Muffled Price Signals: Household Water Demand Under Increasing-Block Prices

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Abstract

In many areas of the world, including large parts of the United States, scarce water supplies are a serious resource and environmental concern. The possibility exists that water is being used at rates that exceed what would be dictated by efficiency criteria, particularly when externaltities are taken into account. Because of this, much attention has been paid by policy makers and others to the use of demand management techniques, including requirements for the adoption of specific technologies and restrictions on particular uses. A natural question for economists to ask is whether price would be a more cost-effective instrument to facilitate water demand management.

As a first step in such an investigation, this paper draws upon a newly-available set of detailed data to estimate econometrically the demand function for household use of urban water supplies. We analyze cross-sectional time-series data that track 1,082 single-family households served by 16 water utilities in 11 urban areas in the United States and Canada. Because of the diverse multiple-block pricing structures that abound, estimating the effects of price and price structure on residential water demand poses some challenging and interesting problems.

We find that the sensitivity of residential water demand to price is quite low, and that the effect of price structure may be more influential than the magnitude of marginal price itself. The household-level data we use allow us to assess the influences on residential water demand of climate, sociodemographic factors, and characteristics of housing stock, including home vintage. Our results indicate substantial heterogeneity in likely household responses to utility demand-management policies.

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1. Introduction

Matching water supply with demand is complicated by natural variability in weather conditions, including the periodic occurrence of extreme events such as droughts and floods. In the United States, arid cities in states such as Texas and California have struggled to manage water scarcity in the face of population increases, consumer demand for swimming pools, landscaping and other water-intensive household uses, and the increasing cost of acquiring new water supplies. In many parts of the United States, annual water use regularly exceeds annual surface water streamflow and is maintained only by depleting groundwater sources, so-called groundwater "mining" [30][31].

Economic approaches to environmental policy have expanded over the past two decades to include market-based approaches to air and water pollution control, including pollution taxes and tradeable permit systems. The use of such incentive-based instruments has been urged because, in theory, a well-designed market instrument can minimize the cost of achieving a given level of environmental quality [67][21][22][58][11]. Likewise, we would expect that raising the price of water, which would encourage households to reduce consumption for their lowest-valued uses, would be a more cost-effective tool for reducing water consumption than non-price programs that target specific uses.

Economists have recommended the use of market prices for the management of natural resources, including water, timber, grazing pasture, and various non-renewable resources. Efficient water management requires clear price signals that provide incentives for efficient use of water by individual consumers, resulting in efficient allocation of water among competing demands. Efficiency would be achieved, in theory, if water was traded on a perfectly competitive market, but this is certainly not the case. While many western U.S. states, as well as parts of Australia and Chile, have experimented with limited water marketing, urban water supplies are largely managed by local public and, to a lesser extent, private monopolies.[1] Within existing systems for local water allocation, however, managers can implement cost-effective incentives for conservative use of water in the face of near-term shortage and long-term scarcity.

The framework of economic thinking has infrequently been applied to water management in practice. Much of the water management literature is rooted in engineering rather than economics, and there is widespread belief that water customers will not respond to price signals. Water utilities have been reluctant to use price to allocate scarce supplies, relying primarily on non-price instruments, such as voluntary and mandatory

[1] The reasons for the absence of markets for water include water's stochastic supply, the economies of scale inherent to water development and distribution projects, water's nature as a common property resource and a public good, and the fact that water is often considered in political contexts to be "too important to be managed by the market"[31]. Adam Smith in *The Wealth of Nations* noted the paradox of water's necessity for human existence and very low price–a paradox that has not been lost on economists since Smith [73].

use restrictions. For example, utilities often restrict landscape watering to certain days, distribute for free or subsidize the use of low-flow water fixtures, or invest in public education programs that may promote water conservation. Empirical evidence of the effectiveness of such programs is mixed. Some studies have failed to identify statistically significant impacts, whereas others have identified small negative impacts on residential water demand.

If price is theoretically the better tool, how sensitive are actual consumers to changes in the price of water? This study is an important addition to the literature that seeks to address that question. Using a unique set of cross-sectional time-series data, we estimate the effects of price and price structure on residential water demand in 11 urban areas in the United States and Canada. Our main contributions include:

- Provision of the first estimates of short-run residential price elasticity of water demand using appropriate treatment of block pricing, an element of water management that makes estimation of demand functions difficult;

- Analysis of differences in price elasticity among households facing different types of price structures: increasing blocks and uniform marginal prices;

- Use of the most precise household-level data yet available to analyze the factors that contribute to heterogeneity in water demand across households; and

- Development of a framework for analyzing the effects of utility conservation programs on household water demand and price elasticity.

As economic growth continues, the long-term and short-term challenges of balancing water supply and demand will require more efficient and more predictable water management tools.[2] This study and anticipated further work building upon the model described here will provide important information for water managers regarding how households may be expected to respond to various demand management tools such as price increases, changes in price structure, and non-price conservation policies.

