the posted speed limit is 45 MPH, but police are only issuing tickets for those caught going over 55 MPH then it will be unlikely that the actual speed limit will be observed by these drivers. An important point is that reducing the official speed limit is fairly easy to do (or passing an ordinance to restrict outdoor water-use), but to attain the full potential of the program will require a good information campaign as well as stringent enforcement.

Chapter 3: Methods and Issues in Modeling Water Demand

As discussed in the last chapter, the intensity in which drought management programs are implemented is expected to influence the overall water savings derived from the program. The empirical challenge is to isolate the influences that the various characteristics of program intensity have on water demand. This chapter reviews the approaches used to estimate changes in water demand due to drought management programs, and to estimate water demand in general.

Approaches to Estimating Impacts of Drought Management Programs

Three broad approaches can be used to estimate reductions in water-use due to drought management programs: 1) engineering approach, 2) comparative approach, and 3) regression (statistical) approach. The engineering approach is potentially the easiest to estimate, but also the most restrictive in terms of situations that it could be used for. It is typically used in programs where there is a physically measurable change in water-use for a given improvement in technology, for example a retrofit program that paid for the installment of 1.5 gallon/flush toilets. The main problem with this approach, aside from limited applicability, is that it does not allow for adjustments in individual behavior after the new technology is in place. For example, it may be the case that people are now more likely to flush the toilet a second time due to incomplete disposal during the first flush. However, the engineering approach does not account for these potential changes in consumer behavior.

The comparative approach is the next easiest method to estimate and can be used in a much broader range of situations. With this method, monthly or seasonal average water-use during program implementation is compared to the water-use for the previous month or previous year without the program in place. Changes in water-use between these two time periods are attributed to the program. The advantages of this approach are that it is easy to conduct, data requirements are comparatively low, and the technique is easily understood by a lay audience. The main disadvantage of this approach is in the implicit assumption that all other factors that could affect water-use between the comparison periods remain unchanged. Due to this assumption, any differences in other factors that affect water-use such as price, weather, and seasonality will give bias to the estimates. In Virginia, the Virginia Department of Health used this approach to estimate the reduction in water-use from Executive Order 33, as mentioned in Chapter 1.

The regression approach is the most widely used method in the literature for estimating the factors that influence water-use and the effectiveness of drought management programs. With this method, data for the dependent variable (water-use) and independent variables (variables hypothesized to influence water-use) are obtained. This approach allows the statistical correlation between these two sets of variables to be tested. Because this method can separate the effects of individual factors, it has the potential of being the most reliable and accurate method to control for the effects of drought management programs. The main disadvantages are that the data requirements are comparatively high and that some level of technical expertise is required for the estimation. However, since it is the only technique with the potential to isolate multiple causal influences on water demand, it will be the technique used in this analysis.

Modeling Water Demand using Regression Analysis

Water demand studies using regression analysis can be distinguished by the data source and level of aggregation of the dependent variable, water-use. The data source and aggregation level chosen will have important implications in terms of the analysis.

First, there are two general sources of water-use data that can be used with the regression approach: 1) water production data and 2) water billing data. Water production data represents the amount of water that is pumped into the distribution system (examples include Nieswiadomy 1992, and Taylor et al 2004). This data source is regularly calculated in Virginia as part of the Department of Health reporting requirements and is thus relatively easy to obtain. However, it is impossible to identify who used the water once it is treated and pumped into the distribution system, and thus there is no distinction between user-types (residential, commercial, industrial, government, etc.) with this data. Moreover, this data does not accurately represent the total consumption of all aggregated user-types since water production totals include water used for line maintenance (cleaning and flushing) as well as leaks in the distribution system.

In contrast, water billing data represents the amount of water that is actually consumed by various user-classes (e.g., residential, commercial, industrial) for a particular billing period. Many local water suppliers distinguish between user-classes in order to charge different rates for water. The billing period is typically monthly, bi-monthly, or quarterly. Since this study will focus on residential water demand, water billing data is used in this analysis.

Next, water demand can be modeled using two levels of aggregation in the water billing data: 1) household-level or 2) aggregated municipal-level. Household-level data is total water consumption per individual household (or residential connection) and is obtained by sampling individual accounts from the billing population of a given locality (examples include Lyman 1992, Renwick and Archibald 1998, Pint 1999). Municipal-level data aggregates all individual accounts by user-type across a locality for a given time period and is expressed as an average water-use per household (or connection) (examples include Billings and Day 1989, Michelsen et al 1999, Renwick and Green 2000). Both of these aggregation approaches can be used to estimate the effectiveness of drought management programs. Intuitively, it would seem that household-level data would provide a more accurate representation of water demand than municipal-level data, as municipal-level data is simply aggregated household-level data.

The main challenges with using household-level data are availability and cost. In general, household-level data is much more difficult and costly to obtain than municipal-level data. In many cases this information is not in electronic format, or in a format that is easily accessible, and thus requires extensive time to make the information usable. Water suppliers may be reluctant to provide household-level data because of the time necessary to obtain it and concerns about maintaining confidentiality of individual users. Furthermore, from the standpoint of the researcher, household-level studies require matching two large and disparate data sets. For household-level studies, water-use data is typically used in conjunction with data on household demographic characteristics derived from property tax records or household surveys. Individual household property tax and water-use information can raise confidentiality concerns and hence add to the reluctance of localities in providing this type of data. Because of these difficulties, most household-level studies evaluate a single locality, and most of these use just one or two years of data. In these cases, comparing and evaluating household responses with multiple drought management programs is nearly impossible.

Aggregated municipal-level data tends to be less costly than household-level data. Moreover, there is no confidentiality concern with this type of data. Because this type of data is easier to obtain, more potential localities can be included in the analysis, as well as for longer time periods. Having a large number of localities in the dataset allows for a richer variety of drought management program experiences. Having a large number of localities in the dataset can also potentially improve the parameter estimates for income and other demographic characteristics where much of the variance in the dataset will be between localities rather than within localities. For these reasons, municipal-level data was chosen for the analysis.

Explaining Residential Water-Use

A substantial literature exists in explaining the behavior of residential water-use using the regression approach (e.g. see Baumann et al 1998). This water demand literature is a direct application of standard economic demand theory to water consumption. The typical independent variables used to explain residential water-use generally fall into six general categories:

1. Price
2. Income
3. Other demographic characteristics
4. Seasonal variation
5. Climatic variation
6. Drought management programs

The first five categories are used in most water demand studies, while the last category, drought management programs, is used in just a limited number of studies. Drought management programs are really policy demand shifters, and would include any explicit attempt (non-price) where water supply managers try to reduce water-use. In the economic terms of consumer theory, this would be equivalent to a shift in the demand schedule for water.

The remainder of this chapter summarizes the theoretical rationale and empirical estimates of these variables in the literature. The discussion begins with how previous studies have estimated the influence of drought management programs on water-use.

Next, general approaches and experiences in modeling price, income, demographic characteristics and seasonal and climatic variation are reviewed. The chapter concludes with a general model used to estimate water demand in Virginia that is capable of isolating the influence of drought demand policies on residential water-use, and specifically, in capturing the effects of drought management programs (voluntary and mandatory restrictions).

Drought Management Programs

While the water demand literature is extensive, relatively few studies have focused on estimating the effects of water conservation programs, and even fewer have attempted to incorporate program intensity into their models. Eight studies were identified in the peer-reviewed literature that included estimates of drought management or closely related conservation programs. These studies and findings are summarized in Table 3.1. The programs that were evaluated included mandatory restrictions, voluntary restrictions, rationing, retrofit programs, and general water conservation programs (any program aimed at reducing water demand).[5]

Most studies modeled individual water conservation programs as a single dummy variable (for example, 1 = voluntary drought management program in effect, 0 otherwise). Three studies (Nieswiadomy 1992, Michelsen et al 1999, Taylor et al 2004) combined all conservation programs (voluntary restrictions, mandatory restrictions, water rationing, etc) into single explanatory dummy variable.[6] Thus, these last studies did not attempt to assess whether a mandatory restriction program had a different influence on residential water demand than a voluntary restriction program as they were both treated the same. The effect that these studies found for this category was quite small and ranged from being insignificant in one study to having a 1-4% reduction for each general conservation program in the other two studies.

Five studies evaluated the effectiveness of voluntary restrictions or informational programs in reducing water-use (Moncur 1987, Billings and Day 1989, Nieswiadomy 1992, Wang et al 1999, Renwick and Green 2000). The main distinction between these two programs is that voluntary restrictions usually target particular activities for temporary reductions in water demand while information programs emphasize general water conservation. However, both types of programs rely on the goodwill of the citizens to reduce water-use on a voluntary basis, and thus from a practical standpoint can be considered similar for estimation purposes. Three of these studies showed either a negligible effect or a general lack of significance in parameter estimates.
The two remaining studies had estimated reductions of 7-16% for the implementation of these programs.

Two studies evaluated mandatory restrictions. Renwick and Archibald (1998) used a sample of 119 households in two localities to estimate a 16% reduction in water-use for mandatory restrictions. Renwick and Green (2000) used municipal-level panel data from

[5] Voluntary restrictions include "information" programs
[6] Nieswiadomy (1992) also included an additional category for information

eight localities in California and found a reduction of 29% in water-use when mandatory restrictions were put into place in two localities. These two studies also estimated the reduction in water demand from water rationing programs and found reductions in water-use of 28% and 19% respectively.

However, the ability to draw conclusions about the effectiveness of drought management programs in reducing water demand from the existing literature is limited for two reasons. First, the studies previously cited reflected limited variation in the range of drought management experiences. Most studies that used billing data examined the influence of drought management or conservation programs with one or two municipal water suppliers. Without variation in different program experiences, it is difficult to extend the results of a particular study to other localities. The most comprehensive study that evaluated conservation programs was the Renwick and Green study (2000). Even though data from eight localities was used in the overall analysis, this data included only two municipal water suppliers that had implemented mandatory restrictions and rationing programs.

Second, in only one study was there an attempt to estimate how program intensity influenced water-use. Billings and Day (1989) examined whether the number of news articles promoting a voluntary restriction program explained differences in residential water-use. Their results showed that this variable had a significant, but small (a 10% increase in information would result in approximately a 2 gallon reduction in daily water-use) effect on water demand. With the exception of this one study, however, differences in program intensity were not measured or estimated.

Without accounting for intensity, programs that would be expected to yield different water savings are treated similarly for estimation purposes. For example, informational campaigns that promote general water conservation through newspaper, television, radio, and water bills would be treated the same as campaigns that used just one of these four outlets. Two mandatory restriction programs that have vastly different enforcement efforts would also be treated the same. Obviously, differences in water-use reductions should be expected with various intensities of program information and enforcement. Practitioners will want to know what level of success can be expected given various levels of program intensity, not simply the average for two or three localities that were targeted in a particular study.

Thus meaningful estimates in the reductions of water-use due to drought management programs has been limited by both the lack of cross-sectional variation and the lack of descriptive measures in program intensity. In a study commissioned by the American Water Works Association, Michelsen et al (1999) claims this last limitation is particularly difficult to overcome. Despite having support and cooperation of the American Water Works Association, these researchers experienced significant problems in obtaining intensity-type data. Michelsen et al state:

> "In order to identify and quantify the effectiveness of individual nonprice conservation programs, it is necessary to have accurate information about specific

program activities, levels of effort, scope and coverage, and the exact periods of program duration corresponding with activities and levels of effort (p597)… Specific information about nonprice conservation program activities, levels of effort, scope and coverage and the exact duration of program activities was difficult to obtain from existing utility records. Nonprice program activities were often aggregated in reports without descriptions of individual program efforts (p597)… There was no consistent accounting across cities for the specific activities and level of effort of each program. One city may expend considerable effort and funds making a particular program work whereas another city may only make a token effort with a program. It should not be expected that the same percentage reduction in water use would result in both cases". (p601).

Given these challenges, Michelson et al. (1999) resorted to modeling drought management policies as a single dummy variable, essentially assuming every drought management program had the same effectiveness in reducing water demand. Chapter 4 will describe the approach used in this study to distinguish between varying intensities of voluntary and mandatory water restrictions.

Table 3.1 – Summary of Drought Management and General Conservation Literature

	Mandatory Restrictions	Information (Voluntary Restrictions)	Rationing	Retrofit Programs	General Conservation Program
Moncur 1987		7-16% Reduction			
Billings and Day 1989		Negligible but Significant [a]			
Nieswiadomy 1992		Significant only in 2 of 12 regional-model combinations [b]			Not Significant in any of 12 regions or models
Renwick and Archibald 1998	16% Reduction		28% Reduction	8-10% Reduction per Retrofit	
Wang et al 1999		Significant only in one of five models [c]		10-20% Reduction with Retrofit [d]	
Michelsen et al 1999					1-4% Reduction Depending on Locality [e]
Renwick and Green 2000	29% Reduction	8% Reduction	19% Reduction	9% Reduction	
Taylor et al 2004					Reduction of 3.5% in one of two models

Note [a]: 10% increase in information would result in approximately a 2 gallon reduction in daily water-use.
Note [b]: The two statistically significant coefficients showed a decrease of 19% and 22% for the implementation of information programs to reduce water-use.
Note [c]: The one statistically significant coefficient showed a decrease of 9% for the implementation of information programs to reduce water-use.
Note [d]: Retrofit was significant in three of five models.
Note [e]: Reduction additive for each conservation program implemented.

Price

The relationship between the price of goods and services and the corresponding quantity demanded is one of the most basic and fundamental relationships in economics. Consequently, the focus of much of the water demand literature has been in estimating the price elasticity for water. Economic theory assumes water demand, like other goods and services, varies inversely with price.

Estimating the responsiveness of price is often challenging due to the considerable variation that exists between municipalities in how water is priced. At the most basic level, municipalities can either charge a variable rate or a flat fee for water usage. The flat fee approach charges a single rate (generally for a particular sized water line) regardless of the quantity consumed. Such pricing occurs in unmetered systems. Since the water bill is not tied to actual water-use, this system tends to encourage higher consumption than the variable rate system. With variable-rate water pricing, consumers are charged based on the quantity of water they actually use. Each unit of water consumed (typically per thousand gallons or hundred cubic feet of water) is billed at the same rate. Thus the total bill increases at a linear rate with water-use. In most situations, however, municipal water suppliers use a combination of fixed fee and variable rate pricing.

A variation of variable-rate pricing is the block rate system. With this approach, consumers face two or more water rates depending on the amount of water consumed. For instance, the rate could be $5 per thousand gallons for the first 5000 gallons consumed, and then $7 per thousand gallons thereafter. This would be referred to as an increasing block rate, as the variable rate increases at some point with water-use. Increasing block rates are generally used with the hope that they will discourage water-use at the higher use levels. A decreasing block rate would be the reverse. For instance, a rate might be $7 per thousand for the first 5000 gallons consumed, and then $5 per thousand for all usage above that level.

Sewer fees are generally charged in conjunction with the water fees in localities that have both services. The sewer fee is almost always directly linked to the metered water usage. Thus the total cost of consuming water is typically determined by both the water and sewer bills.[7] Similarly to water pricing, sewer pricing typically includes both fixed fees and variable charges.

Seasonal water pricing is also used on occasion. Seasonal pricing usually means charging customers a higher variable rate during the summer months if a customer exceeds a certain usage level (this can either be constant across accounts or vary by account based on average winter usage levels). This seasonal structure is often used to

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[7] It is difficult to determine what proportion of the studies reviewed used both water and sewer bills in determining the overall price. Although a number of studies made it a point to say they were using both, few studies explicitly said they were not including sewer charges. It was clear that sewer fees were included for nine out of twenty-one studies reviewed. Nine studies did not indicate if sewer was included, but in only three studies was in discernable that sewer pricing was not included.

discourage excess outdoor water-use and to reflect the higher scarcity value of water during the summer months. However, sewer rates are occasionally reduced or even eliminated during summer months, typically for usage exceeding the winter monthly average. This is sometimes done because outdoor watering does not pose a burden on sewer systems, and the reasoning is that customers should not be charged for something that they are not using.

Finally, emergency pricing of water is sometimes instituted in an effort to reduce demand during times of drought and other water supply emergencies. In this situation, either the variable rate would increase across all consumption levels, or the variable rate would increase if a customer exceeds a base usage level as with seasonal pricing. However, no examples could be found in the literature where price was modeled explicitly for this purpose.

Estimating the response that price has on quantity demanded presents challenges compared to most goods because of the way water is consumed and priced. The first important challenge is that most goods are bought first and consumed later. Water, however, is consumed first, and paid for later (with up to a 1-2 month lag). Thus there is a greater disconnect between consumption and payment. A second important challenge is that water generally has a fixed fee included in the total cost, while most goods do not. The inclusion of this fee creates challenges because from an economic theory standpoint, the fixed fee is considered a sunk cost, which should have no bearing on the final consumption decision. In practice, however, ambiguity exists in how consumers perceive fixed fees related to water pricing.

The two most common methods used to model the response that price has on water consumption are the marginal price and average price specifications. Marginal price refers to the price charged for the last unit of water consumed. Thus with this approach, only the variable pricing rate is used, and in the case of block rates only the variable price for the last block rate that consumption took place in. The justification for using a marginal price specification is that rational consumers will have perfect information of the pricing structures, and will not let fixed fees or previous block rates influence their consumption decisions. The marginal price approach is especially important to many economists because of their adherence to consumer theory where the decision on how much water to consume is made at the margin, and sunk costs (flat fees) have no bearing on the consumption decision.

An additional variable, typically called the “difference variable”, is often used with the marginal price specification. The difference variable accounts for what is often called a minor income effect that would occur through the inclusion of fixed fees and/or previous block rates (e.g. a fixed fee of say $10 would effectively reduce the consumer’s disposable income available for purchasing water on other goods). This variable is typically defined as the actual water bill minus the water bill if all water was charged at the marginal price (no fixed fees or previous block rates considered). Thus, with a single variable rate and a fixed fee, the difference variable will always be positive. With a decreasing block rate the difference variable will also be positive. Under an increasing block rate, the difference variable could be positive or negative depending on the magnitude of the fixed fees and the price of the last block used. However, it seems that for a good such as water that normally accounts for only a small fraction of total household expenditures, and where much of the consumption would be treated as a necessary good, that this income effect would be small. As with the variable price of water, parameter estimates for the difference variable are expected to be negative (i.e. increasing fixed costs and/or previous block rates will lead to decreased water-use).

The other method used to model price is the average price specification. Average price is typically determined by dividing the total bill by the total water consumption. Thus both the variable and fixed costs are included in this calculation, as well as any previous block rates. The justification for using an average price specification is that consumers are not as well informed as to details of their water bills as the marginal price approach would suggest. The average price approach assumes that although consumers may not know how much they are paying at the margin, they do have a rough idea of the total bill as well as the total water consumption for a given month. This allows consumers to develop an intuitive feel for the average price as they will have an idea of the total water used and billed in a given month, relative to other months. While the general water demand literature contains a plethora of examples with both price specifications, the marginal price specification has been somewhat more prevalent.

As previously mentioned, the marginal price specification assumes that consumers know and understand the details of their water bills. If consumers do make a distinction between the fixed fees and marginal price, and in the case of block rates are only concerned with the price for the last block, then this specification would seem to be superior. However, there does not seem to be any empirical evidence to support this claim, one way or the other. If consumers do not generally know the pricing details of their water bills and instead rely more on the total bill to govern their water use decisions, then the average price specification would seem superior. It is quite possible that consumers, on average, respond to some mix of marginal-average price specifications.

Block rates create a challenge in specifying the appropriate marginal price when used with an aggregate water-use model. Since aggregate water-use data represents an average water-use for all users in a user class, it is not always apparent which block rate to use for marginal price. Take for example a block rate system where the first 5000 gallons is billed at $5 per thousand gallons, and $7 thereafter. What marginal price should be used if the average aggregate usage for a given month was 4990 gallons? In all of the aggregate studies evaluated, the marginal price used would have been $5. Clearly, however, many (possibly more than half) of the individual costumers would be facing a $7 marginal price.

A problem with the average price approach is that, even if this type of price signal is used by water consumers, it does not seem reasonable that the fixed fee portion of the water bill would always have the same importance as the variable rate. However, both are essentially treated equal with the average price specification. For example, if a locality had an extremely high fixed fee for water with a correspondingly low variable rate, then it seems reasonable that over time, consumers might develop an intuitive feel for the pricing structure and use more water than the average price would otherwise dictate, even if they never read the details of their water billing structure.

Another problem with the average price specification is that in the typical formulation of the measure, a simultaneity bias will occur. This is because the quantity consumed is used in the calculation of average price, which is then used in the final estimation of water demand (consumption). Thus the dependant variable (water consumption) is found on both sides of the regression equation. Taylor et al (2004) gives a thorough description of this problem with the possible consequences.

Regardless of how price is defined in water demand studies, the empirical estimates for this variable have in general been consistent with economic theory. In all of the studies evaluated, price was found to have a negative effect on water consumption. The range in the estimates varied considerably. The calculated price elasticities ranged from -.01 (high inelastic) to -1.63 (moderately elastic). This range is somewhat similar to that reported in the Meta-Analysis by Epsey et al (1997) where price elasticities ranged from -.03 to -3.33. However, in the large majority of the water demand studies evaluated the price elasticities were in the inelastic range (less than 1.0 in absolute value). This finding was also backed up by Epsey et al that found approximately 95% of all price elasticities falling into the inelastic range. Interestingly, elastic estimates in the reviewed studies tended to come from those studies that used household-level data for a single locality. Most of the price elasticities for the municipal-level studies evaluated were between -.10 and -.50. Almost 60% of all elasticities reported by Epsey et al were in this same range.

Comparing price elasticities for marginal price and average price specifications across studies can be somewhat problematic due to differences observed in mean prices and consumption. However, in general, elasticities for average price specifications tend to be higher than for marginal price specifications. More compelling evidence can be found in studies that estimated models for both price specifications. In these five instances, the elasticities for the average price specifications were, in every case, higher than for the marginal price specifications. One reason for this finding is almost certainly due to the bias created by the mathematical construction of average price, as note by Taylor et al (2004)). However, the practical extent of the bias is not entirely clear and it may also be the case that the average price specification more closely matches actual consumer behavior than the marginal price specification.

Studies that included a difference variable (actual bill less the price if the consumer was charged only at the marginal price) have generally conformed in sign to the theoretical expectations (negative parameter estimates), but the results have often been statistically insignificant. The greatest absolute response was calculated in Billings and Day’s study (1989), where water-use decreased by about forty gallons for each $1 increase in the difference variable. This result seems questionable, as it would imply that increasing fixed costs by $10 would result in zero water consumption with an average daily household consumption of 400 gallons (approximately the mean in this study). Estimates by Jones and Morris (1984), Renwick and Archibald (1998), and Renwick and Green

(2000) seemed much more realistic and ranged from -.63 to -2.3, implying that an increase in fixed costs by $10 would result in a decrease in water use from 6.3 to 23 gallons for the same base average daily household consumption of 400 gallons.

Research also indicates that price elasticities may vary by the season. Conceptually, outdoor water-use (e.g., lawn watering, car washing) might be considered more discretionary than indoor water uses (e.g., laundry, personal hygiene). Since most outdoor water-use occurs during the growing season, changes in price should have more of an impact on water-use during this time. Three of the four studies that had both summer and winter elasticities consistently had higher estimates (more elastic) for the summer months (Howe 1982, Griffin and Chang 1990, and Renwick and Green 2000). Only one study (Pint 1999) showed higher elasticities in the winter compared to the summer months.

A main implication that can be drawn from the literature dealing with price is that even though most price estimates tended to be inelastic, water-use nonetheless is clearly responsive to price. If the price of water (and/or sewer) is set high enough, water usage will almost certainly come down to a desired level of reasonable proportions. In this light, price can be used to effectively reduce demand during times of drought. A more important question is whether localities have the political will to impose water rates that are high enough to make this happen. If not, other measures such as the imposition of drought management programs would be required to alleviate shortages in water supply.

Income

Economic theory suggests that income be included in consumer demand studies. Water is expected to be a normal good, meaning that as income increases, demand for the good will also increase. Thus the theoretical expectation is that as income in a locality (or household) increases, consumers will have additional discretionary income and would on average use more water.

Nearly all water demand studies include income or some proxy for this variable in the model specification. Income elasticities generally ranged between 0 and .50. Using typical values for income and water usage ($50,000 and 400 average daily gallons per account) and an elasticity of .30, this translates roughly into an increase in 2.5 gallons per day for an increase of $1000 in income, or 25 gallons for a $10,000 increase in income.

Income is measured in a number of ways. With household level studies, a proxy such as house value is often used (Jones and Morris 1984, Nieswiadomy and Molina 1989, Hewitt and Hanemann 1995), although a few researchers have also used household surveys to estimate income levels (Moncur 1987, Renwick and Archibald 1998).
With municipal level studies, however, average or median incomes for the locality, available from Census and other data sources, are typically used.

A challenge with municipal-level studies is in distinguishing the influence that income has on water-use from other important demographic variables. This is because many municipal-level variables such as house value, lot size, and household size are highly collinear with income. Moreover, some of these variables (such as lot size) may not be readily attainable at the municipal-level. Because of the difficulty of controlling for all important demographic variables at the municipal level, it is possible that the parameter estimates for income might be capturing the influence of several demographic characteristics and thus not measuring a pure income effect.

Of particular interest in the water demand literature is the relationship between income and the previously mentioned difference variable (see discussion in the previous section). Many researchers have noted that the coefficient estimate for the difference variable should be equal in magnitude but opposite in sign for that of income. However, many of these same researchers have also pointed out that coefficient estimates for the difference variable are rarely found to be close to these theoretical expectations (Howe 1982, Jones and Morris 1984, Nieswiadomy and Molina 1989, Pint 1999).

What has not been explicitly pointed out in the literature is that from an applied standpoint this theoretical ideal would only hold under two conditions: 1) Consumers are responding to a pure marginal price framework, and 2) the income effect being measured is a "true" income effect and does not include surrogates for lot size, house size, etc. (i.e. how water-use would respond given a $1 increase in income while holding constant all other factors that affect water).[8] It is also possible that both of the above conditions do not hold but by pure chance the opposing affects balance out.

If consumers are not responding to a pure marginal price framework and are to some degree responding directly to fixed costs (not in terms of reducing disposable income, but rather by perceiving an increase in the average price of the water bill), then the difference variable should in fact, be greater in magnitude then the "true" income effect. Thus if consumers are not responding to a pure marginal price framework then the difference variable should be measuring two additive effects: 1) the traditionally quoted income effect, and 2) a misspecification effect of the marginal price approach where fixed effects (and previous block rates) are not ignored by the consumer.

Five studies were reviewed that estimated water demand for both the difference variable and income. The theoretical expectations if consumers were responding purely to marginal price for the ratio of parameter estimates of the difference variable over the income variable would be -1.0, since they are opposite and equal magnitude of each other. If consumers are in fact responding to fixed fees then this ratio would increase in absolute magnitude (the difference variable parameter in the numerator would increase). If variables are not being controlled for that have a high positive correlation with income, then the ratio would decrease (the income parameter in the denominator would increase). Thus deviations from theory for parameter estimates for the difference variable and income would have offsetting effects. If the ratio was greater than one in absolute terms (while still negative) then it would seem that the difference variable strayed further from

[8] Nieswiadomy and Molina 1991 come very close with the first condition

its expected value versus the income variable, and vice versa if the ratio was less than one in absolute terms (while still negative).