Section 2 of this paper summarizes the literature on the sensitivity of water demand to price and non-price demand management policies. Section 3 discusses the economic

[2] In addition, global climate change is likely pose further challenges to water management, affecting both the long-term availability and the short-term variability of water resources in many regions. Potential regional impacts of climate change could include increased frequency and magnitude of droughts and floods, and long-term changes in mean renewable water supplies through changes in precipitation, temperature, humidity, wind intensity, duration of accumulated snowpack, nature and extent of vegetation, soil moisture, and runoff [30][29][44][45]. In addition to hydrological and meteorological changes, behavioral changes associated with climate change, such as changes in demand for heating and cooling, will also affect water resources.

theory of block pricing. Section 4 examines related econometric techniques for estimating water demand functions. Section 5 describes our data and basic model of water demand under block pricing. In Section 6, we analyze the implications of our model results for identifying reliable price elasticity estimates, as well as for the influence of housing characteristics, weather, and household demographic characteristics on water demand. We conclude with a discussion of the implications of our results for local and regional water managers, and an overview of planned extensions to the basic model.

2. A Review of the Water Demand Literature

2.1. Price elasticity of residential water demand

A review of the water demand literature suggests that water demand is sensitive to price, but that the magnitude of that sensitivity is small at current prices. Elasticity estimates for urban areas in North America between 1951 and 1991 range from a lower bound of -.01 to an upper bound of -1.63, varying with season, water-user sector, level of aggregation, type of data and model specification [35].

Over the past 40 years, improvements in water demand estimation are associated with correction for the endogeneity of price and quantity under block rate pricing, the proper specification of marginal price and implicit income effects due to changes in infra-marginal rates, and the use of time series rather than cross-sectional data. Studies implementing these improvements have arrived at somewhat higher elasticity estimates.[3] Using the discrete-continuous choice model of water demand, Hewitt and Hanemann (1995) obtain the largest price elasticity estimates in the literature, ranging from –1.57 to –1.63. Using a somewhat different specification, Pint (1999) obtains estimates ranging from –0.04 to –1.24, depending upon season. These most recent analyses have been attempts to appropriately treat one common type of water price structure, block pricing, which makes econometric estimation of water demand functions especially complex. We will explore this issue further in Section 3, where we discuss block pricing.

The estimation of higher price elasticities using models that appropriately treat block pricing has re-opened the debate on household sensitivity to the price of water.[4] This is similar to the labor supply literature, where application of the discrete-continuous choice model, often called the "Hausman model," has estimated greater labor supply distortions (and resulting deadweight losses) from progressive income taxation than

[3]On the question of endogeneity of price and quantity, see, for example, [42][13][27][19][62]. While early water demand studies used average price as an explanatory variable, Gibbs first argued for the use of marginal price [32].

[4]Prior to Hewitt and Hanemann (1995), only three studies had estimated elastic price elasticities [42][23][24].

competing models [50][38]. There have been only two applications of such models in the water demand literature [40][68]. This study builds on this approach to determine whether such a pattern is truly emerging in water demand research.

There are a variety of ways to interpret the finding that water demand is relatively insensitive to price. First, households could be relatively insensitive to the price of water because the primary demands from which the demand for water is derived are so basic that water has no substitutes and the demand curve is close to perfectly inelastic. Here, we need to make an important distinction between long-run and short-run elasticity.

The two studies that have previously estimated water demand elasticities using appropriate treatment of block pricing have used household data over periods of three to ten years. We would expect such elasticities to be greater than those estimated for shorter time periods, given that households have the opportunity in the long run to adapt to price increases by purchasing water-efficient appliances, installing low-flow plumbing fixtures, and planting drought-tolerant landscaping.[5] One meta-analysis of water price elasticity estimates indicates that long-run elasticities are higher, on average, than short-run elasticities for a variety of econometric specifications [26]. We estimate a short-run elasticity from household demand observed over a period of less than one year, generating the first short-run results using appropriate treatment of block pricing and the first such estimates that can be compared with previous short-run estimates in the literature.

Aside from the distinction between short and long-run elasticities, there are other reasons why observed sensitivity to the price of water may be small. The marginal price of water itself in most U.S. cities is very low – in the range of $0.50 to $5.00 per thousand gallons. The median monthly water bill for an average U.S. customer in 1998 was less than $16, a very small portion of household income by any measure [69]. At such low prices, we would expect household responses to changes in the price of water to be very small, indeed.

Given that water consumption represents a tiny portion of household expenditures, there is some debate as to whether households are even aware of the marginal price of water [65][72]. If households are relatively insensitive to price, it could be that they simply do not know the price of water, which could be particularly true in the case of complicated price structures. The model we develop can be used to test the impact on price elasticity of information provision regarding price and the magnitude of a household's water use, relative to various benchmarks.

[5]The distinction has been quite important in the electricity demand literature, in which long-run price elasticity estimates average -0.35 in the short run and -0.77 in the long run, with substantially greater variation in estimates for long-run elasticity [25][12].