The first three studies where ratios could be computed used household data. Jones and Morris (1984) had ratios of -62 to -594 with an average of -410. Renwick and Archibald (1998) had ratios of -65 to -1250 with an average of -148. Nieswiadomy and Molina (1989) had ratios of -648 to +897. This was the only study evaluated that had positive ratios (the positive ratios corresponding to cases where the parameter estimates for the difference variable were positive). The last two of the five studies where ratios could be computed used aggregate data for multiple localities. Renwick and Green (2000) had an overall ratio of about -1000 (calculated by using averages of 300 for average daily gallons, $3 for difference variable, and $75,000 for income). Billings and Day (1989) had an overall ratio of -5833 (calculated by using averages of 400 for average daily gallons, $2 for difference variable, and $20,000 for income).

These studies provide an interesting insight. With the exception of the Nieswiadomy and Molina (1989) study which had both positive and negative ratio estimates, ratio estimates were so much greater in magnitude (in absolute terms) from the theoretical -1.0 expectation that one must immediately question whether consumers are in fact responding to a pure marginal price specification. It also may be that the income effect is also overstated, but if so, is far outweighed by the increase in the difference variable.

Other Demographic Variables

There are additional demographic variables that have theoretical reasons for inclusion in water demand models. Household size, house value, and lot size (yard size), are all expected to influence water-use. Household size is probably the most obvious of these variables. As the number of persons per connection increases, water-use would also be expected to increase. House value is another variable that would be expected to be an important determinant for water usage. Houses of higher value would be expected to have more water-using devices such as dishwashers, washing machines, bathrooms, hot tubs, swimming pools, etc. Lot size is potentially the most important variable that affects water demand during the summer months when irrigation becomes more prominent. Thus all else being equal, houses with larger lots would be expected to use more water than houses with smaller lots, especially during the summer.

In comparing empirical estimates for these demographic variables, a distinction needs to be made between estimates for household-level and municipal-level studies. Household-level studies have generally found a statistically significant and consistent relationship between demographic variables and residential water demand. Estimates for demographic variables in aggregate-level studies, however, have produced more variable results.

By its very nature, little temporal variation occurs in aggregate-level data. Thus most of the significant variation is likely to occur between localities (the cross-sectional data) as opposed to the time series component with a locality. With enough localities in the panel dataset, this would not necessarily be a problem. However, in the panel-level studies reviewed that used billing data (as opposed to production data) the largest number of localities evaluated was eight, with the average being something in the range of 3-4. Obviously, having this number of localities for variables that do not vary much within individual localities poses serious problems from a statistical standpoint. Even where parameter estimates are statistically significant, the ability to transfer results outside the sample would be suspect. The results would seem to be sample specific, and may change drastically if the model was estimated with different localities within a sample region.

Compounding this problem is the correlation between many of the demographic variables used in water demand models, again mainly at the aggregate-level. House value, household size, and lot size are also highly correlated with income, and correlated with each other. For example, house value also includes the value of the lot that the house sits on, which in turn is correlated with lot size.

Household size was used in five of the municipal-level studies evaluated. At the municipal-level, average or median household size can be obtained for Census data. Only one out of five aggregate-level studies found household size to have consistent positive and significant estimates (Billings and Day 1989). One other study (Hoglund 1999) found both positive and negative coefficient estimates that were statistically significant. The other three were either insignificant or had negative coefficient estimates in most models (Nieswiadomy 1992, Nauges and Thomas 2000, Martinez-Espineira 2002).

House value was not used in any of the municipal-level studies evaluated.[9] This finding seems surprising as houses of higher value would be expected to have more water-using devices such as dishwashers, washing machines, bathrooms, hot tubs, swimming pools, etc. They would also be expected, on average, to have larger lawns with the subsequent need for irrigation. However, these are the same factors that were discussed in the income section (that indirectly increase water consumption). Thus it would seem that the two variables, income and house value, are highly collinear. In other words, to a large degree they are measuring the same thing. Because of this collinearity, it is probable that household value has been excluded in municipal-level studies in order to estimate the income effect, which is an important theoretical concept for economists.

Lot size is frequently used in household-level water demand studies.[10] However, at the municipal-level, lot size is difficult to obtain as there is no census variable or other standardized data base that measures this variable. As a consequence, lot size is usually ignored in municipal-level studies. Two aggregate-level studies that were reviewed did

[9] House value, or a proxy, was used in six household-level studies and was generally found to be positive and statistically significant.
[10] Out of five household-level studies reviewed that included this variable, all of them found lot size to have a positive and significant affect on water demand (Renwick and Archibald 1998, Nieswiadomy and Molina 1989, Hewitt and Hanemann 1995, Lyman 1992, Pint 1999). No other demographic variable had such a consistent affect.

use proxies for this variable. An obvious alternative used in one of these studies (Hoglund 1999) was population density, where water-use was expected to increase as population density decreases. However, the effect that this variable had was not found to be statistically significant. A problem with population density is that large areas of open space such as farmland, woods, and parks, as well as large-scale commercial and industrial development will skew population density downward. Thus you could have two localities that had similar sized residential lots, but one with a much lower population density.

In the second municipal-level study, Renwick and Green (2000) used an innovative approach in constructing an alternative proxy for lot size. Using GIS, they subtracted out easily identifiable nonresidential lands in the respective service areas including parks, green spaces, as well as industrial and commercial areas. The resulting variable was found to be statistically significant in their analysis with a 10% increase in lot size resulting in approximately a 2.7% increase in water usage.

Seasonal Variation

Seasonal variables are used in most water demand studies to capture the cyclical nature of water-use. Residential water-use is typically at its lowest level during the winter and at its highest level during the summer. Indoor water usage for the more basic activities such as personal hygiene, cooking, and cleaning, stays relatively constant throughout the year. However, discretionary outdoor water-use increases during the growing season. Lawn and garden watering account for the bulk of this outdoor water-use, typically around 80% (Planning and Management Consultants 1994). Other outdoor uses include car washing, driveway cleaning, and filling/maintenance of swimming pools.

The three most common methods to model seasonal effects are by using 1) seasonal dummy variables, 2) sinusoidal smoothing, and 3) average monthly temperature. The dummy variable method simply uses a binary variable for each month (or other time period) to account for the differences in usage for each month after controlling for all other variables. Thus these dummy variables will act as a base water-use for each month. Renwick and Archibald 1998, and Martin and Wilder 1992 both used this method to account for seasonality.

The sinusoidal method uses sine and cosine functions to estimate the monthly response to water demand. Renwick and Green 2000, was the only study reviewed that used this technique. The sinusoidal method imposes a smooth transition to the seasonal patterns of water-use. Monthly fluctuations in water-use will be smoothed out to conform to sine-cosine functional patterns. In other words, deviations from the functional patterns will be forced, to a large degree, to conform to these patterns. This could be advantageous in situations were there are relatively few observations and monthly water-use increases or decreases for no apparent reason. However, with large numbers of observations or where there are valid reasons for not having smooth water-use over the course of the year, this technique may be less appropriate. For example, the month of December and January are both in the winter dormant seasons where water-use should be at a low. However, if residential water-use in December was higher than January, there may be a logical reason for this. It is possible that workers will have additional time off in December due to the holiday season, spending more time at home and hence using more water than in January. In this case the sinusoidal approach would smooth over a valid and valuable difference in water-use. The dummy variable approach allows for deviations from smooth seasonal patterns that would not be captured using the sinusoidal approach.

The average temperature method uses the average monthly (or other period) temperature to model the seasonal trend in water-use, as increased temperature generally results in increased water consumption. Billings and Day 1989, Lyman 1992, Nieswiadomy 1992, Pint 1999, Michelsen et al 1999, Martinez-Espineira 2002, and Taylor et al 2004 all used this method to account for seasonality. A challenge with this approach is that the response to temperature may vary by season, as it is outdoor water-use that is expected to be most influenced by temperature, and most of the residential outdoor water-use will occur during the growing season. Whether the average January temperature is 5° or 30° Fahrenheit (-15° or -1° Celsius) should make no difference in residential water-use for the month. Possibly an improved approach to model seasonal variation with temperature would be to use this variable in conjunction with a growing season dummy. In this case, temperature would be allowed to have a neutral effect during the dormant season. Another challenge with this approach (even if corrected to deal with the dormant season) is that it implicitly assumes that all cyclical variation in residential water-use is attributable to temperature. However, there may very well be other non-climatic reasons why this cyclical variation occurs. For instance, the summer school recess would conceivably increase the average time spent at home during these months and thus increase average monthly consumption for the residential class of water users. Using the monthly-dummy approach allows these non-climatic factors to be controlled for in the demand specification.

Parameter estimates for the first two approaches in capturing seasonal variation have followed a cyclical pattern where the lowest water-use is in the winter and highest water-use is in the summer. The water-use during the winter months in these studies was relatively constant. For the most part, parameter estimates for the third approach were consistent with theoretical expectations. Five of the studies reviewed for this last approach had consistent positive and statistically significant parameter estimates, indicating that water-use increased as temperature increased (Billings and Day 1989, Pint 1999, Michelsen et al 1999, Martinez-Espineira 2002, and Taylor et al 2004). One study (Nieswiadomy 1992) found both significant positive and negative coefficient estimates for temperature depending on the model. Finally, the last study (Lyman 1992) was indeterminate due to the inclusion of additional variables that interacted with temperature.

Climatic Variation

Although seasonal variation accounts for a great deal of the overall variation in water-use, deviation may also occur from these average seasonal patterns due to varying climatic conditions (deviations from average rainfall and temperature patterns). The estimates for the seasonal variables will in effect be measuring the average water-use given average climatic conditions for each month of the year (or seasons) after controlling for other factors. For example, the seasonal variation may show that the average water-use in July is 300 gallons per day for a particular locality. However, water-use during July may actually range from 250-350 gallons. Much of this variation will be caused by deviations from average climatic conditions (deviations in rainfall and temperature for the given month).

Thus the demand for water not only varies by season, but is also directly influenced by deviations from average climatic conditions (rainfall and temperature). Since most of the discretionary outdoor water-use goes toward watering lawns and gardens, the influence that temperature and rainfall have on water-use is expected to be greatest during the growing season. It would also be expected that rainfall and temperature would have stronger effects in the middle of the summer when this discretionary use is generally highest, than toward the tail ends of the growing season (spring and fall).

It would be expected that a dry and/or hot summer would lead to increased water-use in an effort to keep lawns green and growing. Conversely, a wet and/or cold summer would lead to decreased water-use as there would already be an abundance of moisture for plant growth. Drought conditions would just be an intense manifestation of a hot dry summer. Thus the effects of drought can be controlled by using rainfall and temperature data. Alternately, these effects might also be controlled for by using a locality-specific drought index such as the Palmer Drought Index or the Crop Moisture Index which measure soil moisture conditions.

The most direct method for accounting for climatic variation is to simply add rainfall and temperature variables to the model for the monthly rainfall total and average temperature respectively (Lyman 1992, Nieswiadomy 1992, Pint 1999). A potential problem with this approach used in conjunction with the dummy variable approach is that temperature is highly correlated with the seasons. Having two explanatory variables (temperature and seasonal dummy variables) that are highly correlated can cause estimation problems in the regression analysis, and so it is helpful to normalize the temperature data in a way to remove this correlation. A simple and effective way to accomplish this is to subtract each observation for temperature by the historic average for the particular month (as did Renwick and Green 2000). The resulting differenced variable for temperature will show positive values when the current observation is greater than the historical average and negative values when the current observation is less than the historical average. When the observed temperature is equal to the historic average temperature (zero difference) this transformed variable will have a neutral effect. In other words, it would be a baseline value for temperature for a given month. Similarly, the rainfall variable can also be constructed in this format for ease of interpretation, although the statistical need is not as great.

Although the conceptual reasons for including climatic variables are strong, empirical estimates for their influence on water-use have shown mixed results. Almost half the water demand studies reviewed did not include rainfall in their model specifications and of those that did, often found rainfall to have a statistically insignificant effect on water use (Moncur 1987, Renwick and Archibald 1998, Michelsen et al 1999, Nauges and Thomas 2000, Renwick and Green 2000, Taylor et al 2004). Nieswiadomy (1992) had both positive and negative coefficients estimates depending on the model. Lyman (1992) found a significant effect in only one out of three specifications and that case was next to impossible to interpret due to the additional inclusion of a square term for rainfall that showed a positive coefficient. Depending on the level of water usage and rainfall being evaluated, the net effect could be either positive or negative.

Surprisingly, relatively few studies showed a consistent and statistically significant negative relationships between rainfall and water-use. Billings and Day (1989) found a winter elasticity of -.01 and a summer rainfall elasticity of -.06, which translates into a reduction of approximately 1 and 15 gallons per day for each inch of rainfall for the month (based on my calculations using a typical range of water usage values). Pint (1999) found a reduction of 4.4 gallons per day for each inch of current monthly rainfall, and a reduction of 12.5 gallons per day for each inch of previous month's rainfall. These estimates translate into elasticities of roughly -.03 and -.08 for current and lagged rainfall respectively. Interestingly, Pint's was the only study that included or found a lagged effect for rainfall, and this study showed that the previous month's rainfall had a greater effect than current rainfall by a magnitude of approximately 3.

The general lack of significance for rainfall was perplexing because intuitively, rainfall seems to have such a strong influence on water-use during the growing season. One potential problem is that most studies did not control for rainfall by the growing and dormant seasons. Only in the Billings and Day (1989) study was the effect of rainfall evaluated separately by summer and winter months. That study found that the response during the winter months was much lower than during the summer, which fit the theoretical expectations. Without controlling for the two (or more) seasons, it seems quite likely that the overall response of rainfall is being pulled down by the winter months.

Temperature, on the other hand, has generally showed more favorable results toward theoretical expectations. However, most of these temperature estimates were with temperature also controlling for the seasonal effects, as previously discussed. There was only one study reviewed (Renwick and Green 2000) that separately controlled for both seasonal variables and temperature. This study found an elasticity of .45, which was low compared to the studies that used temperature to control for seasonality. This result seems intuitive from a comparative standpoint as separately controlling for seasonal effects should remove part of the responsiveness of temperature.

General Water Demand Model Used in this Study

As a summary, the general approach for this study is to use regression analysis to establish the relationship between residential water-use and the theoretical explanatory variables. To reflect the range of experiences with implementing drought management programs, billing records were used to derive average monthly residential water-use across multiple municipal water suppliers. In sum, monthly estimates of residential water-use data were obtained from 21 localities across Virginia. To obtain a perspective of how water-use varies across different climatic conditions (drought and non-drought conditions), time series water-use data was obtained for each local water supplier. Historical data for each locality ranged form 2 to 11 years.

The general panel-data water demand model is hypothesized to be related to the following:

Residential Water-Use (average daily gallons per account for each month) = function (price, income, seasonal variation (monthly seasonal dummies), climatic variation (rain and temperature deviations from historical averages), other demographic variables, and water-use restrictions)

Where: water-use restrictions = function (program intensity)

Data from a comparatively large number of localities were obtained for the dataset in order to have a wide range of experiences in implementing water-use restrictions. It was envisioned that by having a large number of localities in the dataset, the problems that Michelsen et al and others have had in measuring program intensity could be overcome. Consequently, a large focus of the next chapter (Chapter 4: Data) is on classifying and measuring the intensity of drought management programs used by these 21 localities.

Chapter 4: Data for Analysis

To estimate the general water demand model identified in the previous section, data was needed for residential water-use as well as for other variables hypothesized to influence this dependent variable. The first part of this chapter describes the procedure used to identify the Virginia localities included in this study. The second section discusses the water-use data associated with these localities, including challenges with this data and a summary of the residential water-use experiences. Next, the procedure for collecting information on the drought management programs and water pricing used by the localities is described. This discussion also details the approach used to classify the intensity of mandatory and voluntary restriction programs based on the levels of information dissemination and enforcement efforts. Finally the last section describes how demographic characteristics and climatic conditions for each locality were obtained, as well as summaries of these variables for the study localities.

Selection of Municipal Water Suppliers

Localities with 4000 or more service connections in Virginia were initially targeted for inclusion in this study. Towns were excluded because it would be difficult to match census demographic information that was unique to the locality (this census data would be mixed with the corresponding county's census data). Military-based service authorities were also excluded for obvious reasons. Other localities that had highly unique demographic characteristics such as the City of Radford with a high university student component were dropped from consideration and not included in this total. A total of 45 municipal water suppliers met these conditions and were contacted in Virginia for initial consideration in this study.

For final inclusion in this study, these municipal water suppliers needed to possess billing records with the following characteristics: 1) billing records included a residential category, 2) billing records included a minimum two years of historical data (including 2002 drought year), 3) billing records were issued on either a monthly or bimonthly basis. Of primary necessity was that localities keep separate records for the residential water users, since data mixed with other types of user categories (e.g. commercial and industrial) would inflate the water-use per connection. Since the focus of the analysis is on the effects that conservation programs had, particularly during the drought, data was needed for the 2002 drought year as well as a minimum of one other year for control purposes. Municipalities that did not impose mandatory or voluntary restrictions were still considered for the study (there were a few areas of the state that were exempt from Executive Order 33) because they could serve as a de facto control groups. Monthly or bimonthly billing records were required so that estimated aggregate water-use would adequately reflect monthly consumption patterns.

Of the 45 localities contacted, six localities billed on a quarterly basis. Four other localities could make no distinction between residential and commercial user groups in their billing data. In five localities, data was not available for the minimum time period needed due to system upgrades or incomplete record keeping. Eight additional localities were unable or unwilling to provide the necessary data.

A total of 22 municipal water suppliers in Virginia provided residential water-use data. One of the suppliers, Rapidan Service Authority, was a compilation of three counties, while the remaining water suppliers were independent counties or cities. One of the localities (Washington County) was subsequently dropped from the final analysis when it was discovered that school water-use was included in the residential data. The most comprehensive dataset came from Stafford County (1991-2003) while the shortest dataset came from the City of Charlottesville (2001-2003). The average dataset covered the period around 1999-2003. The specific municipal water suppliers and the number of years of water-use data for each locality is shown in Table 4.1

Table 4.1 – Summary of Basic Residential Water-Use Data

City	Data Time Period	Month/ Bi-Monthly Billing Period		County	Data Time Period	Month/ Bi-Monthly Billing Period
Bristol City	1/98-6/04	M		Albemarle County	6/96-11/03	M
Charlottesville City	5/01-10/03	M		Augusta County	9/00-7/04	B-M
Colonial Heights City	3/01-7/04	B-M		Chesterfield County	5/93-6/03	B-M
Danville City	6/97-12/03	M		James City County	7/98-11/02	B-M
Hampton City	7/98-11/02	B-M		Prince William County	12/97-3/03	M
Harrisonburg City	7/00-5/04	M		Spotsylvania County	5/01-11/03	M
Manassas City	6/00-5/04	M		Stafford County	1/91-12/03	M
Newport News City	7/98-11/02	B-M		York County	7/98-11/02	B-M
Poquoson City	7/98-11/02	B-M		Rapidan Service Authority	4/01-3/04	M
Richmond City	1/01-12/03	M				
Salem City	6/99-8/04	M				
Suffolk City	12/99-4/04	B-M				

Note: County/City classification is based on municipal legal designation, except for Rapidan Service Authority which is a compilation of three counties.

Residential Water-Use Data

The water-use data provided by the participating municipalities came from billing records and included the number of accounts in each user-type class (residential, commercial, industrial, etc) for each month, as well as the corresponding total water use in gallons or cubic feet. All consumption data was converted to gallons for consistency. The average daily usage per residential connection was calculated by dividing total consumption (in gallons) by the number of accounts and the number of days in the billing cycle. The average daily usage, also called average daily gallons (ADG), was used for all subsequent comparisons and for empirical estimation.

Unfortunately, the definition of user-types (residential, apartment, commercial, industrial, etc.) varied across municipal water suppliers. Since the focus of this analysis is on residential water-use, the definition of this category had important implications. "Residential" was defined as pure single-family detached residential dwellings in some localities, while in others the residential classification included apartment data. Moreover, the way in which this apartment data was incorporated into the residential data also varied. Sometimes apartment data included only single-metered apartments (one meter per apartment), sometimes it included only group-metered apartments (one meter for a group of apartments), and sometimes it included a mix of the two apartment types. Table 4.2 summarizes how the "residential" category differs by locality.

Table 4.2 – Summary of Apartments in Residential Water-Use Data

No Apartments in Residential Data		Single-Metered Apartments in Residential Data		Single-Metered and Group-Metered Apartments in Residential Data
Albemarle County		Bristol		Augusta County
Charlottesville		Danville		Colonial Heights
Chesterfield County		Harrisonburg		Hampton
Manassas		Prince William County		James City County
Salem		Richmond		Newport News
Spotsylvania County				Poquoson
Stafford County				Washington County
Suffolk				York County
Rapidan S.A.				

How apartments are classified into residential water billing data has important consequences because it will shift water-use per account upward or downward from residential data without apartments. This effect on water-use will vary depending on whether the apartments are single-metered or group-metered. Households residing in apartments are generally expected to use less water than single-family households with lawns, particularly during the summer months. Water-use may also be lower for apartment dwellers due to the smaller average household sizes observed for renter households versus owner occupied housing in the Census data (this averaged 9% less across localities in this study). It may also be lower due to apartment users having fewer indoor water-using devices such dishwashers, clothes washers, etc. Thus if residential data includes single-metered apartments, average water-use per account is expected to decrease.

If residential data includes group-metered apartments, average water-use per account is expected to increase. This is because one group-metered account represents multiple apartments. If both single and group-metered apartments are included in the residential data, water-use could be either higher or lower depending on the mix of the two categories.

In order to quantify the extent of this potential problem, additional estimates were requested from localities that had apartment data mixed with the residential category. These localities were asked to estimate the percentages of single and group-metered apartments in their residential data based on the total apartments stock in their locality. For example, if a locality included 400 single-metered apartments in their residential data out of 1000 total apartments in the locality, then their estimate for single-metered apartments would be 40%. In addition, the percentage of apartments included in the total housing stock for each locality was estimated from Census data.[11] The estimates for each locality are reported in Table 4.3.

In four localities for example, apartments made up over 30% of the housing stock. In one of these localities (Charlottesville), these apartments were included in a separate billing category distinct from residential data, thus no apartments were mixed with the residential data in this case. However, the other three localities all had significant percentages of apartments that were included in the residential billing data. Harrisonburg had the highest percentage of apartments in the total housing stock (42.1%) with an estimate from the locality that 60% of these apartments were included in the "residential" user-category (all single-metered). Richmond had 34.2% of its housing stock in apartments with an estimate from the locality that 23% were included in the "residential" user-category (all single-metered). Newport News had 33.7% of its housing stock in apartments with an estimate from the locality that 100% were included in the "residential" user-category (20% single-metered and 80% group-metered).

Two general options existed to deal with apartment data being mixed with the residential category. One option would be to attempt to transform estimates of water-use per account by eliminating apartment water-use from the dependent variable. This option, however, was infeasible because while the number for apartment accounts in each locality can be estimated, the water-use per apartment cannot. A second option was to estimate the percentage of group-metered and single-metered accounts contained in the residential category for each locality and include this estimate as an independent variable in the final regression. This was the approach taken here.

The estimate for the percentage of group-metered and single-metered accounts contained in the residential category was calculated from the percentage of apartments that made up the total housing stock (estimated from Census data) and the percentages of single and group-metered apartments contained in the residential data (estimated by the localities).

[11] The number of apartments was constructed from Census variables for number of units in structure. Any structure that contained three of more units was considered an apartment. This figure was then divided by the total housing stock in the locality to come up with the percent of apartments in the total housing stock for each locality.

The percentage of apartments in the housing stock was multiplied by both the percentage of single-metered apartments and group-metered apartments. For example, Newport News had 33.7% of its overall housing stock in apartments, and had 100% of these mixed into the residential data (80% group-metered and 20% single-metered). Thus the corresponding calculations would be:

Percentage of group-metered apartments in residential data = 33.7 x .80 = 27.0%

Percentage of single-metered apartments in residential data = 33.7 x .20 = 6.7%

These calculation estimates for each locality are reported in the last two columns of Table 4.3.

Table 4.3 - Details of Apartment-Types in Residential Water-Use Data

Locality	% Apartments in Locality (Census) [a]	% of Total Apartments: Group Meter in Residential Data (Estimated)[b]	% of Total Apartments: Single Meter in Residential Data (Estimated)[b]	% of Residential: Group Meter (Calculated)[c]	% of Residential: Single Meter (Calculated)[c]
Albemarle County	18.8%	-	-	-	-
Charlottesville	30.5%	-	-	-	-
Chesterfield County	9.3%	-	-	-	-
Manassas	17.3%	-	-	-	-
Salem	18.3%	-	-	-	-
Spotsylvania County	5.5%	-	-	-	-
Stafford County	7.2%	-	-	-	-
Suffolk	8.0%	-	-	-	-
Rapidan S.A.	3.1%	-	-	-	-
Bristol	16.5%	-	85%	-	14.1%
Danville	18.1%	-	15%	-	2.7%
Harrisonburg	42.1%	-	60%	-	25.2%
Prince William County	14.9%	-	5%	-	0.7%
Richmond	34.2%	-	23%	-	7.9%
Augusta County	4.1%	10%	90%	0.4%	3.7%
Colonial Heights	13.7%	90%	10%	12.3%	1.4%
Hampton	23.0%	80%	20%	18.4%	4.6%
James City County	11.9%	80%	20%	9.5%	2.4%
Newport News	33.7%	80%	20%	27.0%	6.7%
Poquoson	5.9%	80%	20%	4.7%	1.2%
Washington County	7.1%	5%	95%	0.4%	6.7%
York County	8.9%	80%	20%	7.2%	1.8%

Note [a]: Constructed from census data where structures with three or more units were considered as apartments.
Note [b]: Estimated by localities (i.e. 10% means that 10% of overall apartments are contained in the respective category.
Note [c]: Calculated by multiplying the respective estimates in the third and fourth columns by the percentage of apartments in each locality.

Another problem with the raw residential data was that monthly water-use reported in the billing records differed from when the households actually used the water. If a particular customer's bill was issued on June 1, the consumption that corresponded to this billing would be reported as "June" water-use by the locality. However, most of the consumption would have taken place in May. Thus the monthly water-use data needed to be adjusted to account for the potential discrepancy between consumption and billing records. There is also a time lag between when a meter is read and when the bill is issued, which varies from locality to locality. This lag will correspondingly increase the time period between when consumption took place and when the bill was issued.

To adjust the billing records, estimates of the average lagtime between when meters were read and when the corresponding bill was issued were obtained from each locality. This average lagtime varied considerably by locality, from 1-21 days. The lagtime was used in conjunction with the average bill date (typically the middle of the bill month) to come up with the "average" consumption period for each billing cycle. As an example, if a locality billed monthly, had an average bill date in the middle of the month, and had an average lagtime of 10 days, then the average corresponding consumption period for the July billing period would be approximately from the 5th of June to the 5th of July. Thus with this example, roughly 80% of the consumption for a particular billing month actually took place in the previous month, and 20% in the current month. The billing data was transformed to consumption data by accounting for these processes.

The majority of localities billed monthly, however, nine localities billed on a bi-monthly basis. Bi-monthly billing data was adjusted in a similar manner, the only difference being a longer billing period and corresponding consumption period. If a locality billed bi-monthly, had an average bill date that was in the middle of the month, and had an average lagtime of 10 days, then the average corresponding consumption period for the July billing period would be approximately from the 5th of May to the 5th of July. Thus with this example, roughly 40% of the consumption for the July billing period took place in May, roughly 50% took place in June, and roughly 10% took place in July. All billing periods were transformed in this manner and the resulting consumption estimates were added together for the overlapping monthly allocations.