2.2. Responsiveness of Demand to Non-Price Conservation Policies

Price levels sufficient to induce significant water savings are politically and socially controversial.[6] Given that water pricing policies are frequently constrained by politics and by law, utilities frequently rely on non-price conservation programs to induce conservation. This is true despite the fact that non-price programs may actually be more expensive for water customers, once the costs of programs funded through taxation and associated deadweight losses are considered, as well as the relative cost of reducing water consumption in specific uses, rather than reducing those uses most cost-effective for each household.[7] Residential non-price water conservation policies include household-level efforts, such as the installation of water-conserving fixtures, as well as utility-level efforts, such as the requirement for or subsidization of such fixtures, establishment of education programs, or restrictions on particular uses, such as outdoor watering.

Several engineering studies have observed a small number of households in a single region to estimate the water savings associated with low-flow fixtures, one type of household-level conservation effort [2][4]. But most of these studies used intrusive data collection mechanisms, attaching data collection equipment to faucets and other fixtures in homes [16]. Study participants were aware that they were being monitored as they used water within the household, which may have led to confounding behavioral changes. One comprehensive study that was not characterized by this problem indicates that while low-flow fixtures conserve water, the savings may not be as large as expected, given manufacturers' specifications [52].[8]

Non-price management tools also include utility implementation of mandatory water use restrictions, much like the traditional command-and-control approach to environmental regulation. Empirical evidence is mixed regarding the aggregate effects of residential non-price conservation programs. Summer 1996 water restrictions in Corpus Christi, Texas, including prohibitions on landscape irrigation and car-washing, did not prompt statistically significant water savings in the residential sector [71]. A longer-term program in Pasadena, California, the LITEBILL water and energy conservation program, did result in aggregate water savings [48]. One study of the effect of various conservation programs on aggregate water district consumption in California found small but significant reductions in total water use attributable to landscape education programs and watering restrictions, but no effect due to conservation education pro-

[6] For discussions of the political economy of water pricing and water institutions, see [34][36][53].

[7] Here we draw another parallel to the literature on market-based instruments for environmental pollution control. Cost-effectiveness has only recently been considered an important criterion for environmental policy instrument choice. For an analysis of the positive political economy of the choice of regulatory policy instruments, see [46].

[8] This should not be too surprising, given that the fixtures may induce behavioral change that partially negates the benefit of lower water use per minute, per flush, etc. For example, households with low-flow showerheads may take longer showers than they would without these fixtures.

grams, low-flow fixture distribution, or the presentation of drought and conservation information on customer bills [20]. Another aggregate study of southern California cities found that the number of conservation programs in place in a city had a small negative impact on total city residential water demand [54]. Finally, an aggregate-level study in California found that public information campaigns, retrofit subsidies, water rationing, and water use restrictions all had negative and statistically significant impacts on mean agency-level monthly residential water use, and the more stringent policies had stronger effects than voluntary policies and education programs [70].

None of these studies have estimated the effects of residential conservation programs on the behavior of individual households. In addition, a utility's sponsorship of non-price conservation programs may be endogenous with water use, especially with aggregate agency-level water use or agency-level mean household water use, the level at which existing studies have been performed. This endogeneity would have an indeterminate effect on demand estimates. That is, the existence of such programs could be correlated with high average water use–cities may implement them because they need to. Or the presence of these programs could be correlated with low water use in communities with an environmental consciousness–cities may implement them because their customers want them.

We do not attempt to assess the effectiveness of non-price utility conservation programs in this study. For now, any variance in demand resulting from such programs is absorbed into city-level fixed effects. Assessing the direct effects of non-price demand management programs is an important aspect of our ongoing work on this topic.

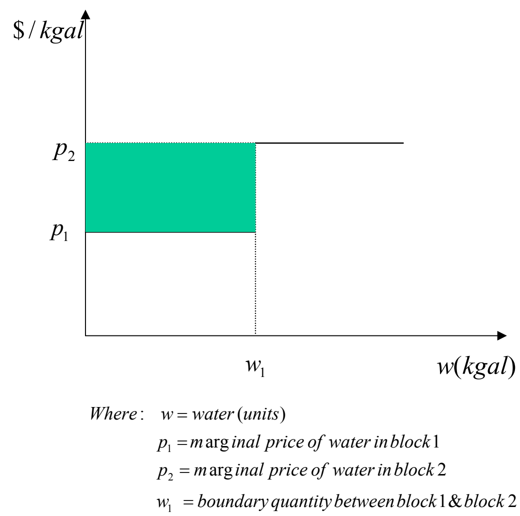
3. Block Pricing and Economic Theory

Urban residential water service pricing typically takes one of three forms in the United States: (1) constant or uniform rates; (2) increasing block rates; or (3) decreasing block rates. All of these price structures are usually accompanied by a fixed water service fee. Under constant or uniform rates, households are charged a single volumetric marginal price at all levels of consumption. Increasing block structures charge higher marginal prices for higher quantities consumed, resulting in a water supply function that resembles a staircase ascending from left to right (Figure 1); decreasing block structures are stacked in the opposite direction. Block rate structures introduce wrinkles in the economic theory of the consumer and in the econometric estimation of water demand functions because price and demand are endogenous.

3.1. Block Pricing and the Marginal Cost of Water Supply

Increasing-block rates are typically introduced by utilities as revenue instruments, but they can also serve as instruments of economic management. In an increasing block

Figure 1: Two-tier increasing block price structure



system, marginal price approaches marginal cost only for households consuming in the upper blocks of a multi-tiered increasing block price structure. At the household level, consumers pay subsidized rates on water consumption for necessities like showering, cooking and drinking, and rates closer to marginal cost for outdoor irrigation.[9]

Economic theory prescribes some variant of marginal cost pricing to signal the value of water as a scarce resource and to foster efficient allocation of water among competing demands, both within and among users. The marginal cost of providing a unit of water consumption to a household – 1,000 gallons is the typical unit priced in the U.S. – is not easily calculated, however. Utilities frequently have multiple sources of supply, with new supplies coming on-line at greater expense than old sources, meaning the long-run marginal cost is increasing. The marginal cost of each source, however, is often flat or decreasing in the short run, because the incremental cost of adding supply from a given source declines as reservoir size (or the total quantity of water obtained from

[9]In this sense, these structures are sometimes described as more “equitable” than across-the-board pricing based on marginal cost because basic needs are subsidized and water consumption is more expensive for landscape irrigation, swimming pools and other less vital uses.

one source) increases. In addition, there is a degree of jointness to the marginal cost of water supply; the marginal cost of providing a gallon of water to a household on a certain day and time depends in part on how many others are drawing on the system at that time.

Most public water supply systems are classic natural monopolies.[10] Pricing is typically driven by accounting considerations rather than economic ones, ensuring that revenues cover variable and historical fixed costs but do not result in the public institution earning a profit. Where marginal cost is below average cost, utilities have historically implemented either average-cost pricing or some form of marginal cost pricing plus fixed charges in order to achieve these accounting goals [36]. This does not mean, however, that water prices reflect full marginal cost. The marginal cost of water supplies also depends on the value of raw water *in situ* (user cost or scarcity rent), an opportunity cost typically excluded from water pricing decisions. The value of raw water depends on the degree of renewability of the water supply, as well as relative costs of the full set of available supplies.[11]

The value of a raw water resource will be nonzero in cases much more common than technical non-renewability [57]. Water utilities typically have rights to a finite amount of water from any given source. To a city facing the prospect that higher-cost sources will be needed in the near future, the economic cost of withdrawals from existing sources includes user cost. Even in the absence of the need to acquire new supplies, if a utility withdraws water from multiple sources with heterogeneous marginal costs, user cost is relevant. Pricing at marginal supply cost in these cases (with the exception of the last, most costly supply if future augmentation is not anticipated) is economic underpricing.[12]

Pricing at full long-run marginal cost will, however, result in utility revenues that exceed expenses, which reflect historical rather than future marginal costs. Moncur and Pollock (1988) estimate that user cost alone for water supply to Oahu, Hawaii

[10]The classic case of natural monopoly occurs when marginal cost lies below average cost. Economies of scale lead to decreasing costs over the relevant range of capacity increases.

[11]In 1931, Harold Hotelling suggested that non-renewable resources be considered as capital asset stocks. The cost of their use therefore includes both marginal extraction costs and the marginal opportunity cost of their consumption, which leaves less to extract and consume in the future [41]. This second portion of the cost of using non-renewables is frequently referred to as scarcity rent or user cost. Given the absence of market-determined prices for water, economic valuation of scarcity rent for water is very difficult [57].

[12]As Moncur and Pollack (1988) note, there are water supplies that are practically limitless, in which user cost would be zero. For example, if a city were considering desalinating sea water at a high marginal cost in the future, the marginal cost of current freshwater supplies would include user cost. But if the technology were adopted, user cost of saline water supplies would then drop to zero. Moncur and Pollock (1988) analyze the example of Oahu, Hawaii considering desalting brackish groundwater, and offer another example of zero scarcity rent in the city of New Orleans' reliance on the Mississippi River [57].

in the mid-1980s was more than twice the existing residential volumetric charge per thousand gallons, and that water prices would need to be more than tripled to reflect long-run marginal cost. In the early 1990s, when the Municipal Water District of Southern California (MWD) was considering implementing water prices that reflected the escalating costs of acquiring future supplies, a similar difference emerged. Rates that reflected the full opportunity cost of water use in normal years were 70 percent higher than rates designed to ensure that total utility revenue equalled total cost [34]. In arid years this percentage difference increased to 118 percent in years with water supplies 10 percent below normal, and as much as 254 percent in years with water supplies 25 percent below normal.

In cases in which water is priced below full marginal cost for accounting, political, social, or legal reasons, economists see increasing block rate structures as second-best attempts to reduce economic overuse.[13] The muffled scarcity signals of increasing block price structures may be better than no signals at all. The logic that increasing block rates induce conservative water use (we cannot go so far as to say efficient water use, given that prices are not equal to full marginal costs) may be responsible for a significant shift away from decreasing and toward increasing block price structures over the past two decades (Table 1).