Thus, an assumption made with this approach is that the water-use rate at the beginning of this billing period is identical to the water-use rate at the end of the period. The longer the billing period, the more critical this assumption becomes. Quarterly billing data was not used in this analysis because this assumption would have meant that water-use would remain stable over four-month long periods (e.g. water-use in April would be the same as water-use in July).

A final problem with the raw water-use data was that in a few cases the account data (number of accounts by user-type) was incomplete. In these instances, the number of accounts by user type was generally available for only one month of the year. Missing account data was estimated by extrapolating between the months where data was available (generally January of each year).

The final estimates of AGD per residential account for the twenty-one localities are shown in Table 4.4. Localities varied substantially in their levels of residential water-use, both by season and by locality (see Table 4.4). The highest water-use for any one month was in James City County with 364 average daily gallons, while the lowest water use for any one month was in Rapidan Service Authority with 107 average daily gallons. The highest average water use for any locality (across the entire year) was 259 daily gallons in Newport News while the lowest average water use was 130 daily gallons in Rapidan Service Authority.

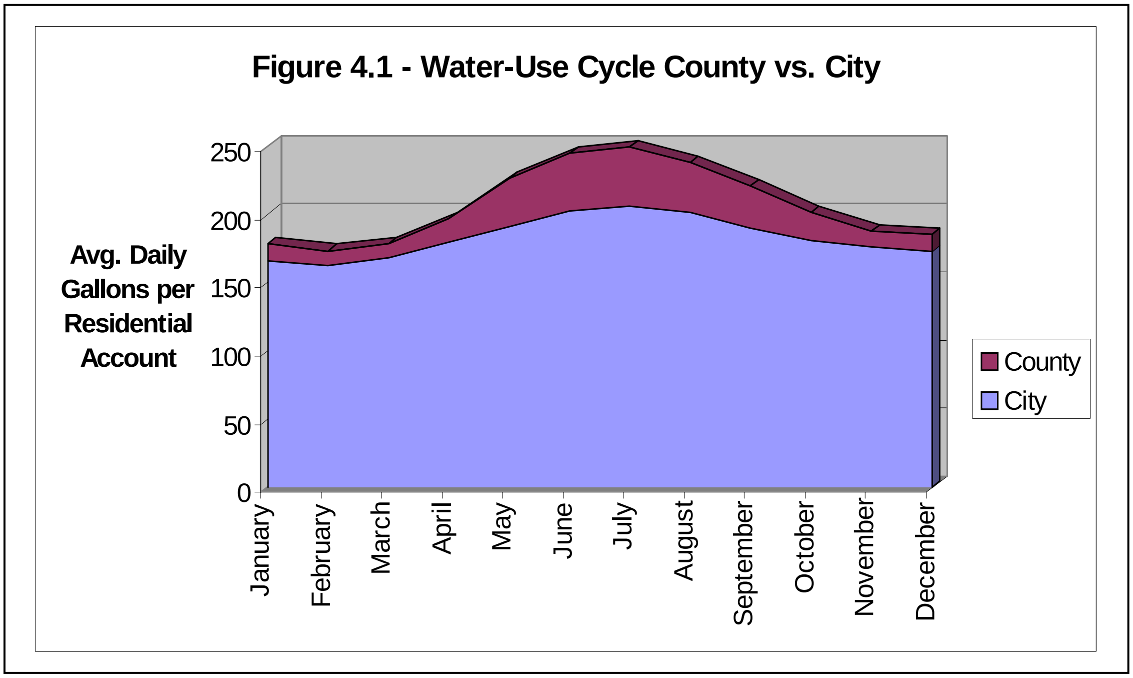
Table 4.4 – Summary of Residential Water-Use Data

Locality	Minimum Water-Use	Average Water-Use	Maximum Water-Use	Apartment Data Included in Residential
Albemarle County	117	182	262	-
Augusta County	135	172	295	Single and Group-Metered
Bristol City	127	143	164	Single-Metered
Charlottesville City	119	157	192	-
Chesterfield County	161	220	319	-
Colonial Heights City	149	188	246	Single and Group-Metered
Danville City	136	166	200	Single-Metered
Hampton City	190	214	239	Single and Group-Metered
Harrisonburg City	126	146	185	Single-Metered
James City County	173	254	364	Single and Group-Metered
Manassas City	188	216	282	-
Newport News City	230	259	293	Single and Group-Metered
Poquoson City	176	212	272	Single and Group-Metered
Prince William County	173	212	313	Single-Metered
Richmond City	158	199	267	Single-Metered
Salem City	139	178	259	-
Spotsylvania County	150	193	255	-
Stafford County	169	215	320	-
Suffolk City	116	151	209	-
York County	186	238	327	Single and Group-Metered
Rapidan Service Authority	107	130	158	-

Note: Figures in average daily gallons per connection.

At this point, however, care should be taken in comparing the water-use across localities where apartments are included in the residential data. As pointed out earlier, single-meter apartments are expected to pull water-use down, while group-metered apartments are expected to pull water-use up. For instance, it is somewhat interesting to note that Newport News, with its high percentage of overall apartments in conjunction with the high percentage of group-metered apartments, had the highest average water-use of all the localities in this study. Thus the true water usage for single-family residents is likely overstated in this locality. The effect that these two apartment classes have on residential usage will be accounted for in the regression analysis.

Some general patterns of water-use are apparent from the data. As mentioned in the previous chapter, water-use is expected to be heavily influenced by yard size. Since houses located in counties generally have larger lot sizes than in cities, the expectation is that water-use will be higher in counties, especially during the growing season. This expectation was borne out by the data. The average water-use was slightly higher in counties during the winter dormant months, but increased substantially during the growing season as compared to the city data, as can be seen in Figure 4.1.



Note: Water-use figures calculated by using means of raw data.

Voluntary and Mandatory Restriction Data

The challenge in modeling drought management programs is in identifying and developing indicators capable of distinguishing differences in program intensity. To develop these indicators, this study used a series of mail surveys and telephone interviews conducted between April and October of 2004. The surveys were sent out to program administrators in the water supply branch of Public Works Departments, but were occasionally completed by other employees such as water conservation planners. After initially contacting these individuals by phone, surveys were distributed by fax or email. The completed surveys were followed up with emails and phone interviews to clarify responses where needed.

The survey was divided into two sections. The first section solicited basic descriptive information about timing and coverage of drought management programs. The second section gathered information on the intensity (information and enforcement levels) of voluntary and mandatory restriction programs (see appendix for the survey form).

The first section was intended to provide a description of the voluntary and mandatory restriction programs used during 2002. From initial research (before the survey was sent out), it appeared that voluntary and mandatory restrictions were the predominant drought management tools used by Virginia localities during the 2002 drought. Consequently, the first section of the survey focused on these two types of restrictions. However, there were questions that covered other forms of possible drought management programs. The general areas covered by this first part of the survey were:

1. Water-use restriction programs used in 2002.
2. Time period these restrictions were in place.
3. Content of these restrictions (what was restricted).
4. Water supply situation during the summer of 2002.
5. Water-use restrictions or programs that were in place during other years.

The focus of the second section of the survey was in measuring the intensity in which voluntary and mandatory water-use restrictions were implemented. The major hypothesized differences in intensity for this part of the survey were information levels for voluntary restrictions, and information levels and enforcement efforts for mandatory restrictions. As discussed in Chapter 2, both information and enforcement efforts have strong theoretical reasons in determining how successful programs are in reducing water-use.

Some of the questions in this section were descriptive in nature. Descriptive questions included asking water managers to list information outlets (water bill, special mailing, newspaper, radio/TV, and other methods) used to disseminate information about the programs, if extra staff time was devoted to enforcement, and if fine schedules were authorized by the locality. Only one question, listing the fine levels imposed for violations, was purely quantitative in this section. Purely quantitative measures for measuring information and enforcement were generally difficult to obtain due to the lack of local records. For instance, when contacted most water managers could not readily identify the exact number of warnings issued or fines levied. Similarly, local managers could not generally provide quantitative indicators for information dissemination (e.g. number of pamphlets distributed, hours of radio or television news time, and column inches of newspaper articles). Given that the records necessary to develop purely quantitative measures of program intensity were inadequate and/or beyond the scope of this study to develop, both ordinal (anchoring approach) and qualitative (subjective self-assessment) questions were also asked.

For the ordinal questions, water managers were asked to rate their enforcement programs on the number of warnings and fines issued with the following anchoring approach: Number of warnings issued per month during mandatory restrictions (0-10 = Low, 10-100 = Medium, over 100 = High). Number of citations issued per month during mandatory restrictions (0-5 = Low, 5-50 = Medium, over 50 = High).

For the qualitative self-assessment questions, water managers were asked to rate their overall enforcement efforts as low, medium, or high. This same type of question was asked for the overall information efforts for both voluntary and mandatory restrictions. Thus three self-assessment questions were asked in the survey:

1. Overall information rating for voluntary restrictions (Low, Medium, High)
2. Overall information rating for mandatory restrictions (Low, Medium, High)
3. Overall enforcement rating for mandatory restrictions (Low, Medium, High)

All of the qualitative and ordinal questions which measured the intensity of the restrictions used this same categorical approach (low, medium, or high).

Survey Results

The three main drought management programs used by the 21 localities during 2002 were voluntary restrictions, mandatory restrictions (self-imposed), and the statewide restrictions imposed by Executive Order 33, as suggested by research prior to the survey. Out of the twenty-one localities, fourteen implemented voluntary programs while only seven implemented mandatory restrictions prior to Executive Order 33 on September 1 (see Table 4.5). In general, most of the self-imposed mandatory restrictions were in place for a short period of time. Only one locality, Spotsylvania County, had self-imposed mandatory restrictions in place for over a month. This is in contrast to voluntary restrictions which were generally in place for longer periods of time.

Table 4.5 – Water-Use Restrictions for 2002

Locality	Executive Order 33[a]	Self-imposed Voluntary Restrictions	Self-imposed Mandatory Restrictions
Albemarle County	X	1/1-8/31[b]	8/22-8/31
Augusta County	X	-	-
Bristol City	-	-	-
Charlottesville City	X	1/1-8/31	8/22-8/31
Chesterfield County	X	4/1-8/15	8/15-8/31
Colonial Heights City	X	-	-
Danville City	X	-	-
Hampton City	X	7/26-8/31	11/10-12/1
Harrisonburg City	X	-	-
James City County	X	7/26-8/31	11/10-12/1
Manassas City	-	-	-
Newport News City	X	7/26-8/31	11/10-12/1
Poquoson City	X	7/26-8/31	11/10-12/1
Prince William County	-	9/1-11/15	-
Richmond City	X	4/1-8/26	8/27-8/31
Salem	X	6/1-8/31	-
Spotsylvania County	X	2/26-3/26	3/26-8/31
Stafford County	X	5/1-8/22	8/22-8/31
Suffolk City	X	6/1-8/31	-
York County	X	7/26-8/31	11/10-12/1
Rapidan Service Authority	X	7/29-8/16	8/17-8/31

Note [a]: Effective September 1 to November 10, 2002.
Note [b]: Albemarle County and Charlottesville also had voluntary restrictions in place from 11/21/02-2/28/03; 8/1/99-9/30/99; 11/1/01-12/31/01

There were a few instances where mandatory or voluntary restrictions were in place even after Executive Order 33 was lifted in mid-November. Albemarle County and Charlottesville switched to voluntary restrictions after the executive order was lifted, and lasted into February of 2003. Five of the localities, Newport News, Poquoson, Hampton City, James City County, and York County, continued to impose mandatory restrictions into

December of 2002. There were also two instances were voluntary water-use restrictions were in place before 2002 in Albemarle County and Charlottesville. These two localities also instituted retrofit programs for low-flow toilets prior to 2002. Three localities (Bristol, Manassas, and Prince William County) were not required to implement mandatory restrictions imposed by Executive Order 33.

Mandatory and voluntary programs generally restricted water-use for similar activities. Both programs targeted the outdoor uses of watering lawns and gardens. This use type was generally expected to be the largest contributor to summer water-use by the localities. There were slight nuances concerning this basic restriction, but in general, there was very little variation in program content. Almost all the restrictions also targeted the filling of swimming pools, washing cars, and washing driveways. There were more differences here than with lawn watering, but not enough as to be able to make meaningful distinctions between the various programs. Executive Order 33, which was in place over most of the state, covered 18 out of the 21 localities included in the analysis. For the most part, these restrictions covered the same types of activities as the self-imposed mandatory restrictions.

Table 4.6 shows the summary of the survey data for both voluntary and mandatory restrictions. As can be seen, there is substantial variation for the different categories that measured the intensity of the restrictions. For voluntary restrictions, four localities had a low overall rating (self-assessment), while five localities had a medium rating and seven localities had a high rating. Six localities used three outlets to disseminate information, while two localities used four outlets and eight localities used five outlets.

Survey responses indicated that the way mandatory drought management programs were implemented varied significantly across the state. Danville and Augusta County had low self-assessment ratings for both overall information and enforcement levels. These ratings were corroborated by responses to descriptive questions indicating that few warning and citations were issued and that only two outlets to disseminate information were used by both localities. Furthermore, no extra staff time was used to enforce restrictions and no penalties were issued for violations in either location. On the other end of the spectrum there was Charlottesville, Albemarle County, and Chesterfield County. Charlottesville and Albemarle County had a high self-assessment information rating and also used five outlets to disseminate information. Their self-assessed enforcement efforts were rated as medium. Chesterfield County had a medium overall information rating but had a high overall enforcement rating. Chesterfield County had high ratings for both the number of warnings and citations issued and increased its staff time to enforce the restrictions.

Thus the restriction data from the survey clearly confirmed that individual municipalities implemented Executive Order 33 with different levels of intensities. These differences in approaches seemed to be dependant to some degree on the local water supply situation. Localities whose water supplies were approaching critical levels were generally most proactive with the restrictions, and generally had higher ratings for the various information and enforcement efforts.

Table 4.6 – Summary of Locality Responses for Program Intensity									
	Voluntary Restrictions		Mandatory Restrictions						
	Self-Assessment Info Rating (L,M,H)[a]	Number of Information Outlets (1-5)[b]	Self-Assessment Info Rating (L,M,H)[a]	Number of Information Outlets (1-5)[b]	Self-Assessment Enforcement Rating (L,M,H)[a]	Number of Warnings (L,M,H)[c]	Number of Citations (L,M,H)[d]	Penalties for Non-Compliance?	Extra Staff Time Spent Monitoring?
Albemarle County	H	5	H	5	M	M	L	Yes	Yes
Augusta County	-	-	L	2	L	L	L	No	No
Bristol City	-	-	-	-	-	-	-	-	-
Charlottesville City	H	5	H	5	M	M	L	Yes	Yes
Chesterfield County	L	3	M	3	H	H	H	Yes	Yes
Colonial Heights City	L	3	M	3	M	L	L	Yes	No
Danville City	-	-	L	2	L	L	L	No	No
Hampton City	H	5	H	5	L	L	L	Yes	No
Harrisonburg City	-	-	M	3	L	L	L	No	Yes
James City County	H	5	H	5	L	L	L	Yes	No
Manassas City	-	-	-	-	-	-	-	-	-
Newport News City	H	5	H	5	L	L	L	Yes	No
Poquoson City	H	5	H	5	L	L	L	Yes	No
Prince William County	L	3	-	-	-	-	-	-	-
Richmond City	M	5	M	5	L	M	L	Yes	No
Salem City	M	3	M	3	L	L	L	Yes	No
Spotsylvania County	M	4	M to H	4	M	M	L	Yes	Yes
Stafford County	L	3	M	3	L	M	L	Yes	No
Suffolk City	M	4	M	4	L	L	L	Yes	No
York County	H	5	H	5	L	L	L	Yes	No
Rapidan S.A.	M	3	M	3	M	M	L	No	No

Note [a]: 1=low, 2=medium, 3=high
Note [b]: Number of information outlets used to disseminate information about restrictions (bill, separate mailing, newspaper, radio or TV, other).
Note [c]: Dependent on number of warning issued per month: 0-10 = L, 10-100 = M, over 100 = H.
Note [d]: Dependent on number of citations issued per month: 0-5 = L, 5-50 = M, over 50 = H.

Classifying the Intensity of Voluntary and Mandatory Restrictions

A key challenge in this analysis was in measuring information and enforcement and in making meaningful distinctions between them that would be operational in the regression analysis. This could be done in one of two ways. The first option was to use continuous measures for these two variables where their effect could be estimated directly in the regression (e.g. estimate the effect that each $1000 in fines had in reducing water-use; estimate the effect that each $1000 spent on promotional efforts had in reducing water-use). However, as previously discussed, this type of data could not be generated by the localities with any amount of precision.

The second option was to categorize information and enforcement efforts into broad groups based on like characteristics. With this option, each possible information and enforcement combination could be represented by a unique dummy variable. A concern with this approach was the potential for having too many dummy variables in relation to the number of voluntary and mandatory restriction observations. If for example, there were three categories each for information and enforcement efforts, this would result in three dummy variables for voluntary restrictions (enforcement is not considered for this restriction-type) and nine dummy variables for mandatory restrictions. It was felt that this was a reasonable number of dummy variables for the data and that additional categories for program intensity would be counter productive.

Thus it was desired to classify programs based on information efforts for both voluntary and mandatory restrictions, and on enforcement efforts for mandatory restrictions, where each of these variables were separated into three categories based on levels of effort (High, Medium, and Low). This classification scheme is intended to broadly distinguish the differences in intensity of both voluntary and mandatory restrictions across localities. While this approach does not provide quantitative measures of program implementation (number of fines, staff hours devoted to monitoring/policing, etc), such an overall rating does provide meaningful delineations between programs with low information and/or enforcement levels from those programs that are aggressive in promoting programs and/or enforcing provisions.

Programs were initially classified in this way based on responses to the information and enforcement self-assessment questions (See table 4.6). These ratings were cross-checked for consistency with descriptive measures of program implementation from other portions of the survey to make sure that the overall ratings were reasonably consistent. A program might be reclassified given answers to the descriptive question. For example, if a locality rated themselves as medium (M) in overall enforcement, but had a low rating (L) for both number of warnings issued and number of citations issued, then the final rating for enforcement would drop to a low rating (L). If a locality rated itself as medium (M) in overall enforcement rating, while having a medium rating (M) for number of warnings and a low rating (L) for number of citations, then the final rating for enforcement would remain medium (M). Using this system, one locality (Colonial Heights) dropped in enforcement rating from a medium to a low rating.

Similarly for information, the self-assessment rating was cross-checked with the response for the number of information outlets used by the locality (water bill, mailing, newspapers, TV/Radio, other). The overall rating could drop if there were discrepancies with the cross-checked response. For example, if a locality had a medium (M) overall rating for information, but had only used newspapers to disseminate information about restrictions (one venue), then the final rating would drop to the low level (L). However, there were no major discrepancies with the information rating and no changes were made.

The final ratings are summarized in Table 4.7. For information ratings under voluntary restrictions, four localities had a low rating, five localities had a medium rating, and seven localities had a high rating. Information ratings under mandatory restrictions were somewhat higher as only two localities had a low rating, eight localities had a medium rating, and eight localities had a high rating. This finding was not surprising as mandatory restrictions, especially those covered under Executive Order 33, were implemented at a time when the drought had reached a critical level.

Table 4.7 – Final Intensity Ratings for Voluntary and Mandatory Restrictions

Locality	Information Rating for Voluntary Restrictions	Information Rating for Mandatory Restrictions	Enforcement Rating for Mandatory Restrictions
Albemarle County	High	High	Medium
Augusta County	-	Low	Low
Bristol City	-	-	-
Charlottesville City	High	High	Medium
Chesterfield County	Low	Medium	High
Colonial Heights City	Low	Medium	Low
Danville City	-	Low	Low
Hampton City	High	High	Low
Harrisonburg City	-	Medium	Low
James City County	High	High	Low
Manassas City	-	-	-
Newport News City	High	High	Low
Poquoson City	High	High	Low
Prince William County	Low	-	-
Richmond City	Medium	Medium	Low
Salem	Medium	Medium	Low
Spotsylvania County	Medium	High [a]	Medium
Stafford County	Low	Medium	Low
Suffolk City	Medium	Medium	Low
York County	High	High	Low
Rapidan Service Authority	Medium	Medium	Medium

Note: Blanks indicate that this program was not in place.
Note [a]: Rating during EO33; Medium rating during self-imposed mandatory restrictions.

The enforcement levels for mandatory restrictions were not particularly impressive. Thirteen localities had low ratings, four had medium ratings, and only one locality (Chesterfield County) had a high rating. Chesterfield County issued 345 citations with fines that totaled over $25,000 for violating mandatory restrictions. The general lack of aggressive enforcement appeared to be compensated to some degree in the higher overall ratings for information levels during this time period.

The distributions of the enforcement ratings during the executive order were on average lower than with self-imposed mandatory restrictions (not shown in table). Essentially, most of the localities that had not implemented mandatory restrictions by the time that Executive Order 33 took effect only devoted minimal effort toward enforcing the state-imposed restrictions. All of the localities that were forced to adopt mandatory restrictions had a low overall rating for enforcement. This observation should not be surprising since Executive Order 33 forced these restrictions on localities but at the same time contained no enforcement requirements.

Other Data

Water Pricing

An additional survey was used to gather water-pricing information from the localities. Sewer pricing information was also obtained because in all cases sewer charges were levied based on water consumption. The pricing information was sometimes compiled directly by the same contact that completed the restriction information, but was more often completed by the billing departments.

This pricing information was relatively straightforward. For water and sewer, both fixed fees (customer account charges that do not vary by usage) and variable fees were obtained. A main challenge with obtaining accurate pricing information was to make sure that pricing information was provided for the entire period corresponding to the water-use data. Another challenge in cases where block rates were present was to verify how these systems worked. Follow-up phone conversations and emails were often needed with these last two points.

The units used for the raw pricing data were not consistent across localities. Most localities had pricing based on 1000 gallons or 100 cubic feet, although a few other formats were used. All pricing data was converted to 1000 gallons for consistency. Sewer pricing was added to the corresponding water pricing to come up with total water/sewer pricing for variable price and fixed fees. This combined pricing will simply be referred to “water pricing” or “price” for the remainder of the analysis for simplicity. All prices were converted to 2004 dollars using the Consumer Price Index.

A summary of the general pricing structure for each locality is summarized in Table 4.8. All localities included a variable rate and a fixed fee in their rate structures. There were 13 localities that used block rates in 2002, ten of which were increasing blocks and three that were decreasing blocks. Five of these localities used the block rates throughout the year. However, eight of the localities only used the block pricing during the summer months (generally from June to October). The summer block pricing schedules were not necessarily set up to reduce water consumption as three of the eight seasonal block programs used decreasing block rates which are generally held to increase water-use. Seven of the localities with block rates had summer charges based on the average winter use. Five of these localities (Hampton, James City County, Newport News, Poquoson, and York County) had increasing rates for the portion of summer month's bills that exceeded winter usage. Two other localities, Stafford County and Prince William County, had increasing rates for water but decreasing rates for sewer charges, with a net effect of having decreasing block rates.

Table 4.8 - General Water Pricing Structures

		Block Rate Information		
Locality	Rate Structure	Block Type	Quantity Break	Applicable Season
Albemarle County	Single Rate	-	-	-
Augusta County	Single Rate	-	-	-
Bristol	Single Rate	-	-	-
Charlottesville	Single Rate	-	-	-
Chesterfield County	Single Rate	-	-	-
Colonial Heights	Block Rates	Increasing	125 ADG[a]	Entire Year
Danville	Block Rates	Increasing	125 ADG[a]	Entire Year
Hampton	Block Rates	Increasing	Winter Avg.	Summer Only
Harrisonburg	Block Rates	Increasing	101 ADG[a]	Entire Year
James City County	Block Rates	Increasing	Winter Avg.	Summer Only
Manassas	Single Rate	-	-	-
Newport News	Block Rates	Increasing	Winter Avg.	Summer Only
Poquoson	Block Rates	Increasing	Winter Avg.	Summer Only
Prince William County	Block Rates	Decreasing	Winter Avg. x 1.3	Summer Only
Richmond	Block Rates	Decreasing	Winter Avg.	Summer Only
Salem	Block Rates	Increasing	167 ADG[a]	Entire Year
Spotsylvania County	Block Rates	Increasing	183 ADG[a]	Entire Year
Stafford County	Block Rates	Decreasing	Winter Avg. x 1.2	Summer Only
Suffolk	Single Rate	-	-	-
York County	Block Rates	Increasing	Winter Avg.	Summer Only
Rapidan S.A.	Single Rate	-	-	-

Note [a]: ADG stands for average daily gallons used per residential account.

There was considerable variation among the localities in the methods and prices charged for water.[12] During 2002 the monthly fixed fee ranged from $1.59 in Suffolk County to

[12] Sewer charges are included with water fees. The combined charges will be referred to as water charges for simplicity.

$36.28 in Richmond with an average of $9.59. For those localities that did not use block pricing, the variable fee (per 1000 gallons) ranged from $3.04 in Richmond to $9.91 for the Rapidan Service Authority in 2002. For those localities that did use block pricing, the variable fee ranged from $0.00 in Salem and Harrisonburg (where the fixed fee was all that was charged for the first block) to $7.42 in Newport News (see Table 4.9 and 4.10). Using a base consumption of 250 average daily gallons (ADG) for comparative purposes, the total bill during July 2002 would have ranged from a low of $36.81 in Chesterfield County, to a high of $86.41 in the Rapidan Service Authority (not shown in tables). The average across localities was $48.14.

In general, prices did not change much over time after adjusting for inflation. Eleven localities had pricing data available for both July of 1998 and July of 2002. For these localities the total price for an average daily water usage of 250 gallons increased by an average of 5% in real dollars (2004 dollars adjusted using the general CPI). Thus although price did not increase drastically in these localities, it increased slightly faster than inflation.

Table 4.9 - Summary of Water Pricing Data for July (Summer) 2002

Locality	Block Rate	Qty Break	Price 1st Block	Price 2nd Block	Fixed Price	Total Bill (Avg.)	Avg. Price	Marg. Price
Albemarle County	-	0	$6.57	-	$4.52	$49.55	$7.22	$6.57
Augusta County	-	0	$6.05	-	$13.70	$54.44	$8.08	$6.05
Bristol	-	0	$4.53	-	$15.41	$35.89	$7.93	$4.53
Charlottesville	-	0	$6.17	-	$2.66	$35.44	$6.67	$6.17
Chesterfield County	-	0	$3.44	-	$11.03	$42.68	$4.63	$3.44
Colonial Heights	Inc Block	125	$2.56	$4.41	$15.89	$41.52	$5.63	$4.41
Danville	Inc Block	125	$2.06	$4.09	$15.41	$30.91	$5.47	$4.09
Hampton	Inc Block	202	$6.56	$7.02	$2.74	$47.71	$7.01	$7.02
Harrisonburg	Inc Block	101	$0.00	$5.92	$13.79	$25.87	$5.10	$5.92
James City County	Inc Block	210	$5.40	$5.85	$2.74	$55.72	$5.84	$5.85
Manassas	-	0	$5.80	-	$3.72	$52.85	$6.24	$5.80
Newport News	Inc Block	246	$6.96	$7.42	$2.74	$61.38	$7.34	$7.42
Poquoson	Inc Block	198	$5.40	$5.85	$2.74	$43.88	$5.86	$5.85
Prince William County	Dec Block	252	$6.16	$2.68	$7.44	$58.95	$6.28	$2.68
Richmond	Dec Block	194	$3.15	$1.22	$36.28	$57.29	$7.15	$1.22
Salem	Inc Block	167	$0.00	$5.10	$24.70	$34.37	$4.98	$5.10
Spotsylvania County	Inc Block	183	$5.29	$6.37	$2.32	$42.47	$5.87	$6.37
Stafford County	Dec Block	236	$5.22	$4.78	$8.90	$56.51	$6.07	$4.78
Suffolk	-	0	$6.05	-	$1.59	$36.31	$6.33	$6.05
York County	Inc Block	220	$5.40	$5.85	$2.74	$50.78	$5.82	$5.85
Rapidan S.A.	-	0	$9.91	-	$12.05	$51.86	$12.92	$9.91

Note: All prices except fixed price based on 1000 gallons consumed; Average Price and Marginal Price figures are for the average consumption level for the locality; Total bill calculated at the average consumption rate.

Marginal and average prices were calculated based on the average monthly usage for each month in each locality. Average price was simply the total bill at the average use level divided by the average quantity used for the month. Marginal price was the variable rate that was in place for the average usage level (see Table 4.9 and 4.10).

Table 4.10 - Summary of Water Pricing Data for January (Winter) 2002

Locality	Block Rate	Qty Break	Price 1st Block	Price 2nd Block	Fixed Price	Total Bill (Avg.)	Avg. Price	Marg. Price
Albemarle County	-	0	$4.73	-	$4.52	$26.59	$5.70	$4.73
Augusta County	-	0	$5.78	-	$13.11	$37.63	$8.87	$5.78
Bristol	-	0	$4.53	-	$15.41	$33.77	$8.32	$4.53
Charlottesville	-	0	$5.55	-	$2.66	$30.66	$6.08	$5.55
Chesterfield County	-	0	$3.44	-	$11.03	$30.76	$5.36	$3.44
Colonial Heights	Inc Block	125	$2.56	$4.41	$15.89	$33.03	$6.05	$4.41
Danville	Inc Block	125	$2.06	$4.09	$15.41	$27.25	$5.73	$4.09
Hampton	-	0	$6.35	-	$2.48	$38.67	$6.78	$6.35
Harrisonburg	Inc Block	101	$0.00	$5.92	$13.79	$21.44	$4.96	$5.92
James City County	-	0	$5.18	-	$2.48	$29.32	$5.66	$5.18
Manassas	-	0	$5.67	-	$3.72	$37.63	$6.30	$5.67
Newport News	-	0	$6.69	-	$2.48	$48.61	$7.05	$6.69
Poquoson	-	0	$5.18	-	$2.48	$30.14	$5.65	$5.18
Prince William County	-	0	$6.16	-	$7.44	$41.11	$7.52	$6.16
Richmond	-	0	$3.04	-	$34.97	$51.03	$9.65	$3.04
Salem	Inc Block	167	$0.00	$5.10	$24.70	$24.70	$5.19	$0.00
Spotsylvania County	Inc Block	183	$5.29	$6.37	$2.32	$28.81	$5.75	$5.29
Stafford County	-	0	$5.22	-	$8.90	$38.38	$6.79	$5.22
Suffolk	-	0	$5.87	-	$1.59	$21.98	$6.32	$5.87
York County	-	0	$5.18	-	$2.48	$31.78	$5.62	$5.18
Rapidan S.A.	-	0	$9.91	-	$12.05	$48.84	$13.16	$9.91

Note: All prices except fixed price based on 1000 gallons consumed; Average Price and Marginal Price figures are for the average consumption level for the locality; Total bill calculated at the average consumption rate.

Price was not used extensively by the sample localities as a drought management tool during 2002. However, Albemarle County and Charlottesville were exceptions. In Albemarle County the variable price of water (per 1000 gallons) increased from $3.27 to $4.50 in mid-September. In mid-October, the variable price increased to $7.48, which amounted to a 129% increase from earlier summer price levels. [13] In Charlottesville, the variable price of water increased from $3.02 to $4.98 in mid-September, and then increased again in November to $7.43. This amounted to a 146% increase from earlier summer price levels. In both cases water prices did not return to normal levels until February 2003. Water-use in these two localities dropped considerably from typical

[13] The variable price for sewer service remained the same during this time period in both localities at $2.91 and 2.80 per thousand gallons respectively in Albemarle County and Charlottesville.

levels during this time period. However, voluntary and mandatory restrictions were in place during these same time periods and thus it is difficult to tell which portion of the water-use reductions are attributable to the restrictions or price increases (or possibly other variables) until all variables are controlled for in the final regression.

Hampton, James City County, Newport News, Poquoson, and York County (all in the Tidewater area) implemented a surcharge program (rationing) in November of 2002 where water rates were to increase substantially for any usage above the winter monthly average. However, this program was only in effect for approximately a week before the heavy rains came in November and Executive Order 33 was lifted along with this surcharge program. Hence this program was probably not in effect long enough to have had a meaningful impact on water-use in these localities.

Climatic Data

Supplemental data was obtained for climatic variables for each of the localities through the Virginia State Climatology Office.[14] Rainfall and temperature were hypothesized to be the most important of these variables. Rainfall was measured in inches of precipitation for each month. Temperature was measured both as the average and the average maximum daily temperature for each month. Data was available for 20-40 years in most cases, giving the opportunity to compare climatic conditions during the study against historical averages.

Virginia has fairly diverse climate patterns due to the wide range in elevations found throughout the state as well as the influence of mountain and valley regions in the western portion of the state and the influence of the ocean on the eastern coast. Temperatures are generally highest in the eastern portion of the state and decrease as you move west, especially in the extreme western mountains. Areas such as the Tidewater area around Newport News have comparatively long growing seasons. Water-use for outdoor purposes would be expected to begin earlier in the spring as compared to regions in the western part of the state, and also extend longer into the fall.

While most of the state receives plentiful amounts of rainfall (around 40 inches), the Shenandoah River and New River valleys generally receive less (33 inches) because they are in the rain shadows of the surrounding mountains. These are two of the driest regions in the eastern United States (Virginia State Climatology Office). In general, the rainfall seems to be distributed fairly evenly throughout the year, although it tends to be slightly lower in the winter and slightly higher in the summer.

Additional data was collected for a drought index. Drought indexes are measures of the how soil moisture or accumulated rainfall compares against normal conditions. It was hypothesized that this variable could potentially take the place for rainfall and possibly even temperature. The Palmer Drought Index for specific locations was obtained from a database from the National Agricultural Decision Support System maintained by the

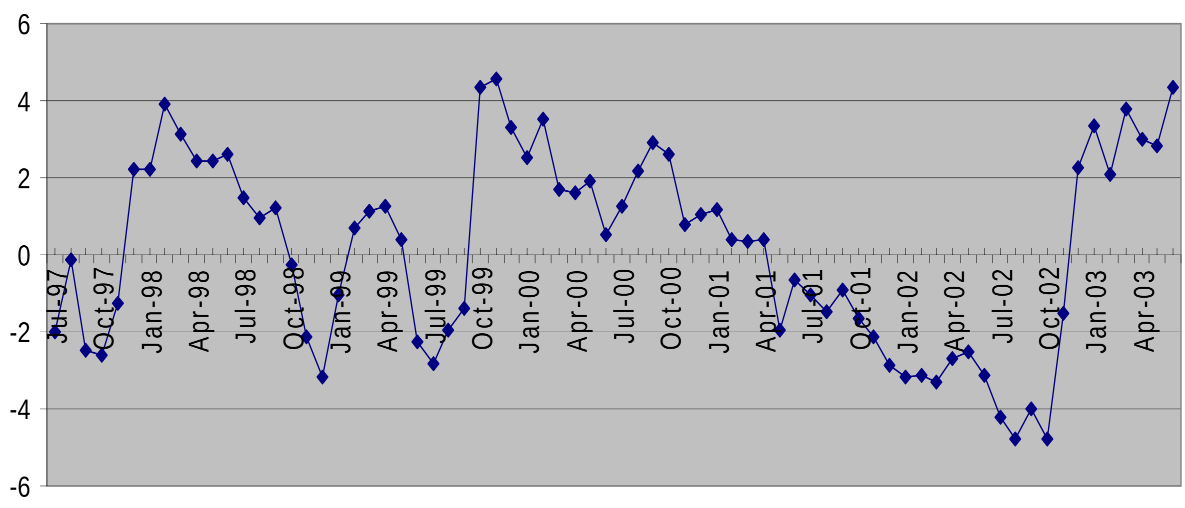
[14] Climatic data was obtained from weather stations in each locality or within 10 miles of each locality.

University of Nebraska. This drought index was selected because it could be computed for the individual stations and time periods and also because it uses a supply and demand model to estimate soil moisture conditions.

The summers of 2001 and 2002 were both hot and dry, while the summer of 2003 was both wet and relatively cool. In much of the state, there was as surplus of water toward the end of 1999, but dry conditions gradually eroded this surplus and resulted in a severe shortage of groundwater by the summer of 2002 (see Figure 4.2).

The severity and extent of the 2002 drought can be seen from a plot of the Palmer Drought index for the Tidewater region of Virginia. Negative and positive values indicate below normal and above normal soil moisture conditions respectively, while a base value of 0 with this index indicates normal soil moisture conditions. Beginning in the spring of 2001, the index dropped below zero and remained negative through November 2002. At the depth of the drought the index approached -5, rated as severe drought. Many other parts of Virginia reflected this same general pattern.

Figure 4.2 - Palmer Drought Index Tidewater Region



Note: Positive observations indicate above normal soil moisture conditions while negative observations indicate below normal soil moisture conditions.

Demographic Data

Supplemental data was also obtained for demographic characteristics, mostly through Census data. The demographic characteristics that were expected to influence water-use were income, house value, household size, and house age. Other data were also obtained that were less obvious but thought might influence water demand at the aggregate level. All Census variables were obtained at the county/city level for both 1990 and 2000 census years.[15] These two censuses were used to extrapolate all other years that data was needed. All census variables that were in dollar amounts were converted to 2004 dollars using the general Consumer Price Index.

From a theoretical perspective, average lot size for residential housing units would be expected to be an important explanatory variable in determining residential water-use. However, this information is not available through the Census or another standardized database. Some water demand researchers have used population density as a proxy for average lot size. The theory being that lower population densities will mean larger lot sizes. This reasoning would probably hold if localities were homogeneous (completely urban or suburban) in nature. The problem, however, is that in cases, especially with counties, where there are even moderate amounts of “open space” such as farmland or forestland, the population density will be skewed downward, indicating an increase in average lot size. This would be especially problematic with counties.

One possible solution to this problem would be to use a method that could systematically subtract out these open spaces. However, accounting for all possible open spaces in multiple localities would likely be systematically impossible, if not time prohibitive. A technique that was found to be operationally feasible is to subtract out all large areas that have consistent estimates at the county-city level. These types of estimates exist for both farmland and forestland, which compromise the bulk of non-residential areas in Virginia. Acreage for agricultural land data was obtained from the Census of Agriculture, and forestland estimates were obtained from the Forest Inventory and Analysis Database through the U.S. Forest Service. These figures were subtracted out of each county’s acreage totals.[16] These totals were then used to come up with a modified population density.

Another possible proxy to use for average lot size is average work commuting time for a locality. This variable is readily available through the Census Bureau. At first glance, this may seem like an odd variable to use as a lot size proxy. However, there would seem to be a strong positive correlation between average commuting time and average lot size. The correlation of course, will not be perfect, but neither would the modified population density described above.

Table 4.11 summarizes the demographic characteristics by locality in January of 2002. As can be seen, there is a wide range in variation among locality by variable. Median household income ranges from a low of $29,959 in Danville to a high of $75,690 in Stafford County. Median house value ranges from a low of $81,111 in Bristol to a high of $188,040 in James City County. Average household size ranges from 2.2 in the cities of Richmond, Charlottesville, Danville, and Bristol, to 3.0 in Stafford County. Median household age varies from 13 years in Stafford and Spotsylvania Counties to 47 years in Richmond. Average lot size ranges from .4 acres in Hampton, Newport News, and Richmond, to 2.4 acres in Albemarle County.

[15] Cities in Virginia have the same demographic status as counties
[16] There was some overlap between the two databases but this was accounted for in the estimates.

A problem encountered with the Census data was that the service areas for the municipal water suppliers did not match precisely with the geographic boundaries of the counties and cities. It was potentially possible to get an exact delineation of these service areas and to use Census data at the block-level to get a better fit between the service areas and Census units. However, it was assumed that the census information provided a reasonable approximation of the demographic characteristics in a given area.

Table 4.11 Summary of Demographic Variables (January 2002)

	Median household income [a, b]	Median House Value [a]	Average Household Size [a, b]	Median House Age [a]	Average Lot Size [c] (acres)
Albemarle County	$56,866	$181,813	2.4	21	2.4
Augusta County	$48,619	$126,521	2.5	24	1.0
Bristol	$30,835	$81,111	2.2	42	0.8
Charlottesville	$34,393	$133,661	2.2	41	0.5
Chesterfield County	$65,368	$135,170	2.7	19	0.6
Colonial Heights	$47,785	$106,058	2.3	35	0.5
Danville	$29,959	$81,769	2.2	43	1.0
Hampton	$43,997	$99,683	2.5	32	0.4
Harrisonburg	$32,806	$137,677	2.6	24	1.3
James City County	$62,427	$188,040	2.4	16	1.5
Manassas	$67,103	$164,983	2.9	20	0.7
Newport News	$40,824	$104,974	2.5	28	0.4
Poquoson	$68,485	$171,528	2.7	27	1.7
Prince William County	$73,607	$161,477	2.9	18	0.8
Richmond	$34,674	$97,345	2.2	47	0.4
Salem	$43,548	$118,170	2.3	36	0.8
Spotsylvania County	$64,559	$141,864	2.8	13	1.6
Stafford County	$75,690	$172,591	3.0	13	0.9
Suffolk	$46,870	$121,868	2.7	25	1.4
Washington County	$37,033	$104,060	2.3	25	0.9
York County	$65,316	$168,915	2.8	18	0.9
Rapidan S.A.	$48,436	$123,015	2.6	22	1.8

Note [a]: Census data extrapolated to 2002.
Note [b]: Owner-occupied households.
Note [c]: Constructed as described in text.

Chapter 5: Empirical Water Demand Model

Two water demand models were specified from the general model introduced at the end of Chapter 3. These models were identical except in the way mandatory and voluntary water-use restrictions were defined. The first model uses one dummy variable each for voluntary restrictions, self-imposed mandatory restrictions, and statewide mandatory restrictions (Executive Order 33). Thus this first model does not account for the intensity of the restrictions. The second model uses twelve total dummy variables to account for all possible combinations of intensity for voluntary and mandatory restrictions as defined in Chapter 4. The reasoning for the inclusion of the final model variables, a discussion of remaining issues, and a general hypothesis of their effects on the dependent variable are described in the rest of this chapter.

Equation 5.1 – Hypothesized Model for Residential Water-Use:

Ln (RESIDENTIAL-ADG $_{it}$) = B_0 +

Seasonal Variables:[17]
B_1*JAN$_{it}$ + B_2*FEB$_{it}$ + B_3*MAR$_{it}$ + B_4*APR$_{it}$ + B_5*MAY$_{it}$ + B_6*JUN$_{it}$ +
B_7*JUL$_{it}$ + B_8*AUG$_{it}$ + B_9*SEP$_{it}$ + B_{10}*OCT$_{it}$ + B_{11}*NOV$_{it}$ +
B_{12}*JAN-CITY$_{it}$ + B_{13}*FEB-CITY$_{it}$ + B_{14}*MAR-CITY$_{it}$ + B_{15}*APR-CITY$_{it}$ +
B_{16}*MAY-CITY$_{it}$ + B_{17}*JUN-CITY$_{it}$ + B_{18}*JUL-CITY$_{it}$ + B_{19}*AUG-CITY$_{it}$ +
B_{20}*SEP-CITY$_{it}$ + B_{21}*OCT-CITY$_{it}$ + B_{22}*NOV-CITY$_{it}$ + B_{23}*DEC-CITY$_{it}$ +

Climate Variables:
B_{24}*RAIN-CO-SUMMER$_{it}$ + B_{25}*RAIN-CO-SUMMER-LAG1$_{it}$ + B_{26}*RAIN-CO-SUMMER-LAG2$_{it}$ + B_{27}*RAIN-CO-SPR/FALL$_{it}$ + B_{28}*RAIN-CO-SPR/FALL-LAG1$_{it}$ + B_{29}*RAIN-CO-SPR/FALL-LAG2$_{it}$ + B_{30}*RAIN-CITY-SUMMER$_{it}$ + B_{31}*RAIN-CITY-SUMMER-LAG1$_{it}$ + B_{32}*RAIN-CITY-SUMMER-LAG2$_{it}$ + B_{33}*RAIN-CITY-SPR/FALL$_{it}$ + B_{34}*RAIN-CITY-SPR/FALL-LAG1$_{it}$ + B_{35}*RAIN-CITY-SPR/FALL-LAG2$_{it}$ +
B_{36}*TEMP-CO-SUMMER$_{it}$ + B_{37}* TEMP-CO-SPR/FALL$_{it}$ +
B_{38}* TEMP-CITY-SUMMER$_{it}$ + B_{39}* TEMP-CITY-SPR/FALL$_{it}$ +

Apartment Variables:
B_{40}*APT-SUMMER$_{it}$ + B_{41}*APT-SPR/FALL$_{it}$ + B_{42}*APT-WINTER$_{it}$ +
B_{43}*GROUP-APT$_{it}$ +

Demographic Variables:
B_{44}*INCOME-SUMMER$_{it}$ + B_{45}*INCOME-SPR/FALL$_{it}$ + B_{46}*INCOME-WINTER$_{it}$ +
B_{47}*HOUSEHOLD-SIZE$_{it}$ +

Price Variables:
B_{48}*MP-SUMMER$_{it}$ + B_{49}*MP-SPR/FALL$_{it}$ + B_{50}*MP-WINTER$_{it}$ +

[17] County water-use for December is used as the base usage for the cyclical variables.

B_{51}*DIFFVAR-SUMMER$_{it}$ + B_{52}*DIFFVAR-SPR/FALL$_{it}$ + B_{53}*DIFFVAR-WINTER$_{it}$+

Water Use Restriction Variables (MODEL A):
B_{54}*VOLUNTARY$_{it}$ + B_{55}*MANDATORY-SELF$_{it}$ + B_{56}*MANDATORY-EO33$_{it}$ +

Water-Use Restriction Variables (MODEL B):
B_{54}*VOL-INFO1$_{it}$ + B_{55}*VOL-INFO2$_{it}$ + B_{56}*VOL-INFO3$_{it}$
+ B_{57}*MAND-INFO1-ENF1$_{it}$ +B_{58}*MAND-INFO1-ENF2$_{it}$ +B_{59}*MAND-INFO1-ENF3$_{it}$
+ B_{60}*MAND-INFO2-ENF1$_{it}$ +B_{61}*MAND-INFO2-ENF2$_{it}$ +B_{62}*MAND-INFO2-ENF3$_{it}$
+ B_{63}*MAND-INFO3-ENF1$_{it}$ +B_{64}*MAND-INFO3-ENF2$_{it}$ +B_{65}*MAND-INFO3-ENF3$_{it}$

where i = 1,…,21 and t = 1,…,164 for the unbalanced panel.

Residential Water-Use

The dependent variable, RESIDENTIAL-ADG, is defined as average daily water-use (in gallons) per residential account. The construction of this variable is described in Chapter 4. An important aspect considered in defining the function form of this variable deals with what will be called "discretionary water-use reduction potential". It would seem reasonable, for instance, that mandatory restrictions in a locality with an average summer usage of 300 ADG might have a greater overall impact than in a locality with summer usage of 200 ADG. If both localities had similar winter usages of water, then the former locality would appear to have a much higher summer discretionary water-use level, and hence there would be more potential to reduce outdoor water-use. This same logic can be applied to the effects that other variables such rainfall and temperature have on water-use. Localities with a higher level of discretionary water-use would be expected to be influenced greater by rainfall and temperature levels during the growing season. In other words, the fluctuations in water-use due to these variables will be greater than in localities that have less discretionary water-use.

Discretionary water-use could not be captured directly in the model. However, part of this effect was captured indirectly by taking the natural log of the dependent variable. With this transformation, the resulting parameter estimates become percentage based. For example, if the parameter estimate for a mandatory restriction is -.10, this would imply that the inclusion of a mandatory restriction program reduces water-use by 10% from the level it would otherwise be. This reduction would translate into an absolute effect of 30 gallons in a locality that would otherwise have used 300 ADG, and 15 gallons in a locality that would otherwise have used 150 ADG. Thus to a certain degree, the natural log transformation will capture the effects that different levels of discretionary water-use would have in absolute values.

Water-Use Restriction Variables

Two separate water demand models were estimated based on two specifications of mandatory and voluntary water restriction programs. Model A used a dummy variable approach to distinguish between three types of drought management programs: voluntary restrictions, mandatory restrictions that were self-imposed, and mandatory restrictions imposed by the state under Executive Order 33. This approach represents the most common way to model nonprice drought management programs. Although locally-imposed and state-imposed mandatory restrictions covered the same basic activities, there may have been structural differences between the two programs. For instance, people may have been more aware of the restrictions covered by the executive order if it was publicized more aggressively. The restriction variables used in model A are defined as MANDATORY-SELF (1=self-imposed mandatory restrictions in effect; 0 otherwise), MADATORY-EO33 (1=EO33 restriction in effect, 0 otherwise); and VOLUNTARY (1= locally imposed voluntary restrictions in effect; 0 otherwise).

Hypothesis # 1a – Inclusion of voluntary restrictions (VOLUNTARY), self-imposed mandatory restrictions (MANDATORY-SELF), or mandatory restrictions imposed under Executive Order 33 (MANDATORY-EO33) will result in a decrease in water-use.

Responses from the survey presented in Chapter 4 indicate significant variation in voluntary and mandatory water-use restrictions implementation. The modeling challenge is to reflect this variation in the statistical model. Continuous variables that would measure implementation intensity (# fines issued, # warnings issued, # staff hours devoted to patrols, # reports appearing in the local media, etc.) could not be obtained due to incomplete records and other data challenges (see Chapter 4). Consequently, a rating procedure was developed to delineate informational and enforcement efforts into three broad levels of effort (Low, Medium, High). A relatively straightforward way to reflect these differences in information and enforcement levels is through the use of binary (0,1) dummy variables.

The second specification of the water demand model (Model B) created a series of 12 dummy variables to correspond with this rating system. Three dummy variables, VOL-INFO1, VOL-INFO2, VOL-INFO3, correspond to the low, moderate, and high information ratings for voluntary informational campaigns respectively (1= if voluntary program in place with a corresponding low, moderate, or high information rating; 0 otherwise). Given that mandatory restriction programs were distinguished based on ratings for both information and enforcement, a total of nine unique dummy variables were possible. For example MAND-INFO3-ENF1 identifies mandatory water-use restriction programs with an aggressive informational campaign but minimal enforcement efforts (1= mandatory programs with high information rating and a low enforcement rating; 0 otherwise). A total of eight dummy variables were ultimately defined in this manner. One combination of program attributes (low information and high enforcement ratings) contained no observations.

An advantage to this approach is that it allows for varying levels in program effectiveness based on differences in information and enforcement levels. If information and enforcement do play key roles in program effectiveness, then we should see consistent increases in parameter estimates as the ratings for both variables increase. One disadvantage to this approach is that there may be too many dummy variables and not enough restriction observations to measure the parameters with confidence. A second disadvantage to this approach is that it can introduce potential bias on the part of both the rater (in answering questions) and the researcher (in constructing the questions and rating system).

As discussed in Chapter 2, the effectiveness of enforcement is dependent on the perception of a credible monitoring and penalty system. Over time people will adjust their behavior based on perceptions for the probability of detection and the potential penalties. Although the imposition of Executive Order 33 (EO33) was general knowledge across the state, citizen experience with how individual localities would enforce the mandatory restrictions was unknown. Citizens in localities that enacted restrictions for the most part did not know how credible enforcement threats were. Thus the effectiveness of enforcement is expected to have somewhat of a lagged effect. For example, two localities could implement mandatory restrictions at the same time but have two different levels of enforcement efforts, the first high and the second low. It would seem reasonable, however, that initially residents in both localities would take the restrictions equally seriously because of the uncertainty about how the restrictions would actually be enforced. It would not be until after residents perceive a lack of enforcement in the second locality that there would be practical differences between the two localities in terms of apparent enforcement efforts.

To deal with this situation, the initial enforcement rating for each locality was increased one level for the first month that restrictions were imposed. For example, Stafford County's overall enforcement ranking was low. However, when Stafford imposed mandatory restrictions under EO33, the overall enforcement rating would increase to "moderate". The reasoning for this was that it would take less than a month for residents to accurate gauge the actual levels of enforcement being undertaken. After the initial month, however, enforcement ratings would return to their original (as derived from survey information) levels.

Hypothesis # 1b – The coefficients on all water-use restriction variables (VOL-INFO1, VOL-INFO2, VOL-INFO3, and MAND-INFO1-ENF1 …MAND-INFO3-ENF3) are expected to be negative. Furthermore, it is expected that increased ratings for 1) information, and 2) enforcement will generally lead to progressive reductions in water-use.

Apartment Variables

As discussed in Chapter 4, there were cases where apartment accounts were mixed with the residential data. The method chosen to deal with this issue was to use estimates obtained from localities as to the percentages of single and group-metered apartments included in the residential water-use data. These estimates were multiplied by the percentage of apartments in the locality, obtained from Census data, to create an estimate of the percentage of accounts that were single metered apartments (APT) and percentage of accounts that were group metered apartments (GROUP-APT) (see Chapter 4 for a discussion).

As previously noted, the inclusion of single-metered apartments is expected to decrease residential water-use. This effect should be most pronounced in the summer months when single-family residential usage rises but apartment usage stays relatively flat. Consequently, APT was transformed by the multiplication of three seasonal dummy variables SUMMER (1=June, July, Aug; 0 otherwise), SPR/FALL (1=April, May, September, October; 0 otherwise), and WINTER (1=Nov., Dec., Jan., Feb., and March; 0 otherwise). The inclusion of group-metered apartments (GROUP-APT) is expected to increase residential water-use.[18]

Hypothesis # 2a – As the percentage of single-metered apartments included in the residential data increases, residential water-use is expected to decrease. Coefficients on APT-SUMMER, APT-SPR/FALL, and APT-WINTER are hypothesized to be negative where APT-SUMMER < APT-SPR/FALL < APT-WINTER.

Hypothesis # 2b – As the percentage of group-metered apartments (GROUP-APT) included in the residential data increases, water-use is expected to increase.

Price Variables

The issue of whether to model price using the marginal or average price approach has been debated endlessly in the literature. As noted by a few researchers, this question is really an empirical one (Opaluch 1982, Nieswiadomy and Molina 1991, Martin and Wilder 1992, Bachrach and Vaughan 1994) that is best left for the data to decide. Hypothesizing how a consumer should react cannot substitute for actual behavior.

However, what has not been suggested by the literature is that everything needed to determine how consumers perceive price can be found by using the marginal price formulation in conjunction with the difference variable. If consumers are not responding to fixed fees or previous block rates, then the coefficient estimate for the difference variable should be opposite in sign but equal in magnitude to the estimate for income (if correctly specified). If the magnitude of the difference variable is greater than that of the income variable, then this would be indicative that consumers are responding in some fashion to fixed fees and/or previous block rates.