Table 1. U.S. Residential Public Water Supply Rate Structures, 1982-1997

	Percent of Sample Utilities			
Rate Structure	1982	1987	1991	1997
Flat fee for service, regardless of volume	1	0	3	2
Uniform volumetric charge	35	32	35	33
Decreasing block	60	51	45	34
Increasing block	4	17	17	31
Total	100	100	100	100
Number of utilities in sample	90	112	145	151

Sources: [66], [69]

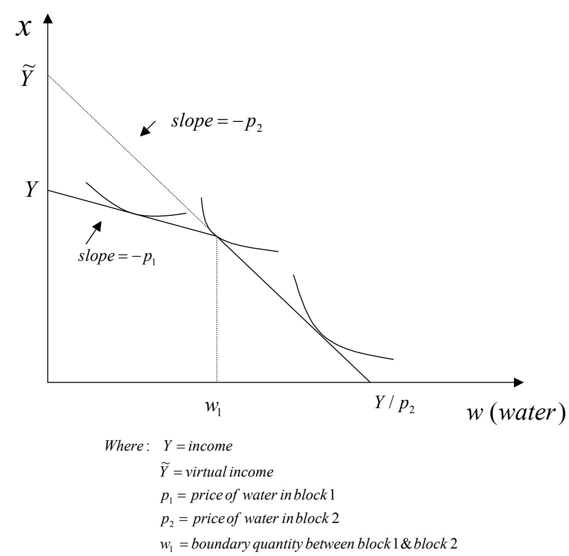
3.2. Block Pricing and the Theory of the Consumer

As economic agents, households are presumed to maximize utility, subject to a budget constraint. If the price of water does not depend on the quantity a household consumes, then we have a standard utility maximization problem with a simple linear budget constraint. This is the case for 39 percent of the households in our study. The remaining 61 percent of sample households face block prices, which means they face

[13] This is true even though the short-run marginal cost of water supply is typically constant or decreasing, not increasing.

a piecewise linear budget constraint. Such budget constraints arise in many economic settings, including government tax and transfer programs, water and electricity pricing, and volume discounts in general. Under increasing blocks, the budget constraint is a series of convex budget subsets with progressively steeper slopes. Figure 2 depicts a simple two-tier increasing block price system in which the consumer has three reasonable consumption choices; consume on the interior of segment one, on the interior of segment two, or at the kink point, the quantity at which the marginal price increase occurs.

Figure 2: Utility maximization under a two-tier increasing block price structure



In theory, consumers equate the marginal price of water to the marginal benefit of water consumption in choosing the quantity to consume. But for households consuming anywhere on a piecewise linear budget constraint with the exception of the first linear segment, the marginal price is not the price paid for every unit consumed. This is the first way in which block prices complicate the application of consumer theory to water demand. It is a relatively easy problem to solve, however. In the example depicted in Figure 2, the household's budget constraint can be described algebraically as in equations (1) and (2), where w is the quantity of water consumed.

$$
Y = \begin{cases} p_1 w + x & for \quad w \leq w_1 \\ p_1 w_1 + p_2(w - w_1) + x & for \quad w > w_1 \end{cases} \tag{1}
$$

or

$$
\begin{aligned} Y &= p_1 w + x \quad for \quad w \leq w_1 \\ \widetilde{Y} &= p_2 w + x \quad for \quad w > w_1 \end{aligned} \tag{2}
$$

If we extend the second face of the budget constraint, that portion with a slope equal to $-p_2$, to intersect with the vertical axis, we obtain $\widetilde{Y}$, frequently called "virtual income." The difference between Y and $\widetilde{Y}$ is simply $(p_2 - p_1) * w_1$, or the difference between what a block-two household would pay in total if all units were priced at p_2, and what it actually pays under the increasing block structure. We have shaded the area that represents this difference in Figure 1. Virtual income "refunds" to the household the implicit subsidy that derives from the block rate structure. We can use marginal price to estimate demand functions, so long as we use virtual income to account for the fact that a lower price was paid for the first w_1 units of water.[14]

Decreasing block systems have an additional complication–non-convex budget sets can lead to multiple tangencies between consumer indifference curves and the budget constraint (Figure 3). The theory and empirics of the non-convex case are straightforward extensions of the convex case described here. The most important difference is that utility maximization cannot occur at kink points for well-behaved preferences, which makes the specification of the likelihood function somewhat easier than the convex case, but assigns zero probability to observations in the neighborhood of the marginal price change. All of the utilities in our sample charge either uniform or increasing block rates, as do approximately 65 percent of U.S. urban water utilities [69]. Hence, we need not consider the decreasing block rate case further.[15]

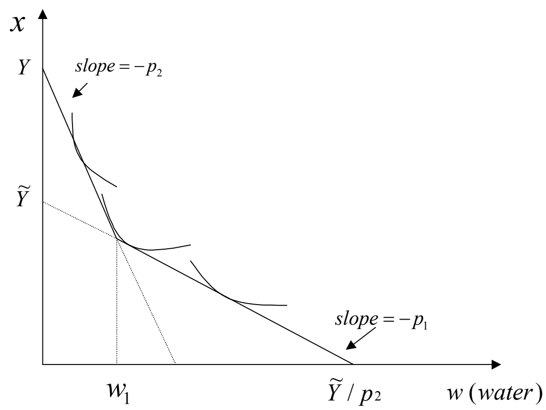
Under increasing block rates, the demand for water emerges from the household's underlying utility maximization problem, which leads to the conditional indirect utility function and utility-maximizing choice as in equations (3) and (4), where x represents all goods other than water with p_x normalized to one.