Subsequently, the marginal price specification is used in the final model.[19] The variable MP is calculated as the variable price charged for the last unit of water consumed by the average customer. All prices are expressed in 2004 dollars adjusted by the CPI. The difference variable is used in conjunction with the marginal price specification.

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[18] Seasonal interactions were not used with group-metered apartments as the number of observations with this apartment-type was relatively small compared to single-meter apartments.
[19] Results for the average price specification, although not detailed in the subsequent chapters, is presented in the Appendix for comparison purposes.

DIFFVAR is calculated as the average water bill less what the bill would have been if the entire usage had been charged at the marginal price (no fixed fees or block rates included). Previous studies also suggest that price elasticities vary across the season (Howe 1982, Griffin and Chang 1990, and Renwick and Green 2000). Consequently, MP and DIFFVAR were multiplied by the SUMMER, SPR/FALL, and WINTER dummies to generate seasonal marginal prices and difference variables.

Hypothesis # 3a – An increase in the marginal price of water will result in a decrease in water-use. This response is expected to be strongest during the summer months and weakest during the winter months (MP-SUMMER, MP-SPR/FALL, and MP-WINTER).

Hypothesis # 3b – An increase in the difference variable will result in a decrease in water-use. This response is expected to be strongest during the summer months and weakest during the winter months (DIFFVAR-SUMMER, DIFFVAR-SPR/FALL, and DIFFVAR-WINTER).

Hypothesis # 3c – The magnitude of the difference variable can be used as an indication of how consumers are responding to fixed fees (and previous block rates). If consumers are disregarding these fees as suggested by neoclassical economic theory, then the parameter estimates for the difference variables should be approximately the same in absolute magnitude as the income variables (due to a minor income effect). If the difference variable parameters are greater in magnitude than the income parameters, than this is an indication that consumers are responding to fixed fees and/or previous block rates.

Demographic Variables

INCOME is measured as the median household income in the city or county in which the local water supplier is located. The variable is derived from Census data and is reported in $1000's (2004 dollars, adjusted using the CPI).

A number of other possible demographic characteristics which included average lot size, household size, and house value, were considered for use in the model. In preliminary analysis, the average lot size proxy discussed in the data section was clearly not having the anticipated effect that this variable, if constructed correctly, would be expected to have. Although considerable effort was expended in creating this variable, it was not adding any useful information to the model. The average lot size proxy was subsequently dropped from the analysis. Household size and house value were also considered. HOUSEHOLD-SIZE is measured as the mean owner-occupied household size in each locality. HOUSE-VALUE is measured as the median owner-occupied house value in each locality. Both of these variables were obtained from Census data.

The challenge with identifying suitable descriptors of demographic characteristics was that all three remaining demographic variables (income, house value, and household size) were highly correlated with one another, revealed by Pearson Correlation coefficients (see Table 5.1). For panel-level data with relatively few localities for which these demographic variables vary, this high correlation can cause problems in terms of efficient estimation. From a theoretical perspective, income was the most important variable and thus it was necessary, at the minimum, to include this variable in the final model. Both house value and household size had similar correlations with income, and thus one or the other could not be easily eliminated from the standpoint of efficient estimation purposes. Intuitively, income and house value seem more alike than income and household size. It was felt that including house value would be less informative than including household size. Income and household size were included in the final models.

Table 5.1 – Pearson Correlations for Demographic Variables

	Household Size	Income	House Value
Household Size	-	.897	.753
Income	.897	-	.889
House Value	.753	.889	-

Care must be taken when interpreting the coefficients on the demographic variables, particularly income. Most of the variation in demographic characteristics occurs between localities, not across time. If income across localities is highly correlated with other demographic variables, and if these other variables cannot be adequately controlled for in the model, then a spurious relationship for income can result. If for instance, income is highly correlated with lot size and lot size cannot be controlled in the model, a part of the effect that is measured by income will be due to lot size. This is the potential problem with interpreting the income effect with municipal-level data.

Since lot size is not controlled for explicitly in the final model, it seems likely that the influence of this variable will be picked up to a certain degree in the parameter estimates for income. If so, then it would be expected that parameter estimates for income would vary by season. Parameter estimates for income should be highest during the summer when lot size would have the greatest impact on water-use, and lowest during the winter when lot size would have a negligible impact on water-use. INCOME was multiplied by the SUMMER, SPR/FALL, and WINTER dummies to generate seasonal income variables.

Hypothesis # 4 – Increase in median household income will result in an increase in water-use. This response is expected to be strongest during the summer months and weakest during the winter months (INCOME-SUMMER, INCOME-SPR/FALL, and INCOME-WINTER).

Hypothesis # 5 – Increase in average owner-occupied household size will result in an increase in water-use (HOUSEHOLD-SIZE).

Seasonal Variables

Many previous studies have shown a strong cyclical nature in water demand, especially with residential usage. The typical cycle will show residential water-use at a minimum during the winter months and then increase and level off by the middle of summer. Increased outdoor water-use occurs during the summer months due to lawn and garden watering, car washing, filling swimming pools, etc. This cycle is expected to be strong enough to estimate the effects for individual months with dummy variables.

Hypothesis # 6a – Water-use during individual months (JAN…NOV) will be cyclical in nature, being at a low point during the winter and peaking during the summer. Coefficients for the dummy variables during the growing season (APRIL …OCT) are hypothesized to be positive since water-use is expected to be greater at this time than during the winter base month (December).

As shown in Chapter 4, the seasonal pattern of water-use in cities differs from those in counties. Water-use in counties is generally slightly higher than cities during the winter dormant season but increases much more rapidly during the growing season. To account for this pattern, a city interaction variable is added to the monthly dummy variables, allowing cities to take on its own unique seasonal pattern (1=City; 0 otherwise).

Hypothesis # 6b – Water-use in cities is expected to be lower than in counties, with the most pronounced effects during the summer months (JAN-CITY …DEC-CITY). Coefficients for the city dummy variables are thus hypothesized to be negative (these coefficients are additive to the variables JAN…NOV).

Climatic variables

Rainfall would be expected to affect water-use during the growing season where the lower the rainfall level for a given month, the more irrigation that is likely to occur in yards and gardens. A cyclical effect is also expected for rainfall where the response for the variable should be greatest during the middle of the growing season when plants and trees are using more water and less of an effect at the beginning and end of the growing season.

Many of the previous studies used rainfall to predict water use (Griffin and Chang 1990, Lyman 1992, Renwick and Green 2000, Martinez-Espineira 2002, Taylor et al 2004), usually by using total rainfall in a given period as the independent variable. One study (Renwick and Green 2000) used deviations from the historical mean for each month as the measure for rainfall. This seems like the best approach when only a few years of data are available for the study (as is typically the case), as these years might not be representative of normal rainfall patterns. If for instance, rainfall was much lower than the historic average throughout the summer months of data, the summer monthly dummy variables might pick up the expected higher water-use, rather than correctly attributing this higher usage to the low rainfall levels. By normalizing the rainfall data by their average monthly means, this would ensure that the low rainfall was given the proper credit for the increase in water consumption during the summer months.

Given this possibility, the variable RAIN is defined as the monthly deviation for each locality, in inches, from the monthly historical norm at the state-level (actual rainfall at the local level – historic rainfall average at the state level). Seasonal rain variables (slope dummies) are created by multiplying RAIN by SUMMER and SPR/FALL. Because rainfall is not expected to influence water-use during the winter dormant season, no winter rain variable was constructed. Because water-use is higher in summer in counties than in cities, it would be expected that the response to rainfall would be stronger in counties than in cities. Thus county and city interaction variables have been added to rainfall: RAIN-CO-SUMMER, RAIN-CO-SPR/FALL, RAIN-CITY-SUMMER, and RAIN-CITY-SPR/FALL.

Monthly rainfall is also expected to have a lagged effect in that above average or below average rainfall in previous months will influence water-use in the current period (e.g. drought is the accumulation of deficit rainfall in successive periods). If soil conditions are dry at the beginning of the month, more water would be expected to be used for irrigation compared to if soil conditions had started out wet. This potential effect can be controlled for by including two lags for RAIN (LAG1 = RAIN in time period t-1 and LAG2 = RAIN in time period t-2). Lags were included for each of the four RAIN interaction variables defined above.

Hypothesis # 7a – During the growing season, increased positive deviations from historical monthly rainfall will lead to decreased water-use. This effect will be most pronounced in the middle of the growing season and less pronounced toward the tails of the growing season. This effect is expected to be more pronounced in counties than in cities (RAIN-CO-SUMMER, RAIN-CO-SPR/FALL, RAIN-CITY-SUMMER, and RAIN-CITY-SPR/FALL).

Hypothesis # 7b – Previous month's rainfall will have an effect on current water-use, but to a lesser degree than the current month's rainfall (RAIN-CO-SUMMER-LAG1, RAIN-CO-SUMMER-LAG2, RAIN-CO-SPR/FALL-LAG1, RAIN-CO-SPR/FALL-LAG2, RAIN-CITY-SUMMER-LAG1, RAIN-CITY-SUMMER-LAG2, RAIN-CITY-SPR/FALL-LAG1, RAIN-CITY-SPR/FALL-LAG2) .

Similar to rainfall, temperature is expected to influence water-use where the higher the temperature, the more evapotranspiration that is likely to occur with grass, plants, and trees and the more water that they would need to grow at an optimal level. Since temperature is not used to control for seasonal variation but rather for the presence of atypical climatic conditions, TEMP is also defined as the monthly deviation (in degrees Fahrenheit) for each locality from the monthly maximum average historical norm at the state-level (actual monthly average maximum temperature – state monthly maximum average temperature). Defining TEMP as deviations from historical averages rather than as absolute values avoids the possible collinearity between the seasonal dummy variables and temperature. As opposed to rainfall however, there is no reason to expect a lagged effect from one month to the next.

Because water-use is higher in counties than in cities during the summer, it is expected that the response to temperature would be stronger in counties than in cities. County and city interaction variables (CO and CITY) are added to TEMP to allow for varying effects with this variable. Similarly, growing season dummy variables (SUMMER and SPR/FALL*)* are added to TEMP because it is expected that temperature will have more of an effect in the summer compared to the spring/fall months.

Hypothesis # 7c – During the growing season, increased positive deviations from historical average maximum daily temperature will lead to increased water-use. The affect that temperature has on water-use is expected to be stronger in counties than in cities (TEMP-CO-SUMMER, TEMP-CO-SPR/FALL, TEMP-CITY-SUMMER, and TEMP-CITY-SPR/FALL).

Summary

As a general summary of the model, monthly residential water-use is hypothesized to approximate the following function:

Natural Log Residential Water-Use = function (water-use restrictions, price, income, month, rainfall, temperature, other demographic variables)

The specific variables and hypothesized effects are noted in the following table:

Table 5.2 – Final Model Variables and Hypothesized Effects on Water-Use

Variable	Influence on Water-Use		Variable	Influence on Water-Use
JAN	Neutral		TEMP-CO-SUMMER	+
FEB	Neutral		TEMP-CO-SPR/FALL	+
MAR	Neutral		TEMP-CITY-SUMMER	+
APR	+		TEMP-CITY-SPR/FALL	+
MAY	+		SINGLE-APT-SUMMER	-
JUN	+		SINGLE-APT-SPR/FALL	-
JUL	+		SINGLE-APT-WINTER	-
AUG	+		GROUP-APT	+
SEP	+		INCOME-SUMMER ($1000)	+
OCT	+		INCOME-SPR/FALL ($1000)	+
NOV	Neutral		INCOME-WINTER ($1000)	+
JAN-CITY	-		HOUSEHOLD-SIZE	+
FEB-CITY	-		MP-SUMMER	-
MAR-CITY	-		MP-SPR/FALL	-
APR-CITY	-		MP-WINTER	-
MAY-CITY	-		DIFFVAR-SUMMER	-
JUN-CITY	-		DIFFVAR-SPR/FALL	-
JUL-CITY	-		DIFFVAR-WINTER	-
AUG-CITY	-		VOL-INFO1	-
SEP-CITY	-		VOL-INFO2	-
OCT-CITY	-		VOL-INFO3	-
NOV-CITY	-		MAND-INFO1-ENF1	-
DEC-CITY	-		MAND-INFO1-ENF2	-
RAIN-CO-SUMMER	-		MAND-INFO1-ENF3	-
RAIN-CO-SUMMER-LAG1	-		MAND-INFO2-ENF1	-
RAIN-CO-SUMMER-LAG2	-		MAND-INFO2-ENF2	-
RAIN-CO-SPR/FALL	-		MAND-INFO2-ENF3	-
RAIN-CO-SPR/FALL-LAG1	-		MAND-INFO3-ENF1	-
RAIN-CO-SPR/FALL-LAG2	-		MAND-INFO3-ENF2	-
RAIN-CITY-SUMMER	-		MAND-INFO3-ENF3	-
RAIN-CITY-SUMMER-LAG1	-			
RAIN-CITY-SUMMER-LAG2	-			
RAIN-CITY-SPR/FALL	-			
RAIN-CITY-SPR/FALL-LAG1	-			
RAIN-CITY-SPR/FALL-LAG2	-			

Note: JAN …, NOV are the seasonal variables for counties (using December as the base usage). Parameter estimates for JAN-CITY …, DEC-CITY are additive with the respective seasonal variables for counties to obtain the seasonal variables for cities.

Chapter 6: Model Results

The two models identified in Chapter 5 (Model A: 3 restriction dummy variables vs. Model B: 12 restriction dummy variables) were first estimated with ordinary least squares (OLS). Since a natural log transformation was made for the dependent variable, all parameter estimates are percentage based. Thus a parameter estimate of .10 means that water-use increases 10% with a one-unit increase in the independent variable, with all other variables held constant.

Results of Ordinary Least Squares (OLS) Models

The results from the two OLS models are shown in Tables 6.2 and 6.3. As seen in these two tables, the overall results were generally consistent with theoretical expectations. The second model had a slightly better fit compared to the first model (.828 vs. .824 adjusted R^2). For the most part however, the parameter estimates for the two models were very similar.

Model 1(A) reflected a conventional approach to modeling nonprice drought management programs where intensity is not evaluated. The presence of voluntary restrictions had a negligible effect on residential water-use. The coefficient on VOLUNTARY was small and not statistically significant. Self-imposed mandatory restrictions and restrictions covered by Executive Order 33 resulted in water-use reductions of 9% and 14% respectively.[20]

In model 1(B), three intensity levels were evaluated for voluntary restrictions and nine for mandatory restrictions. The model found statistical evidence that differences in program intensity have varying effects on water-use. Voluntary restrictions with low to moderate information ratings had no significant effect on water-use. However, voluntary restriction programs with aggressive informational campaigns decreased water-use by 9%. For mandatory restrictions, the two lowest ratings (MAND-INFO1-ENF1 and MAND-INFO1-ENF2) had no significant effect on water use, while the highest rating (MAND-INFO3-ENF3) decreased water-use by 24%. Mandatory restriction programs with high information or enforcement ratings (MAND-INFO3-ENF2 and MAN-INFO2-ENF3) each reduced water use by an estimated 20 percent. Other intensity levels for mandatory restrictions were statistically significant, but had smaller coefficient estimates.[21]

Generally, the other explanatory variables in both models reflected prior expectations and were consistent across models. Seasonal dummies were generally significantly different from the December base with the largest coefficient estimates occurring during the peak of the growing season. As indicated by the parameter coefficients (CITY-DUM), water-use for cities was lower during the growing season than in counties. Rainfall reduced

[20] This model was significantly different than the same model without any restriction parameters at the .001 level using an F-test.
[21] This model was significantly different than the same model without any restriction parameters at the .001 level using an F-test.

water-use from a negligible amount to 2.8% per inch of rainfall above the monthly average. In general, the temperature variables (deviations from historical averages) were not significant across the two models. Income increased water-use by about .6% per $1000 increase in income. Household size increased water-use by 10% per additional person. Marginal price decreased consumption by 3-6% per $1 increase in price depending on the season, with the highest response occurring in the summer months. The difference variables had a mixed effect from +.1% to -.2% for each $1 increase in this variable. The theoretical expectation for this variable was that it would be negative.

Problems with Ordinary Least Squares (OLS) Estimates

Two problems were encountered with the OLS models that raised concern about the validity of these results. The first problem was an apparent autoregressive process in the error terms, revealed by a Durbin-Watson test. The Durbin-Watson test statistic was .655 (model 1B), which showed strong support for autocorrelation. Evidence existed for both an AR(1) and AR(12) process (see Table 6.1), which matched theoretical expectations as monthly panel data was used in the analysis.[22] The second potential problem was possible heteroskedasticity across the panels. Heteroskedasticity can be a problem in panel data as there is no reason to expect the variance to be the same across multiple localities.

Table 6.1 – Estimates of Autoregressive Parameters from OLS

Durbin-Watson	0.655	
Lag	Coefficient	t Value
1	-0.626	-21.89
2	0.103	3.06
3	-0.011	-0.33
4	-0.010	-0.29
5	0.073	2.16
6	-0.175	-5.20
7	0.051	1.52
8	-0.006	-0.17
9	0.019	0.56
10	-0.081	-2.40
11	-0.116	-3.45
12	-0.110	-3.84

Note: These estimates were for model B but both estimates were virtually identical.

Although the previous parameter estimates should theoretically be unbiased, a likely consequence of the autoregressive process and heteroskedasticity is that the standard errors are biased. To deal with this problem in the OLS model, two modifications were made. To correct for autocorrelation, a panel-specific AR(1) process was added to the model. Although evidence existed for both an AR(1) and AR(12) process, the AR(1) process was much stronger and was also more operationally feasible to implement using panel-level data. The AR(1) process was modeled as panel-specific, which allowed the strength of the autoregressive process to vary by locality. To correct for heteroskedasticity, standard errors in the model were adjusted by assuming that the standard errors in the regression varied by locality, using a Prais-Winsten regression with heteroskedastic panel corrected standard errors. This overall process correcting for autocorrelation and heteroskedasticity should give unbiased parameter estimates and standard errors.

[22] AR(1) refers to an autoregressive process where the regression residual from the previous observation affects the dependent value of the current observation. AR(12) refers to an autoregressive process where the regression residual from the same month of the previous year affects the dependent value of the current observation.

Table 6.2 – OLS Model Summary with 3 Restriction Variables (Model 1A)

Source	SS	df	MS		Number of observations	1286		
					F(56, 1229)	108.6		
Model	53.19	56	0.950		Prob > F	0		
Residual	10.74	1229	0.009		R-squared	0.832		
Total	63.93	1285	0.050		Adj R-squared	0.824		
					Root MSE	0.094		
Variable	Coef.	Std. Err.	P>|t|		Variable	Coef.	Std. Err.	P>|t|
Intercept	4.5941	0.0575	0.000		RAIN-CITY-SUMMER	-0.0278	0.0044	0.000
JAN	-0.0431	0.0182	0.018		RAIN-CITY-SUMMER-LAG1	-0.0185	0.0042	0.000
FEB	-0.0747	0.0182	0.000		RAIN-CITY-SUMMER-LAG2	-0.0067	0.0041	0.105
MAR	-0.0489	0.0182	0.007		RAIN-CITY-SPR/FALL	-0.0065	0.0025	0.009
APR	0.1054	0.0649	0.105		RAIN-CITY-SPR/FALL-LAG1	-0.0050	0.0026	0.051
MAY	0.2539	0.0642	0.000		RAIN-CITY-SPR/FALL-LAG2	-0.0157	0.0045	0.000
JUN	0.4704	0.0695	0.000		TEMP-CO-SUMMER	0.0043	0.0032	0.172
JUL	0.4914	0.0702	0.000		TEMP-CO-SPR/FALL	0.0088	0.0023	0.000
AUG	0.4403	0.0707	0.000		TEMP-CITY-SUMMER	-0.0022	0.0035	0.541
SEP	0.2652	0.0647	0.000		TEMP-CITY-SPR/FALL	0.0000	0.0025	0.986
OCT	0.1722	0.0648	0.008		APT-SUMMER	-0.7744	0.1125	0.000
NOV	0.0168	0.0180	0.351		APT-SPR/FALL	-0.3537	0.0961	0.000
JAN-CITY	-0.0080	0.0202	0.694		APT-WINTER	-0.0902	0.0837	0.281
FEB-CITY	-0.0081	0.0202	0.689		GROUP-APT	1.7818	0.0443	0.000
MAR-CITY	0.0019	0.0201	0.926		INCOME-SUMMER ($1000)	0.0058	0.0007	0.000
APR-CITY	-0.0088	0.0216	0.683		INCOME-SPR/FALL ($1000)	0.0065	0.0006	0.000
MAY-CITY	-0.0719	0.0207	0.001		INCOME-WINTER ($1000)	0.0062	0.0006	0.000
JUN-CITY	-0.0659	0.0218	0.003		HOUSEHOLD-SIZE	0.1108	0.0250	0.000
JUL-CITY	-0.0801	0.0214	0.000		MP-SUMMER	-0.0598	0.0050	0.000
AUG-CITY	-0.0493	0.0233	0.034		MP-SPR/FALL	-0.0429	0.0042	0.000
SEP-CITY	-0.0675	0.0207	0.001		MP-WINTER	-0.0297	0.0031	0.000
OCT-CITY	-0.0301	0.0210	0.151		DIFFVAR-SUMMER	-0.0017	0.0008	0.028
NOV-CITY	-0.0032	0.0197	0.869		DIFFVAR-SPR/FALL	-0.0016	0.0007	0.031
DEC-CITY	0.0020	0.0202	0.921		DIFFVAR-WINTER	0.0011	0.0007	0.121
RAIN-CO-SUMMER	-0.0194	0.0040	0.000		VOLUNTARY	-0.0102	0.0144	0.477
RAIN-CO-SUMMER-LAG1	-0.0253	0.0045	0.000		MANDATORY-SELF	-0.0881	0.0346	0.011
RAIN-CO-SUMMER-LAG2	-0.0140	0.0046	0.003		MANDATORY-EO33	-0.1426	0.0171	0.000
RAIN-CO-SPR/FALL	-0.0120	0.0024	0.000					
RAIN-CO-SPR/FALL-LAG1	-0.0095	0.0024	0.000					
RAIN-CO-SPR/FALL-LAG2	-0.0043	0.0034	0.216					

Note: Dependent Variable: Ln (Avg. Daily Gallons per Account per Month)

Table 6.3 – OLS Model Summary with 12 Restriction Variables (Model 1B)

Source	SS	df	MS		Number of observations	1286		
					F(64, 1221)	97.6		
Model	53.47	64	0.836		Prob > F	0		
Residual	10.46	1221	0.009		R-squared	0.836		
Total	63.93	1285	0.050		Adj R-squared	0.828		
					Root MSE	0.093		
Variable	Coef.	Std. Err.	P>|t|		Variable	Coef.	Std. Err.	P>|t|
Intercept	4.6092	0.0572	0.000		RAIN-CITY-SPR/FALL	-0.0077	0.0025	0.002
JAN	-0.0432	0.0180	0.016		RAIN-CITY-SPR/FALL-LAG1	-0.0043	0.0025	0.090
FEB	-0.0749	0.0180	0.000		RAIN-CITY-SPR/FALL-LAG2	-0.0148	0.0044	0.001
MAR	-0.0496	0.0180	0.006		TEMP-CO-SUMMER	0.0056	0.0031	0.078
APR	0.1028	0.0646	0.112		TEMP-CO-SPR/FALL	0.0096	0.0023	0.000
MAY	0.2529	0.0639	0.000		TEMP-CITY-SUMMER	-0.0018	0.0035	0.596
JUN	0.4657	0.0691	0.000		TEMP-CITY-SPR/FALL	0.0001	0.0025	0.961
JUL	0.4861	0.0697	0.000		APT-SUMMER	-0.7674	0.1114	0.000
AUG	0.4371	0.0701	0.000		APT-SPR/FALL	-0.3753	0.0955	0.000
SEP	0.2665	0.0645	0.000		APT-WINTER	-0.0892	0.0829	0.282
OCT	0.1659	0.0645	0.010		GROUP-APT	1.7801	0.0444	0.000
NOV	0.0183	0.0178	0.305		INCOME-SUMMER ($1000)	0.0060	0.0007	0.000
JAN-CITY	-0.0083	0.0200	0.677		INCOME-SPR/FALL ($1000)	0.0067	0.0006	0.000
FEB-CITY	-0.0084	0.0200	0.677		INCOME-WINTER ($1000)	0.0064	0.0006	0.000
MAR-CITY	0.0027	0.0199	0.890		HOUSEHOLD-SIZE	0.0992	0.0248	0.000
APR-CITY	-0.0052	0.0215	0.808		MP-SUMMER	-0.0577	0.0049	0.000
MAY-CITY	-0.0714	0.0205	0.001		MP-SPR/FALL	-0.0418	0.0042	0.000
JUN-CITY	-0.0688	0.0216	0.001		MP-WINTER	-0.0290	0.0031	0.000
JUL-CITY	-0.0812	0.0212	0.000		DIFFVAR-SUMMER	-0.0018	0.0008	0.017
AUG-CITY	-0.0489	0.0230	0.034		DIFFVAR-SPR/FALL	-0.0018	0.0007	0.013
SEP-CITY	-0.0692	0.0207	0.001		DIFFVAR-WINTER	0.0010	0.0007	0.152
OCT-CITY	-0.0346	0.0211	0.101		VOL-INFO1	-0.0128	0.0237	0.590
NOV-CITY	-0.0068	0.0195	0.728		VOL-INFO2	0.0334	0.0197	0.090
DEC-CITY	0.0011	0.0200	0.957		VOL-INFO3	-0.0924	0.0265	0.001
RAIN-CO-SUMMER	-0.0197	0.0040	0.000		MAND-INFO1-ENF1	-0.0092	0.0629	0.884
RAIN-CO-SUMMER-LAG1	-0.0252	0.0045	0.000		MAND-INFO1-ENF2	-0.0414	0.0654	0.527
RAIN-CO-SUMMER-LAG2	-0.0151	0.0046	0.001		MAND-INFO2-ENF1	-0.0952	0.0359	0.008
RAIN-CO-SPR/FALL	-0.0125	0.0024	0.000		MAND-INFO2-ENF2	-0.1075	0.0278	0.000
RAIN-CO-SPR/FALL-LAG1	-0.0092	0.0024	0.000		MAND-INFO2-ENF3	-0.1990	0.0496	0.000
RAIN-CO-SPR/FALL-LAG2	-0.0044	0.0034	0.205		MAND-INFO3-ENF1	-0.1084	0.0308	0.000
RAIN-CITY-SUMMER	-0.0267	0.0044	0.000		MAND-INFO3-ENF2	-0.2004	0.0294	0.000
RAIN-CITY-SUMMER-LAG1	-0.0189	0.0041	0.000		MAND-INFO3-ENF3	-0.2402	0.0641	0.000
RAIN-CITY-SUMMER-LAG2	-0.0071	0.0041	0.079					
Note: Dependent Variable: Ln (Avg. Daily Gallons per Account per Month)								

Results with Autoregressive and Heteroskedastic Panel Corrected Models

The two models were re-estimated to correct for autocorrelation and heteroskedasticity. The results of these two models are shown in Table 6.4 and Table 6.5. For ease in notation the OLS models will be called Model 1A and Model 1B and the new models will be called Model 2A and Model 2B respectively. In general, procedures to correct for autocorrelation and heteroskedasticity did not result in substantial changes in the parameter estimates from Model 1A or Model 1B, although there were a few exceptions. In comparing between Models 2A and Model 2B most parameter estimates are also very similar. The main differences between the two new models are in the parameter estimates for the restriction variables (3 dummy variable approach vs. 12 dummy variable approach). These differences will be discussed in detail as they have important implications for applied research. The results for the other variables will be discussed from the standpoint of model 2B only as there are no practical differences between Models 2A and 2B for these variables.

As seen in Tables 6.4 and 6.5, the overall results were generally consistent with the theoretical expectations. The model R^2 was quite high at .994 and .995 for the 3 restriction and 12 restriction models respectively. However, this increase in R^2 from the OLS models was largely due to the inclusion of the AR(1) process in the new models. The model-fit without accounting for autocorrelation was .832 and .836 for models 1A and 1B respectively.

The following discussion provides a detailed description of the model results after corrections were made for the autoregressive process and heteroskedasticity. Again, after the results for the restriction variables are discussed, the remaining variables will be discussed from the standpoint of Model 2B only to avoid unnecessary duplication.

Table 6.4 – Prais-Winsten Regression Heteroskedastic Panels Corrected Standard Errors - 3 Restriction Variables (Model 2A)								
Panels:	Heteroskedastic (unbalanced)				Obs per group: min	30		
Autocorrelation:	Panel-specific AR(1)				Obs per group: avg.	61.2		
Estimated covariances	21				Obs per group: max	156		
Estimated autocorrelations	21				R-squared	0.9943		
Estimated coefficients	57				Wald chi2(64)	4192.59		
Number of obs	1286				Prob > chi2	0		
Number of groups	21							
		Het-corrected					Het-corrected	
Variable	Coef.	Std. Err.	P>|z|		Variable	Coef.	Std. Err.	P>|z|
Intercept	4.5296	0.0924	0.000		RAIN-CITY-SUMMER	-0.0110	0.0023	0.000
JAN	-0.0422	0.0091	0.000		RAIN-CITY-SUMMER-LAG1	-0.0053	0.0022	0.017
FEB	-0.0703	0.0117	0.000		RAIN-CITY-SUMMER-LAG2	0.0005	0.0021	0.812
MAR	-0.0436	0.0130	0.001		RAIN-CITY-SPR/FALL	-0.0028	0.0011	0.012
APR	0.0875	0.0443	0.048		RAIN-CITY-SPR/FALL-LAG1	-0.0012	0.0011	0.267
MAY	0.2262	0.0441	0.000		RAIN-CITY-SPR/FALL-LAG2	-0.0007	0.0022	0.732
JUN	0.3151	0.0578	0.000		TEMP-CO-SUMMER	0.0070	0.0021	0.001
JUL	0.3234	0.0584	0.000		TEMP-CO-SPR/FALL	0.0039	0.0014	0.004
AUG	0.2683	0.0585	0.000		TEMP-CITY-SUMMER	0.0019	0.0020	0.332
SEP	0.2263	0.0442	0.000		TEMP-CITY-SPR/FALL	0.0026	0.0012	0.026
OCT	0.1363	0.0437	0.002		APT-SUMMER	-0.7606	0.1218	0.000
NOV	0.0172	0.0092	0.061		APT-SPR/FALL	-0.5635	0.1053	0.000
JAN-CITY	0.0199	0.0204	0.330		APT-WINTER	-0.4735	0.1111	0.000
FEB-CITY	0.0174	0.0205	0.394		GROUP-APT	1.6419	0.0531	0.000
MAR-CITY	0.0255	0.0204	0.210		INCOME-SUMMER ($1000)	0.0041	0.0010	0.000
APR-CITY	0.0038	0.0202	0.851		INCOME-SPR/FALL ($1000)	0.0040	0.0009	0.000
MAY-CITY	-0.0646	0.0200	0.001		INCOME-WINTER ($1000)	0.0034	0.0010	0.000
JUN-CITY	-0.0773	0.0208	0.000		HOUSEHOLD-SIZE	0.2207	0.0449	0.000
JUL-CITY	-0.0775	0.0209	0.000		MP-SUMMER	-0.0487	0.0055	0.000
AUG-CITY	-0.0468	0.0215	0.030		MP-SPR/FALL	-0.0434	0.0045	0.000
SEP-CITY	-0.0622	0.0200	0.002		MP-WINTER	-0.0304	0.0040	0.000
OCT-CITY	-0.0251	0.0200	0.210		DIFFVAR-SUMMER	-0.0052	0.0009	0.000
NOV-CITY	0.0111	0.0200	0.578		DIFFVAR-SPR/FALL	-0.0063	0.0008	0.000
DEC-CITY	0.0167	0.0203	0.412		DIFFVAR-WINTER	-0.0053	0.0009	0.000
RAIN-CO-SUMMER	-0.0127	0.0023	0.000		VOLUNTARY	0.0010	0.0128	0.939
RAIN-CO-SUMMER-LAG1	-0.0133	0.0027	0.000		MANDATORY-SELF	-0.0608	0.0289	0.036
RAIN-CO-SUMMER-LAG2	-0.0044	0.0028	0.116		MANDATORY-EO33	-0.1128	0.0157	0.000
RAIN-CO-SPR/FALL	-0.0066	0.0015	0.000					
RAIN-CO-SPR/FALL-LAG1	-0.0057	0.0015	0.000					
RAIN-CO-SPR/FALL-LAG2	-0.0002	0.0021	0.930					
Note: Dependent Variable: Ln (Avg. Daily Gallons per Account per Month)								

Table 6.5 – Prais-Winsten Regression Heteroskedastic Panels Corrected Standard Errors - 12 Restriction Variables (Model 2B)								
Panels:	Heteroskedastic (unbalanced)				Obs per group: min	30		
Autocorrelation:	Panel-specific AR(1)				Obs per group: avg.	61.2		
Estimated covariances	21				Obs per group: max	156		
Estimated autocorrelations	21				R-squared	0.995		
Estimated coefficients	65				Wald chi2(64)	4312.3		
Number of obs	1286				Prob > chi2	0		
Number of groups	21							
		Het-corrected					Het-corrected	
Variable	Coef.	Std. Err.	P>|z|		Variable	Coef.	Std. Err.	P>|z|
Intercept	4.5617	0.0903	0.000		RAIN-CITY-SPR/FALL	-0.0036	0.0011	0.001
JAN	-0.0430	0.0090	0.000		RAIN-CITY-SPR/FALL-LAG1	-0.0012	0.0010	0.238
FEB	-0.0714	0.0116	0.000		RAIN-CITY-SPR/FALL-LAG2	-0.0005	0.0022	0.821
MAR	-0.0446	0.0129	0.001		TEMP-CO-SUMMER	0.0070	0.0021	0.001
APR	0.0890	0.0444	0.045		TEMP-CO-SPR/FALL	0.0045	0.0013	0.001
MAY	0.2282	0.0443	0.000		TEMP-CITY-SUMMER	0.0021	0.0020	0.286
JUN	0.3212	0.0579	0.000		TEMP-CITY-SPR/FALL	0.0030	0.0012	0.012
JUL	0.3299	0.0585	0.000		APT-SUMMER	-0.7347	0.1222	0.000
AUG	0.2803	0.0585	0.000		APT-SPR/FALL	-0.5477	0.1061	0.000
SEP	0.2325	0.0444	0.000		APT-WINTER	-0.4391	0.1120	0.000
OCT	0.1372	0.0439	0.002		GROUP-APT	1.6590	0.0537	0.000
NOV	0.0190	0.0091	0.037		INCOME-SUMMER ($1000)	0.0044	0.0009	0.000
JAN-CITY	0.0170	0.0202	0.401		INCOME-SPR/FALL ($1000)	0.0043	0.0009	0.000
FEB-CITY	0.0145	0.0203	0.474		INCOME-WINTER ($1000)	0.0038	0.0009	0.000
MAR-CITY	0.0229	0.0202	0.257		HOUSEHOLD-SIZE	0.1989	0.0431	0.000
APR-CITY	0.0015	0.0200	0.939		MP-SUMMER	-0.0478	0.0054	0.000
MAY-CITY	-0.0672	0.0198	0.001		MP-SPR/FALL	-0.0426	0.0044	0.000
JUN-CITY	-0.0804	0.0207	0.000		MP-WINTER	-0.0301	0.0040	0.000
JUL-CITY	-0.0804	0.0207	0.000		DIFFVAR-SUMMER	-0.0050	0.0009	0.000
AUG-CITY	-0.0518	0.0213	0.015		DIFFVAR-SPR/FALL	-0.0062	0.0008	0.000
SEP-CITY	-0.0677	0.0199	0.001		DIFFVAR-WINTER	-0.0052	0.0009	0.000
OCT-CITY	-0.0323	0.0198	0.104		VOL-INFO1	0.0206	0.0182	0.257
NOV-CITY	0.0062	0.0199	0.754		VOL-INFO2	0.0164	0.0193	0.395
DEC-CITY	0.0148	0.0201	0.463		VOL-INFO3	-0.0677	0.0208	0.001
RAIN-CO-SUMMER	-0.0129	0.0023	0.000		MAND-INFO1-ENF1	-0.0450	0.0441	0.307
RAIN-CO-SUMMER-LAG1	-0.0138	0.0027	0.000		MAND-INFO1-ENF2	-0.0359	0.0383	0.349
RAIN-CO-SUMMER-LAG2	-0.0053	0.0027	0.053		MAND-INFO2-ENF1	-0.0600	0.0284	0.035
RAIN-CO-SPR/FALL	-0.0069	0.0015	0.000		MAND-INFO2-ENF2	-0.0852	0.0239	0.000
RAIN-CO-SPR/FALL-LAG1	-0.0055	0.0015	0.000		MAND-INFO2-ENF3	-0.1998	0.0503	0.000
RAIN-CO-SPR/FALL-LAG2	-0.0001	0.0021	0.947		MAND-INFO3-ENF1	-0.1176	0.0279	0.000
RAIN-CITY-SUMMER	-0.0111	0.0023	0.000		MAND-INFO3-ENF2	-0.1540	0.0232	0.000
RAIN-CITY-SUMMER-LAG1	-0.0068	0.0022	0.003		MAND-INFO3-ENF3	-0.2211	0.0407	0.000
RAIN-CITY-SUMMER-LAG2	-0.0008	0.0021	0.696					
Note: Dependent Variable: Ln (Avg. Daily Gallons per Account per Month)								

Restriction Variables (Models 2A and 2B)

Table 6.6 summarizes the restriction parameter estimates for the two models. The broad theoretical expectation was that these coefficients would be less than or equal to zero. In general, mandatory restrictions were expected to show a greater reduction in water-use than voluntary restrictions, and mandatory restrictions imposed by Executive Order 33 were expected to show a greater reduction in water-use than self-imposed mandatory restrictions. These expectations were supported by the parameter estimates from Model 2A. On average, voluntary restrictions essentially had no impact on water-use, self-imposed mandatory restrictions reduced water-use by 6%, and mandatory restrictions mandated by the state reduced water-use by 11%. Thus, under this conventional approach in specifying water-use restrictions, the water savings from these restrictions had did not appear particularly large.[23]

Table 6.6 – Comparison of 3 Restriction and 12 Restriction Approaches

Variable	Coef.	Std. Err.	P>|z|
Model 2(A)			
VOLUNTARY	0.00	0.0128	0.939
MANDATORY-SELF	-0.06	0.0289	0.036
MANDATORY-EO33	-0.11	0.0157	0.000
Model 2(B)			
VOL-INFO1	0.02	0.018	0.257
VOL-INFO2	0.02	0.019	0.395
VOL-INFO3	-0.07	0.021	0.001
MAND-INFO1-ENF1	-0.05	0.044	0.307
MAND-INFO1-ENF2	-0.04	0.038	0.349
MAND-INFO2-ENF1	-0.06	0.028	0.035
MAND-INFO2-ENF2	-0.09	0.024	0.000
MAND-INFO2-ENF3	-0.20	0.050	0.000
MAND-INFO3-ENF1	-0.12	0.028	0.000
MAND-INFO3-ENF2	-0.15	0.023	0.000
MAND-INFO3-ENF3	-0.22	0.041	0.000

However, information ratings for voluntary restrictions, and information and enforcement ratings for mandatory restrictions were expected to play an important role in the ultimate water-use reductions evaluated in Model 2B. Higher ratings for information and enforcement were expected to result in corresponding increases in water-use reductions. The re-estimation of the OLS model did not change the basic conclusion that program success depends on the intensity in which restrictions are implemented.

For voluntary restrictions, the only parameter estimate that was statistically significant was for the highest information rating (VOL-INFO3). This parameter estimate implies that a voluntary restriction program with a high information rating reduced water-use by 7% on average. The other two information ratings for this variable were not statistically significant and were also positive, which implies that these programs had no meaningful effect in reducing water-use (similar to OLS estimation).

Consistent with Model 2A, all parameter estimates were negative for mandatory restrictions. The results show large differences in parameter estimates for mandatory restriction programs with estimated reductions in water-use progressively increasing with

[23] Parameter estimates for VOLUNTARY compared to MANDATORY-SELF and VOLUNTARY compared to MANDATORY-EO33 were statistically different at the .05 level, while MANDATORY-SELF compared to MANDATORY-EO33 was statistically different at the .10 level.

higher informational and enforcement ratings. Parameter estimates for mandatory restriction programs with low information ratings (MAND-INFO1-ENF1 and MAN-INFO1-ENF2), although negative, were not statistically different from zero at the .05 level. However, these two estimates did fit the general pattern of relative ordering and magnitude with the rest of the parameter estimates. Mandatory restriction programs that had a moderate rating for information and a low-level rating for enforcement (MAND-INFO2-ENF1) resulted in a 6% reduction in water-use, on average, while mandatory restriction programs that had a moderate rating for both information and enforcement (MAND-INFO2-ENF2) resulted in a 9% reduction in water-use. Similar in magnitude to the OLS results, the largest reductions in water-use occurred under MAND-INFO2-ENF3 and MAND-INFO3-ENF3, resulting in an estimated 20 and 22 percent reduction in water-use compared to having no restrictions in place. Thus, statistical evidence from the 2002 drought in Virginia suggests that on average, the reductions in water-use from mandatory restrictions ranged from 0 to 22 percent depending on the intensity of program implementation.[24]

Table 6.7 provides testing details to determine if mandatory restriction parameter estimates are statistically different from each other. As can be seen in this table, approximately 60% of the estimates are statistically significant at the .10 level or better. It would not be expected that all combinations would be statistically different from each other given the large number of parameter estimates in relation to the overall range in values. Generally, adjacent intensity levels (e.g. MAND-INFO2-ENF1 and MAND-INFO2-ENF2) were not statistically significant from each other due to the corresponding close parameter estimates.

Table 6.7 - Level of Significance for Differences between Joint Mandatory Restriction Parameters

	MAND-INFO1-ENF1	MAND-INFO1-ENF2	MAND-INFO2-ENF1	MAND-INFO2-ENF2	MAND-INFO2-ENF3	MAND-INFO3-ENF1	MAND-INFO3-ENF2	MAND-INFO3-ENF3
MAND-INFO1-ENF1	-	*0.82*	*0.77*	*0.42*	*0.02*	*0.16*	*0.03*	*0.00*
MAND-INFO1-ENF2		-	*0.61*	*0.26*	*0.01*	*0.08*	*0.01*	*0.00*
MAND-INFO2-ENF1			-	*0.35*	*0.01*	*0.13*	*0.01*	*0.00*
MAND-INFO2-ENF2				-	*0.03*	*0.37*	*0.03*	*0.00*
MAND-INFO2-ENF3					-	*0.15*	*0.40*	*0.74*
MAND-INFO3-ENF1						-	*0.17*	*0.02*
MAND-INFO3-ENF2							-	*0.08*
MAND-INFO3-ENF3								-

Note: Numbers indicate the probability that the two corresponding restrictions are not statistically different.
Note: Shaded estimates indicate significance at the .10 level or better.

[24] The possibility that water-use reductions would continue to occur after restrictions were lifted was also tested in the model (i.e. that restrictions would have a lagged effect). Parameter estimates were not statistically different from zero and were not included in the final model.

Cyclical Variables

County water-use during the month of December was the base water-use for the cyclical variables. Thus the parameter estimate of .330 for JUL-DUM implies that water-use in counties, on average, increased by 33% in July compared to usage in December. The parameter estimate of -.080 JUL-CITY-DUM implies that water-use, on average, was 8% lower in cities as compared to counties during the month of July.

Monthly residential water-use followed the general pattern established in Chapter 4 for counties and cities. In both locality types, water-use was at a low point from roughly November to March and then began increasing steadily until it reached its peak in July. Also confirmed by these results was the steeper increase in summer water-use in counties relative to cities. July water-use was 8% greater in counties than in cities after adjusting for all other factors. Water-use between cities and counties did not differ significantly during the dormant season as indicated by the statistically insignificant levels on the coefficients for the CITY-DUM during these months.[25]

Climatic Variables

In almost all cases the parameter estimates for the rainfall and temperature variables coincided with their theoretical expectations. The coefficients for the rainfall were in all instances negative and for temperature were in all cases positive. Ten out of the 16 climatic parameter estimates were significant at the .01 level or greater. Only 5 parameter estimates were not significantly different from zero at the .05 level. Three of these were for the second rainfall lag.

The parameter estimates for rainfall implied that for each inch of monthly rainfall deficit (less than the long-term average during the growing season) water-use would increase approximately by .01% to 1.4%. Thus a three inch rainfall deficit would result in a 4.2% increase in water-use for the upper range, and a .03% increase for the lower range. The responsiveness of this variable was generally highest for current rainfall and progressively decreased with each of the two lags (the first summer county lag was the only exception). The responsiveness was also generally higher in counties compared to cities (the second fall lag was the only exception). These results are consistent with prior expectations.

The parameter estimates for temperature implies that for each degree above the long-term average during the growing season, water consumption would increase .2% to .7%. Thus a five degree increase from the average maximum temperature would result in 3.5% increase in water-use for the upper range, and a 1% increase for the lower range. Again, these results were generally consistent with prior expectations, the only exception being a

[25] This result does not imply that water-use was similar in counties and cities during the dormant season. This is because on average, income and household size are both larger in counties and these parameter estimates will increase water-use in counties relative to cities.

slightly higher response rate in cities during the spring/fall seasons as compared to the summer months.

The combined effects of rainfall and temperature can be substantial when evaluated during an extreme climate pattern such as the 2002 drought. Take for instance the climatic conditions during July 2002 in Richmond, which had a current rain deficit of 2.76”, a previous month deficit of 2.20”, a two-month previous deficit of .51”, and a current monthly temperature surplus of 5.25 degrees. The combined effects of this scenario would be expected to increase water-use by approximately 10% as compared to water-use during the normal climatic pattern in July.

However, one of the most noticeable changes in parameter estimates from the OLS models (Models 1A and 1B) was that all twelve parameter estimates for the rainfall variables decreased in absolute magnitude, generally by 25-75%. It appears as if the AR(1) process is capturing part of the responsiveness that rainfall otherwise had in the first set of models. This may be in part because the rainfall variables and the autoregressive process both use lags. Wooldridge (2000) warns that the autoregressive process can produce misleading results where there are lagged independent variables. Consequently, the estimates for rainfall for the second set of models may be under-representative of the true effect that rainfall has on water-use.

Parameter estimates for temperature were mixed as there were both increases and decreases compared to the OLS estimates. However, parameter estimates for temperature were generally statistically significant in the second set of models.

Demographic and Income Variables

All of the parameter estimates for the demographic and income variables conformed to theoretical expectations and were statistically significant at the .001 level. These variables are grouped into three categories: apartment variables, income, and household size.

It was expected that with single-meter apartment accounts, water-use would show the largest decrease as compared to single-family usage during the summer months and the smallest decrease during the winter months. This is because apartment water-use is expected to remain relatively stable throughout the year as compared to single-family households. Because residential water-use increases sharply during the growing season, it would be expected that the difference between residential water-use and apartment water-use would progressively increase during the summer months. This hypothesis was supported by the parameter estimates. For a locality where 10% of its users are single-meter apartments, water-use would be expected to decrease by 4.4% during the winter (APT-WINTER), 5.9% during the spring and fall months (APT-SPR/FALL), and 7.4% during the summer (APT-SUMMER) as compared to single-family usage.[26]

[26] SINGLE-APT-SUMMER compared to SINGLE-APT-SPR/FALL and SINGLE-APT-SUMMER compared to SINGLE-APT-WINTER were both statistically different at the .05 level.

For group-metered apartments the expectation was that GROUP-APT would have a positive relationship with water-use because there are multiple apartments connected to each meter. This hypothesis was also supported by the parameter estimates. For a locality where 10% of its users are group-meter apartments, water-use per account would be expected to increase by 17%.

The parameter estimates for income were statistically significant and fairly stable across the three seasons. As expected, the effect that income had on water-use was strongest during the summer and weakest during the winter. However, the magnitude of these differences was less than originally anticipated. A $10,000 increase in household income in a locality would be expected increase water-use by 4.4% during the summer, 4.3% during spring/fall, and 3.8% during the winter. These parameter estimates translate into income elasticities of .28, .27, and .24 for the three respective seasons. The estimates for income decreased 30-40% compared to the OLS models.

The parameter estimate for household size was .20, which implies that an increase in average household size from 2.0 to 3.0 persons would increase water-use by 20%. This estimate was roughly double the magnitude estimated by OLS. It was expected that the response of this variable would be less than unitary in terms of the elasticity (i.e. a 1% increase in household size would lead to less than a 1% increase in water-use). This is because, as previously noted, there are efficiencies in water-use that occur with additional family members. In the above example, a unitary response would be a 50% increase in water-use, thus the expected increase of 20% is consistent with the theoretical expectation.

Price variables

Parameter estimates for all price variables were negative and statistically significant at the .001 level. The expectation for marginal price was that it would show the strongest response during the summer and the weakest response during the winter. An increase of $1 in the marginal price of water (per 1000 gallons) was estimated to decrease residential water-use by 4.8% in the summer, 4.3% during spring/fall, and 3.0% in the winter. These estimates translate into elasticities of -.26, -.23, and -.16 respectively. The elasticities fell roughly into the lower third of the price elasticities reviewed from previous studies (See Appendix D). [27,28]

Table 6.8 – Key Elasticities

Variable	Elasticity
Income-Summer	0.28
Income-Spr/Fall	0.27
Income-Winter	0.24
MP-Summer	-0.26
MP-Spr/Fall	-0.23
MP-Winter	-0.16
DiffVar-Summer	-0.05
DiffVar-Spr/Fall	-0.06
DiffVar-Winter	-0.04

Parameter estimates for the difference variable were fairly stable throughout the year. An increase in the difference variable by $10 resulted in a decrease in

[27] Lagged prices were also tried in the model but proved unsatisfactory.
[28] MP-SUMMER compared to MP-WINTER and MP-SPRING/FALL compared to MP-WINTER were both statistically different at the .01 level.

water-use by 5% during the summer, 6% during the spring/fall, and 5% during the winter. Thus as opposed to parameter estimates for marginal price, there was no consistent seasonal trend. These parameter estimates translate into elasticities of -.05, -.06, and -.04 respectively. The absolute effects for the parameter estimates fall about in the middle of the reviewed studies that estimated this variable.

Discussion of Results for Drought Management Programs

The overall reductions in water-use ranged from 0-7% for voluntary restrictions and from 0-22% for mandatory restrictions with the 12 variable restriction model. Thus the intensity with which these programs were carried out clearly had an impact on residential water demand during the 2002 Virginia drought. Moreover, the relative magnitude of these reductions fit a pattern of increasing program effectiveness as information and enforcement ratings went up. This lends some credence against the possibility that the results were sample specific and that information and enforcement levels would not have significant effects in other localities and in other situations.

If the intensity of the restrictions had not been evaluated in the final model, as in Model 2A, then the overall findings would have been very different. It would have appeared that voluntary restrictions had resulted in no meaningful reductions in water-use. However, as seen in Model 2B, this was only true for the programs without an aggressive informational campaign. Voluntary restriction programs with the highest intensity level reduced water use by 7% on average. It would have also appeared that mandatory restrictions resulted in only slight to at best moderate reductions in water-use, as evident by the parameter estimates for self-imposed and state-imposed mandatory restrictions which showed reductions of 6% and 11% respectively. However, as seen in Model 2B, these were essentially true only for the average program. The actual effects ranged from negligible reductions to over 20% reductions in water-use depending on information and enforcement ratings.

Technically, the estimates for the marginal price parameters were “inelastic” by economic standards. However, this does not mean that the demand for water is not responsive to price. Estimates from this study show this is far from the case. A $1 increase in the marginal price of water per 1000 gallons is expected to reduce water-use during the summer by 4.8%. With a $5 increase, such as was used in emergency situations by two localities during the 2002 drought in Virginia, the expected reduction in water-use is almost 25%. This reduction is slightly higher than the estimate for the highest intensity level implemented under mandatory restrictions.

Water-use restrictions can also be combined with price increases as was done in Albemarle County and Charlottesville during the late stages of the 2002 drought. In both localities the marginal price of water increased a number of times in the fall from its base summer price. The estimated change in water-use is shown in Table 6.9 along with the estimated change in water-use due to voluntary and mandatory restrictions that were in place at the time. The estimated combined change due to the price increases and restrictions is also shown in the last column.[29] In June, under voluntary restrictions and with no price increase, the total reduction in water-use is estimated to be 6.8%. This is in contrast to the months of September through November when the county had implemented price increases and switched to mandatory restrictions. At these times, the estimated reductions in water-use were much more substantial, ranging from 28% in September to 36% in November. In November, the increase in marginal price by itself is estimated to reduce water-use by almost 25%.

Table 6.9 – Estimated Change in Albemarle County Water-Use [a]

	Marginal Price	Change in Marginal Price	Est. Change in Water-Use due to Price [b] (%)	Est. Change in Water-Use due to Restrictions [c] (%)	Est. Combined Change in Water-Use [d] (%)
June (Base)	$5.26	-	-	-6.8%	-6.8%
September	$7.04	$1.78	-7.6%	-22.1%	-28.0%
October	$9.02	$3.76	-16.0%	-15.4%	-28.9%
November	$11.04	$5.78	-24.6%	-15.4%	-36.2%

Note [a]: Charlottesville had similar price increases and restrictions in effect.
Note [b]: Using parameter est. of -.043 for marg. price; Change relative to marg. price of $5.26.
Note [c]: Change relative to no water-use restrictions in place.
Note [d]: Previous two columns are not directly additive.

Thus it is quite evident from this analysis that mandatory water-use restrictions implemented in an aggressive manner combined with a moderate price increase can have a substantial impact in reducing residential water consumption.

Discussion of Results for other Variables

There was no strong expectation for the magnitude of the difference variable. However, it was believed that if the relative magnitude of this variable was similar to the parameter estimates (but opposite in sign) for the income variable, then this would lend support to the belief that consumers are responding to a pure marginal price framework. Alternatively, if the relative magnitude of the difference variable was greater compared to that of the income variables, then this would lend support to the belief that consumers are also responding to fixed fees and/or previous block rates in their water bills.