$$
V(P,Y) = \max_{w,x} U(w,x) = \max_{w} U(w(P,Y), Y - pw(P,Y)) \tag{3}
$$

[14] Use of virtual income in the electricity demand literature [64][75] pre-dates the development of the discrete-continuous choice model in the labor supply literature [17]. Its use in the estimation of water demand functions was first applied by [14]. Without including virtual income in demand estimation, households facing the same marginal price but different infra-marginal rates would receive identical treatment, and shifts in prices below the marginal price would be modeled as if they had no effect. Virtual income treats the infra-marginal rate changes as lump-sum changes in household income.

[15] The case of decreasing block price structures has been developed generally [56][55]; for the case of water supply [39][40]; and in the literature on labor supply and taxation [17][37].

Figure 3: Utility maximization under a two-tier decreasing block price structure

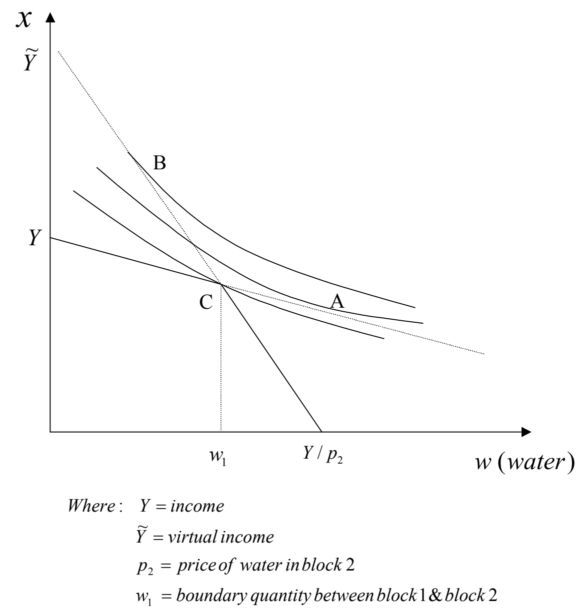


$$
\begin{array}{llll}
\textit{resulting in}: & & & \\
w < w_1 & iff & V(p_1, Y) > U(w_1, Y - p_1 w_1) \textit{ and } V(p_1, Y) > V(p_2, \widetilde{Y}) & \\
w > w_1 & iff & V(p_2, \widetilde{Y}) > U(w_1, Y - p_1 w_1) \textit{ and } V(p_2, \widetilde{Y}) > V(p_1, Y) & (4) \\
w = w_1 & iff & U(w_1, Y - p_1 w_1) > V(p_1, Y) \textit{ and } U(w_1, Y - p_1 w_1) > V(p_2, \widetilde{Y}) &
\end{array}
$$

Consumption at the kink point will occur only if the utility maxima along the linear sections of the budget constraint occur in the infeasible range of both. This situation is depicted in Figure 4 [39][56]. Given price and income (p_1, Y), a household would maximize utility by consuming $w > w_1$, as at point A; given price and income $(p_2, \widetilde{Y})$, a household would maximize utility by consuming $w < w_1$, as at point B. With both A and B unattainable, the household consumes at point C, or w_1 gallons of water.

The kinks in the budget constraint create a more complicated relationship between price, income, and quantity than the relationship that results from a simple, linear budget constraint. The expected negative relationship between price and quantity demanded and positive relationship between income and quantity demanded will hold

Figure 4: Consumption at the kink in a two-tier increasing block price structure



within blocks, but even in the case of a convex budget set and subsets (increasing block pricing), marginal income and price effects may be zero for households consuming at a kink [55]. The resulting consumer demand can be discontinuous, as consumption can stick at kinks in the budget constraint or, alternatively, change abruptly and non-marginally from one block to another.

4. Block Pricing and Econometrics

The complications of non-linear budget constraints for utility maximization present problems for the econometric estimation of demand functions. First, the discrete choice of block or kink and the continuous choice of quantity, made simultaneously, must both be modeled. In addition, the choice of block, hence quantity, and marginal price are endogenous. If a typical single-error stochastic specification of an econometric model is employed, the size of the error term, marginal price, and virtual income (a function of marginal price) will be systematically correlated.

Under piecewise-linear budget constraints, ordinary least squares (OLS) estimates of the parameters of the demand function will be biased and inconsistent, due to the simultaneous determination of price and the block of consumption. A larger value of the error term will increase the likelihood that water consumption will be observed in a higher block (at a higher marginal price), and the opposite will be true for a small value of the error term. This problem was first treated by estimating simultaneous equations models, such as two-stage least squares (2SLS) and other instrumental variables models, an idea borrowed from the labor supply and energy demand literatures [1][24][63][62].

While the use of such models can address the problem of endogeneity and result in parameter estimates that reflect a downward-sloping demand curve, they do not model both portions of the consumption choice – the discrete choice of block or kink and the continuous choice of quantity. As a result, the effect of changes in the price structure, such as a shift from two blocks to three, or a change in the consumption quantity threshold that moves a household from one block to another, cannot be assessed. The true price elasticity under block rates includes both the conditional elasticity of demand given consumption within a block, and the elasticity of the probability of consuming within that block.

In addition, the usual IV methods disregard the fact that some households are observed consuming at or within the neighborhood of a kink point, where it is unclear which value of marginal price should be assigned to these observations (especially in a stochastic econometric model that includes one or more error terms). Arbitrary treatment of these observations, such as assigning them to one block or another or throwing them out entirely ignores the utility maximization process operating behind the demand curve.

The best model that treats all of the theoretical and econometric issues associated with block pricing is the two-error discrete-continuous choice model, a maximum likelihood model. The model was first applied to water demand in the early 1990s [39][40], although the original development was for labor supply functions under graduated marginal income tax rates [17], and subsequent generalizations noted the potential application of the model to water and electricity demand [56][55].[16]

The discrete-continuous choice (DCC) model is essentially a probability statement in which each observation is treated as if it could actually have occurred at any kink or linear portion of the household's budget constraint. The probability statement for an individual observation is a sum of joint probability statements, one for each kink and

[16] While it is a relatively recent arrival to the water economics literature, the labor literature contains many applications and critiques of this "Hausman model". Surveys of applications include [37] and [15]. The strongest critiques are presented in [50][49]; a summary of critiques and responses are contained in [38]. The debate over the strengths and weaknesses of the Hausman model continues. We plan to estimate other types of models eventually, including non-parametric models, to assess the validity of these critiques vis-à-vis water demand.

linear block in the budget constraint. Each joint probability includes the probability of the continuous choice of quantity consumed and the conditional probability that optimal consumption occurred at that kink or block, given the choice of quantity. The form of the likelihood function differs depending on the price structure faced by each household; our data include households that face a uniform marginal price for water, as well as two- and four-tier increasing block price structures. Maximizing the probability statement, in the form of a likelihood function, generates the parameter estimates. For a mathematical derivation of the likelihood function that we use, see Appendix A.

5. Data and Basic Econometric Model

5.1. Data description

The data comprise 1,082 households in 11 urban areas in the United States and Canada, served by 16 water utilities.[17] Urban areas include Denver, Colorado; Eugene, Oregon; Seattle, Washington; San Diego and Lompoc, California, as well as the areas surrounding Walnut and Calabasas, California; Tampa, Florida; Phoenix and Tempe/Scottsdale, Arizona; and the regional municipality of Waterloo (cities of Waterloo and Cambridge) in Ontario, Canada.[18] These cities were chosen because of the availability of uniquely rich data on water demand and household characteristics. However, the group of cities is also notable for its geographic and climatic variation, including cities in the rainy Pacific Northwest, arid southern California, desert cities in Arizona, and cities in mountainous Colorado, temperate Ontario, and sub-tropical Florida.

We observe daily household water demand and weather conditions over two periods of two weeks each, once in the outdoor irrigation season and once in the non-irrigation season. For each household, the two seasons of observation cover a total period of less than one year. Daily demand data were gathered by automatic data loggers, attached to magnetic household water meters by utility staff. These devices were hidden from sight during most, if not all, uses of water. Daily weather observations were drawn from local data collection stations to reflect local micro-climates.[19] Weather data reflect the

[17]The household-level data used in this study were gathered by Mayer et al. (1998) for a study sponsored by the American Waterworks Association.

[18]Among the sample cities, households in Denver, Eugene, San Diego, Tampa, Phoenix, Tempe, Scottsdale, and Lompoc are served by city water or combined utility departments. Households in Seattle are served either directly by Seattle Public Utilities (SPU), a regional wholesale and retail water agency, or directly by one of three SPU wholesale customers: the city of Bellevue Utilities Department, Highline Water District, and Northshore Utility District. Sample households in Ontario are served either by the regional municipality of Waterloo, or by one of its wholesale customers, the City of Cambridge. Households in the area of Walnut, California are served by the Walnut Valley Water District, and households in the area of Calabasas, California are served by the Las Virgenes Municipal Water District.

[19]For example, observations were drawn from four different weather stations in each of three cities:

maximum daily temperature and estimated moisture needs of lawns at the location of each household.[20] The effects of these characteristics on demand can be particularly important with respect to climate change and other policy contexts.

Data regarding characteristics of individual households and homes, including gross annual household income, family size, and home age and size, were collected using a one-time household survey. Households chosen for the study were randomly sampled from a subset of utilities' customer databases: residential single-family households. Surveys were anonymous and were field-tested prior to distribution. Sampling procedures, response rates, and statistical tests for differences between respondents and single-family customers as a whole are described in Mayer et al. (1998, Appendix A).[21] The distributions of daily water demand and its natural logarithm, the dependent variable in our analysis, are portrayed in Figure 5. Each of the two seasons of observation (irrigation and non-irrigation) are presented separately to demonstrate the effect of seasonal irrigation on the distribution of water demand.

Each household faces one price structure throughout each season of observation, but

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Seattle, Denver and Phoenix. Five stations were used in San Diego, and three in the Los Angeles area. Observations were drawn from a single station in each of the remaining urban areas: Eugene, Tampa, Tempe/Scottsdale, and Waterloo/Cambridge.

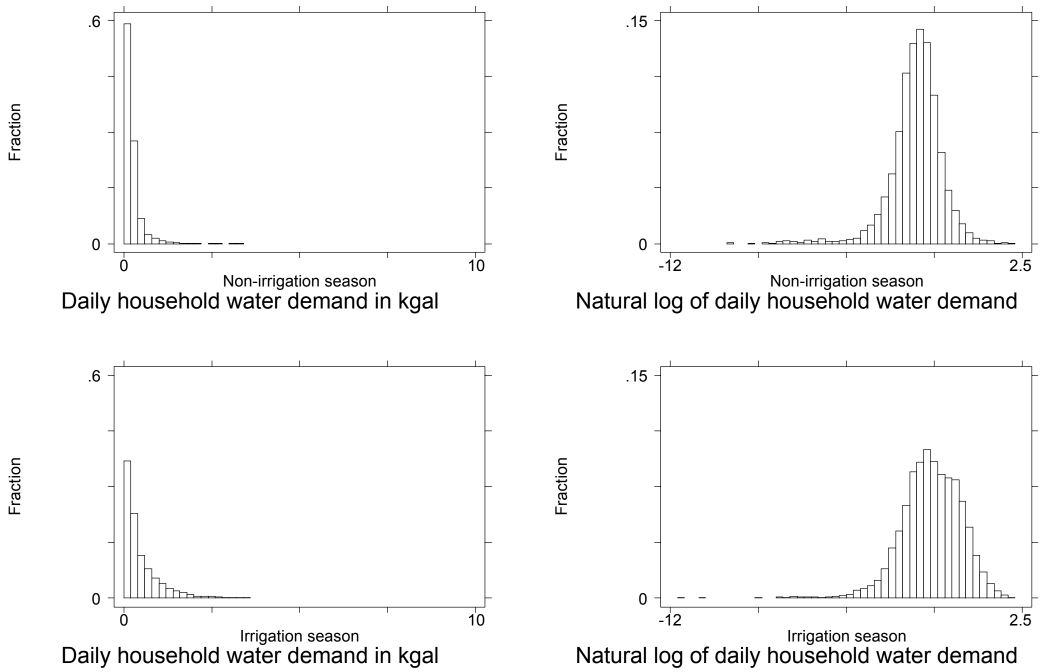
[20] An evapotranspiration variable is included primarily to account for the effects of temperature, precipitation and other climate factors on outdoor irrigation – it is a summary measure of the water needs of a reference "crop", which in our case is green grass. The measure we use for this purpose is explained further in Appendix B.

[21] Survey data included censored categorical variables and missing observations. Of the variables included in our models, income, square footage of the home, lot area, and the age of the home were all top-censored categorical variables. Category numbers were converted to means of category ranges. Means of the top-censored ranges were estimated by fitting distributions to the uncensored data, and using the resulting parameters to estimate the mean of the top-censored range. This was done using a Pareto distribution for income, and normal distributions for square footage of home and lot areas, and age of the home.

Missing values were also a problem, but the surveys contained a wide variety of information that could be used to predict missing values. For example, where households did not identify the number of bathrooms in the home, many households did identify the number of toilets in the home, or the number of bathroom sinks. These data are close proxies for number of bathrooms and we have used them as such.

Other cases were more difficult. For example, approximately 20 percent of observations on lot area were missing. Lot area is highly correlated with the value of the home (rho=.38), whether the home has a swimming pool (rho=.27), and square feet of housing (rho=.44). Missing values of lot area were filled in using fitted values of an OLS regression of lot area on the value of the home, square footage of the home, the presence of a swimming pool, and the presence of a seasonal vegetable or flower garden. In cases in which the home was rented and not owned, we used a common formula to convert monthly rent into home value: $r * F = V$, where r is monthly rent and V is home value. The series present worth discount factor $F = \frac{(1+i)^n - 1}{i * (1+i)^n}$, $n = 360$ months or 30 years, and $i =$ typical 1995 mortgage rate of 0.0067/month, or about eight percent per year [52]. Upon request, the authors can provide detailed information on the processes by which missing values and the means of top-censored categories were estimated.

Figure 5: Distribution of Water Demand in Each of Two Seasons



many price structures changed between the two periods. As a result, there are 26 price structures in the data; eight two-tier increasing block structures, ten four-tier increasing block structures, and eight uniform marginal prices. Marginal prices range from \$0.00 per thousand gallons (kgal) for the first 4,490 gallons per month in Phoenix, to \$4.96 per kgal in the most