In comparing estimates for the difference variable to those for income (see Table 6.5), it does initially appear that the relative parameter estimates for income and the difference variable are close indeed. However, the income variable was measured in $1000 increments, while the difference variable was measure in $1 increments. Hence the magnitude of the difference variable is about 1000 times as strong as the magnitude of

[29] The estimated changes in water-use due to price increases and restrictions are not directly additive. For example, if the estimated change due to price and restrictions were both 50%, the combined change would be 75% rather than 100%.

the income variable.[30] This relative difference in magnitude was almost identical to that found by Renwick and Green (2000) and about fivefold less than that found by Billings and Day (1989). These were the only two panel-level studies reviewed where this ratio could be computed.

Thus from this data, it appears that the difference variable is measuring something in addition to a pure income effect. This finding lends support to the belief that consumers are responding to fixed fees and/or previous block rates in the pricing schedules, which runs counter to neoclassical consumer theory. As corroborating evidence for this finding, consider the effect that increasing the fixed fee by $30 per month would have with estimates from this study. Using the parameter estimate for the summer months, an increase in the fixed fee by $30 would be expected to reduce water-use by about 15%. Increasing the marginal price by $5 per 1000 gallons would also result in about a $30 increase in the total monthly bill based on the average summer usage in this study. This increase in the marginal price would be expected to decrease water-use by 25%. Thus although the expected responsiveness of the fixed fee is not as great as the marginal price (15% vs. 25% reductions in water-use), it is nonetheless much more responsive than economic theory would suggest.[31] Alternatively, if consumers were responding to a pure average price approach, we would expect the $30 increase in the fixed fee and total marginal cost to have equal effects.

An important question posed in previous chapters was whether the estimates for the income parameters are measuring more than the “income effect” conceptualized in economic theory. Although a definitive statistical answer cannot be made on this issue, two observations from this study provide suggestive evidence against the proposition that these parameters are measuring a pure income effect. First, parameter estimates for income differed by season, with the highest estimates being in the summer and the lowest estimates being in the winter. This suggests that the income variable is also acting as a proxy for a variable whose effect on water-use changes by the season. Such a variable could be lot size, which as previously explained, could not be controlled for in this study. Second, if the variable for household size is removed from the model, the parameter estimates for income increase 40-50%. This provides further evidence that the income variables are acting as proxies for variables that are not controlled for in the model. Thus overall, it seems highly unlikely that the income parameters are measuring a pure income effect.

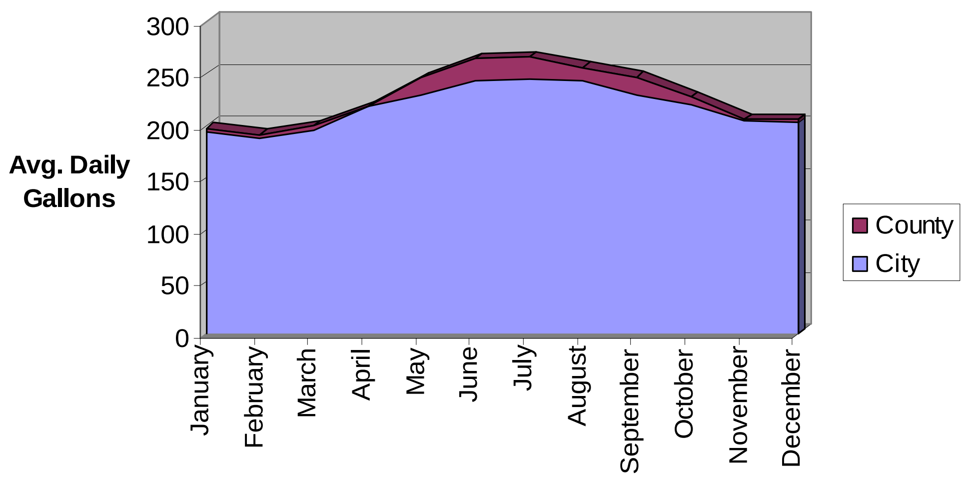
Water-use patterns between counties and cities matched more closely after controlling for all other variables in the final regression (Figure 6.1) compared to using the means in the original data (not controlling for other factors as in Figure 4.1). After controlling for these other variables, especially apartments and income, the dormant-season water-use pattern is almost identical in both counties and cities. However, there still is a small discrepancy during the growing season which peaks in the summer (although the

[30] Income and difference variable parameters were statistically different at the .001 level.

[31] The theoretical effect for a $30 increase in fixed fees is expected to be a .013% decrease in water-use using the income parameter estimate, as compared to the 15% estimated effect (951 X difference in magnitude).

magnitude is reduced considerably). If all important variables were controlled for that influence water-use, then these two water-use patterns should be identical. Hence, it appears that there is an important variable that is still not controlled for that would increase water-use during the summer, and that is more prominent in counties as opposed to cities. Again, lot size could be this missing variable, as the effect that lot size has on water-use should only be important during the growing season, and the average lot size in counties would clearly be expected to be greater than in cities.

Figure 6.1 - Cyclical Water-Use Controlling Other Variables



Note: Base water-use of 200 ADG used for comparative purposes.

An observation made over the course of this study is that the water demand literature seems to have ignored the possible effects of apartment accounts being mixed with residential data. Most of these previous studies have made cursory references to having "residential" data, and have given the impression that this data is composed of pure single-family user types. However, based on the data from this study, this possibility seems to be rather remote. Only 9 localities out of the 21 total had pure single-family residential data, and even with these localities it was not always readily apparent which category apartments were included in. It was only after repeated follow-up contacts that apartment data could be classified correctly.

As previously discussed from a theoretical perspective and supported by the parameter estimates in this study, having apartment data included in residential data will shift the consumption patterns in the residential data. Single-metered apartments will cause downward shifts in consumption patterns, while group-metered apartments will cause upward shifts in consumption patterns.

An interesting comparison is provided in Table 6.10 that shows the average water-use for each locality (using raw data) and then adjusts this usage based on the apartment parameter estimates from this study. Notice that many of the localities that had outlier water-use patterns in the raw data now conform better to the average usage of their locality-types. Take for instance Newport News that had an unadjusted average usage of 259 gallons per day per connection. After accounting for apartments in the data, the average usage drops to 184 gallons per day which is now close to the 176 gallons average across all cities. Not having accounted for the apartment data in the analysis would have biased the results.

Table 6.10 – Water-Use Patterns Adjusted for Apartment Inclusion

Locality	% Apartments in Locality (Census)[a]	% of Total Apartments: Group Meter in Residential Data (Estimated)[b]	% of Total Apartments: Single Meter in Residential Data (Estimated)[b]	ADG Avg.	ADG Avg. Adjusted [c]
Counties:					
Albemarle County	18.8%	-	-	182	182
Augusta County	4.1%	10%	90%	172	174
Chesterfield County	9.3%	-	-	220	220
James City County	11.9%	80%	20%	254	222
Prince William County	14.9%	-	5%	212	213
Spotsylvania County	5.5%	-	-	193	193
Stafford County	7.2%	-	-	215	215
York County	8.9%	80%	20%	238	215
Rapidan S.A.	3.1%	-	-	130	130
County Average				*202*	*196*
Cities:					
Bristol	16.5%	-	85%	143	155
Charlottesville	30.5%	-	-	157	157
Colonial Heights	13.7%	90%	10%	188	157
Danville	18.1%	-	15%	166	169
Hampton	23.0%	80%	20%	214	167
Harrisonburg	42.1%	-	60%	146	169
Manassas	17.3%	-	-	216	216
Newport News	33.7%	80%	20%	259	184
Poquoson	5.9%	80%	20%	212	198
Richmond	34.2%	-	23%	199	208
Salem	18.3%	-	-	178	178
Suffolk	8.0%	-	-	151	151
City Average				*186*	*176*

Note [a]: Constructed from census data where structures with three or more units were considered as apartments.

Note [b]: Estimated by localities (i.e. 10% means that 10% of overall apartments are contained in the respective category.

Note [c]: This adjustment used the -.548 parameter estimate for APT-SPR/FALL and 1.659 parameter estimate for GROUP-APT.

Chapter 7: Conclusions, Policy Implications, and Future Research

Primary Conclusions

This study found statistical evidence that the intensity in which drought management programs are implemented has a significant effect on residential water demand. When using the conventional approach to estimate the effect of drought management programs where intensity is not considered, voluntary restrictions showed no noticeable reductions in water-use, while mandatory restrictions showed a 6% reduction for self-imposed restrictions and an 11% reduction under the state-wide restrictions of Executive Order 33. However, the intensity in which voluntary and mandatory restrictions were implemented had a significant effect on the water-use reductions for these programs when evaluated in the non-conventional approach. After controlling for program intensity (information and enforcement efforts) water-use reductions ranged from 0-7% for voluntary restrictions, and 0-22% for mandatory restrictions. These reductions followed a pattern of increasing program effectiveness as levels of information and enforcement increased for all significant parameter estimates. In localities with only moderate overall mandatory restriction intensities (Med-Info/Low-Enforce, or Med-Info/Med-Enforce), these reductions were relatively small in magnitude (6-9%). Only with the highest intensity levels (Med-Info/High-Enforce, High-Info/Med-Enforce, or High-Info/High Enforce) did the water savings approach impressive levels (15-22%).

The results also indicate that price can be used effectively as a drought management tool, with potential water savings in excess of the savings achieved by the most aggressive mandatory restriction programs. A $5 increase in the price per 1000 gallons during the summer months would be expected to lead to a 24% decrease in residential water-use. Price increases of this magnitude were used by two localities evaluated in this study during the 2002 drought. Thus the most successful programs for reducing water-use would combine mandatory restrictions (implemented with high intensity) with a price increase.

Secondary Conclusions

An important secondary conclusion was the finding that consumers were responding to a mix of pure marginal price and fixed fees/previous block rates. This finding runs counter to neoclassical consumer theory which suggests that fixed fees and previous block rates should have no bearing on the consumption decision. The overall magnitude of the response for fixed fees/previous block rates was roughly half that estimated for the marginal price parameters on a total dollar basis. This finding implies that many consumers have less than perfect information about the details of the billing structure, and should not be surprising given that water bills comprise a relatively small component of total disposable income.

Another finding of this study was that income parameter estimates seemed to be measuring more than a pure income effect as conceptualized by consumer theory. This possibility is especially important with aggregate-level studies that cannot control for lot size and/or other important demographic variables that are highly correlated with income. In these cases, the parameter estimates for income may be picking up part of the response of these variables, and as a consequence be overstated.

A final conclusion is that apartment accounts were included in approximately 60% of the residential water-use data used in this study, and that their inclusion had a significant impact on water-use in these localities. The inclusion of single-metered accounts reduced average water-use while the inclusion of group-metered accounts increased average water-use. Not accounting for apartments in residential data could lead to substantial bias in the regression estimates. However, this possibility has generally been ignored in the water demand literature.

Policy Implications

Virginia's draft Water Supply Planning regulation sets guidelines for when voluntary and mandatory water-use restrictions should be triggered (9 VAC 25-780-130), and includes estimates for their expected effectiveness in reducing water demand. The Virginia regulations state that 5-10% reductions in water-use can be expected for voluntary restrictions programs and 10-15% reductions for mandatory restrictions. These estimates are within the range of the reductions estimated in this study, but were only achieved with significant efforts on the part of local water suppliers to disseminate information and to enforce program provisions. For the most common program intensities evaluated in this study, however, these estimates likely overstate the actual water savings that occurred during the 2002 drought.

Possibly a greater problem, however, is that the Water Supply Planning regulation does not provide guidelines or suggestions on how to effectively implement these programs. Nor does the plan provide an accurate representation of the wide range of expected reductions that are possible given the various levels of implementation intensity. Simply enacting water-use restrictions without making a serious effort to inform the public about their importance or to enforce provisions will likely result in only negligible to at best moderate reductions in water-use. Mandatory restrictions are required to obtain substantial reductions in water-use (15% and greater) and need to be implemented with a high level of either information or enforcement, and at least a moderate level of the other factor. The Drought Response Plan should stress that water-savings will be highly dependent on the intensity in which these programs are implemented, and provide examples of programs that were successful in information and enforcement efforts (e.g. Albemarle County, Charlottesville, and Chesterfield County).

A policy implication applicable at both the state and local-level is that even with an aggressive information program, voluntary restrictions were unable to achieve substantial reductions in residential water-use. In this analysis, the most aggressive voluntary programs reduced water-use by only 7% on average. As opposed to mandatory restrictions which were mostly enacted in the fall, the majority of voluntary restrictions (especially those with the highest information rating) were enacted during the summer months, at the height of the drought. During the summer when discretionary water-use is at its highest, the potential water savings should also be at a maximum. Thus there is no obvious reason to expect improved estimates had there been a wider range of voluntary program experiences.

Policy implications also emerged from this analysis concerning the use of price as a drought management tool. Although price was only used by two localities as a drought management tool in 2002, it was clear that the expected water-use reductions due to price increases can be substantial. Based on the estimates for the overall price data in this analysis, a modest price increase of $3 per 1000 gallons would result in a 13% reduction in water-use during the fall months. This magnitude of reduction was greater than all but the highest intensity levels for mandatory restrictions during this same seasonal period. An important advantage in using price as a drought management tool is that the infrastructure for enforcing this program is already in place in every locality through the billing mechanism. Extra staff time is not needed to monitor compliance.

There are equity, political, and legal issues involved with raising the price of water. However, a pricing program that is potentially attractive from both an equity and politically standpoint is a "rationing" program that uses block rates. The first block could have only a modest price increase from the current schedule, but the second block could have a substantial increase for water-use above the base level (absolute level or a percentage of average winter use).[32] By basing the block-level on average winter usage, this emergency pricing program would place less of the overall burden on those households that are using water for mostly indoor-uses, and place more of the burden on households that use large amounts of outdoor water-use during the summer months. The localities of Newport News, Poquoson, Hampton, and York County in the Tidewater region initiated such a program at the very end of the 2002 drought, but it was rescinded after heavy fall rains came just as the program got under way.

Virginia's Drought Response Plan should discuss how water pricing programs can be used as an effective drought management tool. The plan should stress that in order to achieve truly substantial levels of residential water-use reductions, a combination of mandatory restrictions and price increases will be needed.

Caveats and Limitations

One limitation of this analysis is the short duration that most of the water-use restrictions were in place. It is worth mentioning again that mandatory restrictions covered mostly outdoor water-uses such as watering lawns and gardens, filling swimming pools, and washing cars. Consequently, it would be expected that these restrictions would have their maximum effect during the summer months, especially during dry, hot conditions. However, the majority of observations for mandatory restrictions in this analysis occurred

[32] The base level of this program would be the "rationed" amount of water allowed. The second block rate for water-use over this base amount is essentially the penalty for exceeding the rationed amount.

during the fall months when the potential to reduce outdoor water-use would be comparatively low. It would seem reasonable that during the summer these parameter estimates would be higher on average. Reductions of 30% may be reasonable estimates for the highest intensity levels of mandatory restrictions implemented during the summer months. Ideally, with a wide range of restriction experiences that covered a period of years rather than months, the estimates for restrictions would be used in conjunction with seasonal dummy variables (summer, spring/fall, and winter). This was, unfortunately, not possible with the data in this study.

Moreover, the months of October and November actually had above-average rainfall in most of the localities during 2002. This is why the executive order was lifted in mid-November. Thus even for fall conditions, the parameter estimates for mandatory restrictions are probably not at levels that would be expected had the drought continued into the winter months.

Another consequence of the short duration that restrictions were in place is that the citizen response to the restrictions may change over time given a constant intensity level. For example, it is possible that public support for the restrictions could wane over time, especially where enforcement efforts are minimal. Even where enforcement is moderate, residents may learn how to avoid detection (e.g. irrigate at night when detection is difficult). However, these and other possible effects could not be tested with the restriction data used in this analysis.

A second limitation of this study concerns the conversion of the billing data to estimated consumption periods. Even though considerable effort was expended in adjusting the billing data to match consumption periods, the process was not perfect. The lags between billing and consumption were average estimates for each locality. However, it was stressed by some of the localities that there is considerable variance in these lags from month to month. For example, the timing of the billing process would be disrupted when a meter reader went on vacation. Although the process used in analysis is arguably a considerable improvement over ignoring the problem, there will still be a certain amount of noise remaining in the data from imperfect adjustments.

A third limitation of this study comes from water service authority boundaries not being precisely matched by municipal boundaries. The consequences of this limitation are most pronounced with the use of demographic data obtained through the Census. The census municipal figures for income, household size, and apartments will not match the true figure for the service boundary. The larger the discrepancy between the service and municipal boundaries, the larger will be the potential for biased demographic variables.

A fourth limitation of this study deals with the climate data (rainfall and temperature). Climate data was obtained from climate stations where generally one to two stations were used per locality (see Appendix C). However, climatic conditions, especially rainfall, can vary substantially within a geographical size such as a county. Thus the rainfall data obtained for this analysis will vary somewhat from the true average for the locality (as well as the service area).

A fifth limitation of this study concerns the application of this analysis to other geographical locations. Although the 21 localities used in this analysis represent a broad range of the major municipal water suppliers in Virginia and possibly the Mid-Atlantic Region, estimates obtained from this study should be used with care in other geographical regions. For instance, it was noted in Chapter 1 that summer water-use is much higher in the arid southwest states, and consequently, parameter estimates for drought management programs would be expected to be somewhat more responsive due to a larger discretionary component of total water-use. However, there is no obvious reason to suspect that program intensity would not have a significant impact on water-use reductions in other regions.

A final limitation of this study is that the effects of average lot size were not directly controlled for in the model. Consequently, the effect that lot size has on water-use may be partially incorporated into the other demographic variables (income and household size) as well as the seasonal dummy variables. As a result, the parameter estimates for income and household size may be biased.

Directions for Future Research

Very few of the localities had aggressive enforcement efforts, even though as this study showed, there are clear benefits from doing so. One potential reason for the low enforcement efforts is that it may be cost prohibitive for some localities to set up intensive enforcement programs. Violations need to be detected and citations issued in order to have an effective program. An interesting area for future research would be to evaluate the cost of implementing various levels of both enforcement and information efforts. These costs could then be compared to the benefits derived (i.e. water savings) from the programs. It is possible that the optimal intensity levels (from the localities perspective) may not result in the highest water savings. It is also possible that the optimal combination of information and enforcement levels may be different in two localities. For example, if one locality already has personnel that can be used to detect violations and issue tickets then they may want to place their emphasis on enforcement. Conversely, a locality that does not have extra staff time for enforcement may place their emphasis on information dissemination.

Only two attributes of program intensity (information and enforcement) were evaluated for voluntary and mandatory restrictions in this study. As discussed in Chapter 2, program content (the types of activities restricted by voluntary or mandatory programs) was also expected to influence the potential water savings. However, there was not enough variance in the data for this variable to be evaluated in this study. Future research could potentially estimate the effect that this variable has on water-use. It may also be possible to evaluate more specific indicators for enforcement efforts such as total fines issued ($) or total hours devoted to patrolling neighborhoods, as well as more specific indicators for information efforts such as number of newspaper articles or number of radio advertisements devoted to promoting water-use restrictions.

Only residential water-use was evaluated in this analysis. However, industrial, commercial, and government accounts also have important impacts on total municipal water-use. Future research aimed at evaluating the effects that voluntary and mandatory restrictions have on these user groups would be an important contribution to this research area.

It would be informative to evaluate the intensity of voluntary and mandatory restrictions in a region with much different water-use dynamics than Virginia such as the southwest U.S. As previously indicated, it would be expected that the resulting water-use savings would be higher in this region for the same intensity level compared to Virginia, especially for the highest intensity levels.

As pointed out in the previous section, most of the restrictions were in place for a relatively short period, and as consequence, there were two hypotheses that could not be formally tested. First, it is likely that the impact that mandatory restrictions have would be dependent on the season. Parameter estimates would be expected to be highest during the summer months and lowest during the winter months. However, mandatory restrictions were predominately in place during the fall months in this study and thus this possible effect could not be tested. Second, it is also possible that the impact that restrictions have might change over a long period of time. Analysis into both of these areas could prove useful to practitioners.

Although the influence that price has on water-use has been estimated extensively in the literature, there are no know instances where this effect has been estimated separately by "normal" periods and "drought" periods. In other words, it does not appear that price has ever been evaluated specifically as a drought management tool. It would seem reasonable that the response that price has during a drought would be higher than during other periods, especially if used concurrently with information campaigns.[33] Future research testing this possibility would be extremely valuable for drought management planning.

[33] There were too few observations in this study to separately control for price during the 2002 drought.

References:

Bachrach, Miguel, and William Vaughan 1994. "Household Water Demand Estimation". *Inter-American Development Bank*, Working Paper ENP106: March 1994.

Baumann, Duane, John Boland, and W. Michael Hanemann. 1998. Urban Water Demand Management and Planning. McGraw-Hill, Inc.

Becker, Gary. 1968. Crime and Punishment: An Economic Approach. *Journal of Political Economy* 76(2):169-217.

Billings, R. Bruce, and W. Mark Day 1989. "Demand Management Factors in Residential Water Use: The Southern Arizona Experience". *Journal of American Water Works Association* 81(3):58-64.

De Loe, Rob, Liana Moraru, Reid Kreutzwiser, Karl Schaefer, and Brian Mills. 2001. "Demand Side Management of Water in Ontario Municipalities: Status, Progress, and Opportunities". *Journal of the American Water Resources Association* 37(1): 57-72.

Espey, M, J. Espey, and W.D. Shaw. 1997. "Price Elasticity of Residential Demand for Water: A Meta-Analysis". *Water Resources Research* 33(6): 1369-1374.

Hoglund, Lena 1999. "Household Demand for Water in Sweden with Implications of a Potential Tax on Water Use". *Water Resources Research* 35(12): 3853-3863.

Griffin, Ronald, and Chan Chang 1990. "Pretest Analyses of Water Demand in Thirty Communities". *Water Resources Research* 26(10): 2251-2255.

Hewitt, Julie, and W. Michael Hanemann 1995. "A Discrete/Continuous Choice Approach to Residential Water Demand under Block Rate Pricing". *Land Economics* 71(2): 173-192.

Howe, Charles 1982. "The Impact of Price on Residential Water Demand: Some New Insights". *Water Resources Research* 18(4): 713-716.

Jones, C.Vaughan, and John Morris. 1984. "Instrumental Price Estimates and Residential Water Demand". *Water Resources Research* 20(2): 197-202.

Lyman, R. Ashley 1992. "Peak and Off-Peak Residential Water Demand". *Water Resources Research* 28(9): 2159-2167.

Martin, Randolph, and Ronald Wilder 1992. "Residential Demand for Water and the Pricing of Municipal Water Services". *Public Finance Quarterly* 20(1): 93-102.

Martinez-Espineira, Roberto 2002. "Residential Water Demand in the Northwest of Spain". *Environmental and Resource Economics* 21: 161–187.

Maddock, Thomas and Walter Hines 1995. "Meeting Future Public Water Supply Needs: A Southwest Perspective". *Water Resources Bulletin* 31(2): 317-329.

Michelsen, Ari, J. Thomas McGuckin, and Donna Stumpf 1999. "Nonprice Water Conservation Programs as a Demand Management Tool". *Journal of the American Water Resources Association* 35 (3): 593-602.

Moncur, James 1987. "Urban Water Pricing and Drought Management". *Water Resources Research* 23(3): 393-398.

National Agricultural Decision Support System (University of Nebraska): http://nadss.unl.edu/index.jsp

Nauges, Celine and Alban Thomas 2000. "Privately Operated Water Utilities, Municipal Price Negotiation, and Estimation of Residential Water Demand: The Case of France". *Land Economics* 76(1): 68-85

Nieswiadomy, Michael, and David Molina 1989. "Comparing Residential Water Demand Estimates under Decreasing and Increasing Rates Using Household Data". *Land Economics* 65(3): 280-289.

Nieswiadomy, Michael 1992. "Estimating Urban Residential Water Demand: Effects of Price Structure, Conservation, and Education". *Water Resources Research* 28(3): 609-615.

Opaluch, James 1982. "Urban Residential Demand for Water in the United States: Further Discussion". *Land Economics* 58(2): 225-227.

Pint, Ellen 1999. "Household Responses to Increased Water Rates During the California Drought". *Land Economics* 75(2):246-266.

Renwick, Mary, and Sandra Archibald 1998. "Demand Side Management Policies for Residential Water Use: Who Bears the Conservation Burden". *Land Economics* 74(3): 343-359.

Renwick, Mary, and Richard Green 2000. "Do Residential Water Demand Side Management Policies Measure Up? An Analysis of Eight California Water Agencies". *Journal of Environmental Economics and Management* 40: 37-55.

Shabman, Leonard and William Cox 2004. "Urban Water Supply and the Environment: Extending the Reach of Section 404 of the Clean Water Act". *Virginia Journal of Environmental Law,* Spring.

Taylor, R., John McKean, Robert Young 2004. "Alternative Price Specifications for Estimating Residential Water Demand with Fixed Fees". *Land Economics* 80(3): 463-475.

Virginia Department of Environmental Quality 2002, *Drought Management Report*, June and August Reports.

Virginia State Climatology Office, Historical Climate Summaries for Virginia: http://www.sercc.com/climateinfo/historical/historical_va.html

Virginia State Climatology Office (rainfall and temperature data): http://climate.virginia.edu/online_data.htm

Virginia, State of, Drought Response Plan 2004. Chapter 780 - Local and Regional Water Supply Planning (9 VAC 25-780).

Wang, Young-Doo, Jae-Shuck Song, John Byrne, and Sun-Jin Yun 1999. "Evaluating the Persistence of Residential Water Conservation: A 1992-1997 Panel Study of a Water Utility Program in Delaware". *Journal of the American Water Resources Association* 35:5 (1269-1276).

Wooldridge, Jeffrey 2000. Introductory Econometrics: A Modern Approach; South-Western College Publishing

Appendix A – Survey Form:

Water-Use Restrictions

1) Please indicate water-use restrictions that were in place in 2002 including both voluntary (no enforcement) and mandatory restrictions.
Please include the approximate date that restrictions went into place and/or were lifted.

The following activities were restricted by Executive Order 33 (In effect from 9/1/02 to 11/15/04): watering of lawns, washing vehicles, filling swimming pools, and irrigation of golf courses (with some exceptions).

2) Were any additional water use restrictions put into place in your locality at the time of EO33? *Yes or No*

If so please indicate the restrictions ______________________________

If voluntary restriction were in place include this question:
3) What restrictions were covered (or suggested) by your 2002 voluntary restrictions (implemented prior to EO33)? (Check all that apply)

_____ Lawn watering
_____ Vehicle washing
_____ Swimming pool filling
_____ Golf course watering
_____ Suggested general water conservation
_____ Other (please describe) ______________________________

If mandatory restriction in place prior to EO33, include the additional question:
4) What water use restrictions were covered by the mandatory restrictions that were in place prior to Executive Order 33? (Check all that apply)

_____ Lawn watering: Generally all forms of lawn watering restricted
_____ Lawn watering: Some forms of lawn watering restricted
_____ Vehicle washing restrictions
_____ Swimming pool filling restrictions
_____ Golf courses watering restrictions
_____ Water rationing (please describe) ________________________________
_____ Other (please describe) ____

5) What was the degree of severity for your locality's water supply during this time period (please describe details below if necessary)?

1 = water supply was at or near full capacity
2 = water supply was at less than full capacity but was not considered a problem
3 = water supply was at less than full capacity and was considered a problem
4 = water supply was near depletion and considered as an emergency situation

5) Did your locality ever impose other voluntary or mandatory water use restrictions between … and …? *Yes or No*

If yes, please indicate the dates and type of restriction ______________________

6) Have you ever used a rationing program during times of water scarcity? *Yes or No*

If yes, please describe the program and dates it was in effect.

7) Was any other major water conservation effort conducted between … and … aimed at reducing water use (e.g. instituting a rebate programs on retrofitting with low flow plumbing fixtures (please indicate approximate number of retrofits and type); major outreach effort to work with large water users to reduce demand; new position devoted to water conservation efforts; or general education campaign on water conservation)?

Yes or No

If yes, please describe the program and dates it was in effect.

____

____

____

____

____

____

Enforcement Efforts

8) Was extra staff time devoted to enforcement with mandatory restrictions? *Y or N*

9) Executive Order 33 did not formally set penalties for non-compliance but gave authorization for localities to do so. Did your locality establish fines/penalties for non-compliance? (Circle)

Yes *or* *No*

If known, please indicate level(s) of fines ___________________________________

10) How often were warnings issued? (Circle best answer)

1 = few to no warnings (less than 10/month)
2 = moderate number of warnings
3 = high number of warnings (more than 100/month)

11) How often were citations issued? (Circle best answer)

1 = few to no citations (less than 5/month)
2 = moderate number of citations
3 = high number of citations (more than 50/month)

12) Overall, how would you rate the enforcement of the mandatory restrictions? (Circle best answer)

1 = Technically required but little to no active enforcement
2 = Moderate level of enforcement
3 = High level of enforcement

Information and Promotional Efforts

Information/promotion programs are activities and efforts that helped educate households about water-use restrictions and water-use reduction efforts.

13) Please check ways that information/promotion programs were disseminated

_____ Included in water bill
_____ Separate mailing
_____ Local newspaper notices/articles
_____ Radio/TV coverage
_____ Other (please explain) _______________________________________

14) Please indicate the situation that best describes your locality's efforts *during* the enactment of Executive Order 33 (Sept. 2002 to Nov. 2002):

1 = little to no information/promotion; little to no news articles, etc.
2 = Moderate level of information/promotion and/or news articles, etc.
3 = High level of information/promotion and/or news articles, etc.

15) Please indicate the situation that best describes your locality's efforts *prior* to the enactment of Executive Order 33:

1 = little to no information/promotion; little to no news articles, etc.
2 = Moderate level of information/promotion and/or news articles, etc.
3 = High level of information/promotion and/or news articles, etc.

Water and Sewer Pricing

We would like to have the complete pricing structure for water and sewer *(… to ….)*. Would you please provide information on the rate structures for (please include dates that prices were in effect):

Residential users (… to ….)

Commercial users (… to ….)

Is there an additional account charge (i.e. flat fee regardless of usage)? *Yes or No*

If yes, please indicate the fee(s) amount & include dates that fee(s) were in place.

Do these fixed fees apply to residential water users, commercial users, or all users?

Do you or have you ever used block rate pricing between (… to ….)? *Yes or No*

If yes, please indicate how this structure works and the block prices.

Do you levy (or have ever levied) an additional charge for water use during periods of high water use (e.g. the summer)? (Circle best answer) *Yes or No*

Is the sewer bill linked to water usage? *Yes or No*

If yes, please indicate how the sewer bill is linked to water usage.

Appendix B – Post Regression Tests:

Post Regression Test for Joint Mandatory Restriction Variables Significance								
	Mand-Info1-Enf1	Mand-Info1-Enf2	Mand-Info2-Enf1	Mand-Info2-Enf2	Mand-Info2-Enf3	Mand-Info3-Enf1	Mand-Info3-Enf2	Mand-Info3-Enf3
Mand-Info1-Enf1	-	*0.82*	*0.77*	*0.42*	*0.02*	*0.16*	*0.03*	*0.00*
Mand-Info1-Enf2		-	*0.61*	*0.26*	*0.01*	*0.08*	*0.01*	*0.00*
Mand-Info2-Enf1			-	*0.35*	*0.01*	*0.13*	*0.01*	*0.00*
Mand-Info2-Enf2				-	*0.03*	*0.37*	*0.03*	*0.00*
Mand-Info2-Enf3					-	*0.15*	*0.40*	*0.74*
Mand-Info3-Enf1						-	*0.17*	*0.02*
Mand-Info3-Enf2							-	*0.08*
Mand-Info3-Enf3								-

Note: Numbers indicate the probability that the two corresponding restriction estimates are not statistically different using Chi Square test.
Note: Shaded estimates indicate significance at the .10 level or greater.

Post Regression Test for Joint Mandatory Restriction Variables Significance			
	Voluntary	Mandatory-Self	Mandatory-EO33
Voluntary	-	*0.04*	*0.00*
Mandatory-Self		-	*0.08*
Mandatory-EO33			-

Note: Numbers indicate the probability that the two corresponding restriction estimates are not statistically different using Chi Square test.
Note: Shaded estimates indicate significance at the .10 level or greater.

Post Regression Test for Joint Marginal Price Variables by Seasonal Significance			
	MP-Summer	MP-Spring/Fall	MP-Winter
MP-Summer	-	*0.27*	*0.00*
MP-Spring/Fall		-	*0.00*
MP-Winter			-
Note: Numbers indicate the probability that the two corresponding price estimates are not statistically different using Chi Square test. Note: Shaded estimates indicate significance at the .10 level or greater.			

Post Regression Test for Joint Difference Variables by Seasonal Significance			
	DiffVar-Summer	DiffVar-Spring/Fall	DiffVar-Winter
DiffVar-Summer	-	*0.11*	*0.89*
DiffVar-Spring/Fall		-	*0.20*
DiffVar-Winter			-
Note: Numbers indicate the probability that the two corresponding price estimates are not statistically different using Chi Square test. Note: Shaded estimates indicate significance at the .10 level or greater.			

Post Regression Test for Joint Income Variables by Seasonal Significance			
	Income-Summer	Income-Spr/Fall	Income-Winter
Income-Summer	-	*0.83*	*0.35*
Income-Spr/Fall		-	*0.30*
Income-Winter			-
Note: Numbers indicate the probability that the two corresponding income estimates are not statistically different using Chi Square test. Note: Shaded estimates indicate significance at the .10 level or greater.			

Post Regression Test for Joint Apartment Variables by Seasonal Significance			
	Single-Apt-Summer	Single-Apt-Spr/Fall	Single-Apt-Winter
Single-Apt-Summer	-	*0.05*	*0.02*
Single-Apt-Spr/Fall		-	*0.24*
Single-Apt-Winter			-

Note: Numbers indicate the probability that the two corresponding apartment estimates are not statistically different using Chi Square test.
Note: Shaded estimates indicate significance at the .10 level or greater.

Appendix C – Weather Stations:

Weather Stations	
Locality	Weather Station(s)
Albemarle County	Charlottesville 2W
Augusta County	Staunton Sewage Plant
Bristol	Abingdon 3S
Charlottesville	Charlottesville 2W
Chesterfield County	Richmond WSO Airport and Hopewell
Colonial Heights	Hopewell
Danville	Danville
Hampton	Langley Air Force Base
Harrisonburg	Dale Enterprise
James City County	Williamsburg 2N
Manassas	Washington WB Chantilly
Newport News	Langley Air Force Base and Williamsport
Poquoson	Langley Air Force Base
Prince William County	Washington WB Chantilly
Rapidan	Piedmont Research Center
Richmond	Richmond WSO Airport
Salem	Roanoke WSO Airport
Spotsylvania County	Corbin
Stafford County	Corbin
Suffolk	Suffolk Lake Kilby
Washington County	Abingdon 3S
York County	Langley Air Force Base

Appendix D – Price and Income Elasticities from Selected Studies:

Price and Income Elasticities from Selected Studies							
Author	Year	Data Level	Time Unit	Price Elasticity	Income Elasticity	Water Use Restrictions	Region
Jones, C.Vaughan, and John Morris.	1984	Household	yearly	-.14 to -.44	.40 to .55	no	Colorado
Renwick, Mary, and Sandra Archibald	1998	Household	monthly	-.33	0.36	yes	California
Nieswiadomy, Michael, and David Molina	1989	Household	monthly	-.36 to -.86	.10 to .20	no	Texas
Hewitt, Julie, and Michael Hanemann	1995	Household	monthly	-1.57 to -1.63	.15 to .16	no	Texas
Lyman, R. Ashley	1992	Household	bi-monthly	-.43 to -1.38	-	no	Idaho
Moncur, James	1987	Household	bi-monthly	-.03 to -.68	.04 to .08	yes	Hawaii
Martin, Randolph, and Ronald Wilder	1992	Household	monthly	-.32 to -.70	.04 to .27	no	South Carolina
Wang et al	1999	Household	yearly	-0.53	-	yes	Delaware
Pint, Ellen	1999	Household	bi-monthly	-.04 to -.1.24	-	no	California
Howe, Charles	1982	Municipal	N/A	-.06 to -.57	-	no	East/West U.S.
Renwick, Mary, and Richard Green	2000	Municipal	monthly	-.16 to -.20	0.25	yes	California
Nieswiadomy, Michael	1992	Municipal	yearly	-.11 to -.60	.28 to .44	yes	U.S.
Hansen, Lars Garn	1996	Municipal	yearly	-.00 to -.10	-.31 to .10	no	Denmark
Martinez-Espineira, Roberto, and Celine Nauges	2001	Municipal	quarterly	-.21 to -.84	-	no	Spain
Martinez-Espineira, Roberto	2002	Municipal	monthly	-.12 to -.42	-	no	Spain
Michelsen et al	1999	Municipal	monthly	-.23	-.90	yes	Western U.S.
Billings, R. Bruce, and W. Mark Day	1989	Municipal	2X / year	-.52 to -.70	.31 to .36	yes	Arizona
Griffin, Ronald and Chan Chang	1990	Municipal	monthly	-.16 to -.38	.30 to .48	no	Texas
Nauges, Celine and Alban Thomas	2000	Municipal	2X / year	-.22	0.10	no	France
Hoglund, Lena	1999	Municipal	yearly	-.08 to -.26	.07 to .13	no	Sweden
Carver, Philip and John Boland	1980	Municipal	monthly	-.02 to -.70	-	no	Washington D.C.
Taylor et al	2004	Municipal	monthly	-.28 to -.30	0.38	yes	Colorado

Appendix E – Results from Average Price Specification:

OLS Results - 3 Restriction Variables (Average Price)								
Source	SS	df	MS		Number of obs	1286		
					F(53, 1232)	93.2		
Model	51.17	53	0.965		Prob > F	0		
Residual	12.77	1232	0.010		R-squared	0.800		
Total	63.93	1285	0.050		Adj R-squared	0.792		
					Root MSE	0.102		
Variable	Coef.	Std. Err.	P>|t|		Variable	Coef.	Std. Err.	P>|t|
Intercept	4.8306	0.0621	0.000		Rain-City-Summer	-0.0231	0.0048	0.000
Jan-Dum	-0.0421	0.0198	0.033		Rain-City-Summer-Lag1	-0.0149	0.0045	0.001
Feb-Dum	-0.0722	0.0198	0.000		Rain-City-Summer-Lag2	-0.0055	0.0045	0.214
Mar-Dum	-0.0460	0.0198	0.020		Rain-City-Spring/Fall	-0.0055	0.0027	0.044
Apr-Dum	0.0650	0.0734	0.376		Rain-City-Spring/Fall-Lag1	-0.0049	0.0028	0.080
May-Dum	0.2115	0.0721	0.003		Rain-City-Spring/Fall-Lag2	-0.0133	0.0049	0.006
Jun-Dum	0.3760	0.0781	0.000		Temp-Co-Summer	0.0076	0.0034	0.029
Jul-Dum	0.3921	0.0787	0.000		Temp-Co-Spring/Fall	0.0102	0.0025	0.000
Aug-Dum	0.3378	0.0795	0.000		Temp-City-Summer	0.0059	0.0037	0.117
Sep-Dum	0.2176	0.0727	0.003		Temp-City-Spring/Fall	0.0020	0.0027	0.457
Oct-Dum	0.1256	0.0730	0.086		Single-Apt-Summer	-0.6129	0.1216	0.000
Nov-Dum	0.0158	0.0196	0.420		Single-Apt-Spring/Fall	-0.2770	0.0899	0.002
Jan-City-Dum	-0.0068	0.0221	0.758		Single-Apt-Winter	-0.4039	0.1047	0.000
Feb-City-Dum	-0.0057	0.0221	0.798		Group-Apt	1.4999	0.0452	0.000
Mar-City-Dum	-0.0008	0.0219	0.971		Income-Summer ($1000)	0.0056	0.0008	0.000
Apr-City-Dum	-0.0118	0.0236	0.618		Income-Spring/Fall ($1000)	0.0056	0.0007	0.000
May-City-Dum	-0.0842	0.0225	0.000		Income-Winter ($1000)	0.0062	0.0007	0.000
Jun-City-Dum	-0.0893	0.0237	0.000		Household-Size	0.0395	0.0267	0.139
Jul-City-Dum	-0.1020	0.0234	0.000		AP-Summer	-0.0388	0.0046	0.000
Aug-City-Dum	-0.0807	0.0254	0.002		AP-Spring/Fall	-0.0309	0.0039	0.000
Sep-City-Dum	-0.0777	0.0226	0.001		AP-Winter	-0.0208	0.0029	0.000
Oct-City-Dum	-0.0367	0.0229	0.110					
Nov-City-Dum	-0.0058	0.0214	0.785					
Dec-City-Dum	-0.0123	0.0220	0.577					
Rain-Co-Summer	-0.0231	0.0043	0.000		Voluntary	-0.0271	0.0155	0.081
Rain-Co-Summer-Lag1	-0.0261	0.0049	0.000		Mandatory-Self	-0.1352	0.0375	0.000
Rain-Co-Summer-Lag2	-0.0152	0.0051	0.003		Mandatory-EO33	-0.1396	0.0186	0.000
Rain-Co-Spring/Fall	-0.0117	0.0026	0.000					
Rain-Co-Spring/Fall-Lag1	-0.0091	0.0026	0.000					
Rain-Co-Spring/Fall-Lag2	-0.0051	0.0038	0.177					

OLS Results - 12 Restriction Variables (Average Price)								
Source	SS	df	MS		Number of obs	1286		
					F(61, 1224)	85.2		
Model	51.74	61	0.848		Prob > F	0		
Residual	12.19	1224	0.010		R-squared	0.809		
Total	63.93	1285	0.050		Adj R-squared	0.800		
					Root MSE	0.100		
Variable	Coef.	Std. Err.	P>|t|		Variable	Coef.	Std. Err.	P>|t|
Intercept	4.8438	0.0613	0.000		Rain-City-Spring/Fall	-0.0074	0.0027	0.007
Jan-Dum	-0.0423	0.0194	0.029		Rain-City-Spring/Fall-Lag1	-0.0040	0.0027	0.139
Feb-Dum	-0.0725	0.0194	0.000		Rain-City-Spring/Fall-Lag2	-0.0125	0.0048	0.009
Mar-Dum	-0.0474	0.0194	0.015		Temp-Co-Summer	0.0086	0.0034	0.011
Apr-Dum	0.0651	0.0724	0.369		Temp-Co-Spring/Fall	0.0107	0.0025	0.000
May-Dum	0.2132	0.0712	0.003		Temp-City-Summer	0.0055	0.0037	0.133
Jun-Dum	0.3709	0.0769	0.000		Temp-City-Spring/Fall	0.0022	0.0027	0.408
Jul-Dum	0.3867	0.0775	0.000		Single-Apt-Summer	-0.6127	0.1192	0.000
Aug-Dum	0.3335	0.0781	0.000		Single-Apt-Spring/Fall	-0.2700	0.0882	0.002
Sep-Dum	0.2249	0.0718	0.002		Single-Apt-Winter	-0.4330	0.1030	0.000
Oct-Dum	0.1224	0.0721	0.090		Group-Apt	1.5175	0.0449	0.000
Nov-Dum	0.0162	0.0192	0.400		Income-Summer ($1000)	0.0059	0.0008	0.000
Jan-City-Dum	-0.0081	0.0216	0.707		Income-Spring/Fall ($1000)	0.0059	0.0007	0.000
Feb-City-Dum	-0.0068	0.0216	0.752		Income-Winter ($1000)	0.0065	0.0007	0.000
Mar-City-Dum	0.0000	0.0215	0.999		Household-Size	0.0256	0.0262	0.329
Apr-City-Dum	-0.0083	0.0232	0.721		AP-Summer	-0.0377	0.0045	0.000
May-City-Dum	-0.0831	0.0221	0.000		AP-Spring/Fall	-0.0306	0.0038	0.000
Jun-City-Dum	-0.0915	0.0233	0.000		AP-Winter	-0.0200	0.0029	0.000
Jul-City-Dum	-0.1018	0.0230	0.000					
Aug-City-Dum	-0.0755	0.0249	0.003					
Sep-City-Dum	-0.0759	0.0224	0.001					
Oct-City-Dum	-0.0459	0.0228	0.044		Vol-Info1	-0.0404	0.0253	0.110
Nov-City-Dum	-0.0122	0.0211	0.563		Vol-Info2	0.0395	0.0211	0.062
Dec-City-Dum	-0.0137	0.0216	0.526		Vol-Info3	-0.1412	0.0283	0.000
Rain-Co-Summer	-0.0232	0.0043	0.000		Mand-Info1-Enf1	-0.0087	0.0678	0.897
Rain-Co-Summer-Lag1	-0.0259	0.0048	0.000		Mand-Info1-Enf2	-0.0450	0.0705	0.524
Rain-Co-Summer-Lag2	-0.0162	0.0050	0.001		Mand-Info2-Enf1	-0.0438	0.0385	0.256
Rain-Co-Spring/Fall	-0.0125	0.0025	0.000		Mand-Info2-Enf2	-0.1345	0.0299	0.000
Rain-Co-Spring/Fall-Lag1	-0.0090	0.0026	0.000		Mand-Info2-Enf3	-0.1955	0.0535	0.000
Rain-Co-Spring/Fall-Lag2	-0.0055	0.0037	0.137		Mand-Info3-Enf1	-0.1082	0.0332	0.001
Rain-City-Summer	-0.0218	0.0048	0.000		Mand-Info3-Enf2	-0.2248	0.0316	0.000
Rain-City-Summer-Lag1	-0.0157	0.0045	0.000		Mand-Info3-Enf3	-0.3043	0.0689	0.000
Rain-City-Summer-Lag2	-0.0062	0.0044	0.156					

Prais-Winsten Regression Heteroskedastic Panels Corrected Standard Errors - 3 Restriction Variables (Average Price)

Panels:	Heteroskedastic (unbalanced)				Obs per group: min	30		
Autocorrelation:	Panel-specific AR(1)				Obs per group: avg.	61.2		
Estimated covariances	21				Obs per group: max	156		
Estimated autocorrelations	21				R-squared	0.9964		
Estimated coefficients	54				Wald chi2(64)	4261.18		
Number of obs	1286				Prob > chi2	0		
Number of groups	21							
		Het-corrected					Het-corrected	
Variable	Coef.	Std. Err.	P>|z|		Variable	Coef.	Std. Err.	P>|z|
INTERCEPT	4.7185	0.0917	0.000		RAIN-CITY-SUMMER	-0.0096	0.0020	0.000
JAN-DUM	-0.0407	0.0085	0.000		RAIN-CITY-SUMMER-LAG1	-0.0039	0.0020	0.046
FEB-DUM	-0.0660	0.0109	0.000		RAIN-CITY-SUMMER-LAG2	0.0011	0.0019	0.567
MAR-DUM	-0.0422	0.0121	0.000		RAIN-CITY-SPRING/FALL	-0.0021	0.0010	0.031
APR-DUM	0.1099	0.0412	0.008		RAIN-CITY-SPRING/FALL-LAG1	-0.0008	0.0009	0.399
MAY-DUM	0.2360	0.0409	0.000		RAIN-CITY-SPRING/FALL-LAG2	0.0002	0.0019	0.929
JUN-DUM	0.3112	0.0549	0.000		TEMP-CO-SUMMER	0.0074	0.0020	0.000
JUL-DUM	0.3196	0.0554	0.000		TEMP-CO-SPRING/FALL	0.0032	0.0012	0.011
AUG-DUM	0.2661	0.0556	0.000		TEMP-CITY-SUMMER	0.0032	0.0018	0.072
SEP-DUM	0.2371	0.0409	0.000		TEMP-CITY-SPRING/FALL	0.0019	0.0011	0.072
OCT-DUM	0.1559	0.0405	0.000		SINGLE-APT-SUMMER	-0.4159	0.1351	0.002
NOV-DUM	0.0150	0.0086	0.081		SINGLE-APT-SPRING/FALL	-0.2221	0.1263	0.079
JAN-CITY-DUM	-0.0202	0.0196	0.301		SINGLE-APT-WINTER	-0.3063	0.1227	0.013
FEB-CITY-DUM	-0.0196	0.0196	0.318		GROUP-APT	1.4882	0.0595	0.000
MAR-CITY-DUM	-0.0105	0.0194	0.587		INCOME-SUMMER ($1000)	0.0019	0.0010	0.048
APR-CITY-DUM	-0.0349	0.0193	0.070		INCOME-SPRING/FALL ($1000)	0.0017	0.0010	0.069
MAY-CITY-DUM	-0.0997	0.0189	0.000		INCOME-WINTER ($1000)	0.0019	0.0009	0.049
JUN-CITY-DUM	-0.1212	0.0196	0.000		HOUSEHOLD-SIZE	0.2402	0.0468	0.000
JUL-CITY-DUM	-0.1239	0.0197	0.000		AP-SUMMER	-0.0566	0.0048	0.000
AUG-CITY-DUM	-0.0948	0.0203	0.000		AP-SPRING/FALL	-0.0450	0.0037	0.000
SEP-CITY-DUM	-0.1030	0.0189	0.000		AP-WINTER	-0.0559	0.0040	0.000
OCT-CITY-DUM	-0.0671	0.0190	0.000					
NOV-CITY-DUM	-0.0238	0.0191	0.213					
DEC-CITY-DUM	-0.0236	0.0193	0.223					
RAIN-CO-SUMMER	-0.0122	0.0022	0.000		VOLUNTARY	0.0108	0.0118	0.363
RAIN-CO-SUMMER-LAG1	-0.0118	0.0026	0.000		MANDATORY-SELF	-0.0475	0.0298	0.111
RAIN-CO-SUMMER-LAG2	-0.0036	0.0026	0.161		MANDATORY-EO33	-0.0939	0.0148	0.000
RAIN-CO-SPRING/FALL	-0.0062	0.0014	0.000					
RAIN-CO-SPRING/FALL-LAG1	-0.0053	0.0014	0.000					
RAIN-CO-SPRING/FALL-LAG2	0.0001	0.0019	0.971					

Prais-Winsten Regression Heteroskedastic Panels Corrected Standard Errors - 12 Restriction Variables (Average Price)

Panels:	Heteroskedastic (unbalanced)				Obs per group: min	30		
Autocorrelation:	Panel-specific AR(1)				Obs per group: avg.	61.2		
Estimated covariances	21				Obs per group: max	156		
Estimated autocorrelations	21				R-squared	0.996		
Estimated coefficients	62				Wald chi2(64)	4209.0		
Number of obs	1286				Prob > chi2	0		
Number of groups	21							
		Het-corrected					Het-corrected	
Variable	Coef.	Std. Err.	P>|z|		Variable	Coef.	Std. Err.	P>|z|
INTERCEPT	4.7475	0.0884	0.000		RAIN-CITY-SPRING/FALL	-0.0029	0.0010	0.004
JAN-DUM	-0.0414	0.0085	0.000		RAIN-CITY-SPRING/FALL-LAG1	-0.0008	0.0009	0.395
FEB-DUM	-0.0669	0.0108	0.000		RAIN-CITY-SPRING/FALL-LAG2	0.0007	0.0019	0.723
MAR-DUM	-0.0426	0.0120	0.000		TEMP-CO-SUMMER	0.0073	0.0019	0.000
APR-DUM	0.1149	0.0411	0.005		TEMP-CO-SPRING/FALL	0.0036	0.0012	0.004
MAY-DUM	0.2407	0.0408	0.000		TEMP-CITY-SUMMER	0.0030	0.0018	0.084
JUN-DUM	0.3195	0.0548	0.000		TEMP-CITY-SPRING/FALL	0.0023	0.0010	0.026
JUL-DUM	0.3285	0.0554	0.000		SINGLE-APT-SUMMER	-0.3592	0.1379	0.009
AUG-DUM	0.2810	0.0555	0.000		SINGLE-APT-SPRING/FALL	-0.1649	0.1296	0.203
SEP-DUM	0.2458	0.0409	0.000		SINGLE-APT-WINTER	-0.2540	0.1262	0.044
OCT-DUM	0.1599	0.0405	0.000		GROUP-APT	1.5099	0.0571	0.000
NOV-DUM	0.0172	0.0086	0.044		INCOME-SUMMER ($1000)	0.0024	0.0010	0.014
JAN-CITY-DUM	-0.0194	0.0194	0.317		INCOME-SPRING/FALL ($1000)	0.0023	0.0009	0.014
FEB-CITY-DUM	-0.0189	0.0194	0.331		INCOME-WINTER ($1000)	0.0024	0.0009	0.012
MAR-CITY-DUM	-0.0104	0.0192	0.590		HOUSEHOLD-SIZE	0.2167	0.0445	0.000
APR-CITY-DUM	-0.0350	0.0191	0.068		AP-SUMMER	-0.0573	0.0048	0.000
MAY-CITY-DUM	-0.0995	0.0187	0.000		AP-SPRING/FALL	-0.0458	0.0037	0.000
JUN-CITY-DUM	-0.1205	0.0194	0.000		AP-WINTER	-0.0567	0.0040	0.000
JUL-CITY-DUM	-0.1234	0.0195	0.000					
AUG-CITY-DUM	-0.0962	0.0201	0.000					
SEP-CITY-DUM	-0.1046	0.0188	0.000					
OCT-CITY-DUM	-0.0719	0.0189	0.000		VOL-INFO1	0.0395	0.0170	0.020
NOV-CITY-DUM	-0.0253	0.0190	0.182		VOL-INFO2	0.0118	0.0170	0.487
DEC-CITY-DUM	-0.0217	0.0192	0.258		VOL-INFO3	-0.0672	0.0213	0.002
RAIN-CO-SUMMER	-0.0123	0.0021	0.000		MAND-INFO1-ENF1	-0.0454	0.0395	0.251
RAIN-CO-SUMMER-LAG1	-0.0123	0.0026	0.000		MAND-INFO1-ENF2	-0.0372	0.0346	0.282
RAIN-CO-SUMMER-LAG2	-0.0046	0.0026	0.074		MAND-INFO2-ENF1	-0.0397	0.0243	0.102
RAIN-CO-SPRING/FALL	-0.0066	0.0014	0.000		MAND-INFO2-ENF2	-0.0773	0.0222	0.001
RAIN-CO-SPRING/FALL-LAG1	-0.0052	0.0014	0.000		MAND-INFO2-ENF3	-0.1554	0.0424	0.000
RAIN-CO-SPRING/FALL-LAG2	0.0002	0.0019	0.936		MAND-INFO3-ENF1	-0.1214	0.0290	0.000
RAIN-CITY-SUMMER	-0.0096	0.0020	0.000		MAND-INFO3-ENF2	-0.1416	0.0247	0.000
RAIN-CITY-SUMMER-LAG1	-0.0052	0.0020	0.008		MAND-INFO3-ENF3	-0.2193	0.0405	0.000
RAIN-CITY-SUMMER-LAG2	-0.0001	0.0019	0.948					

Appendix F – Locality Map: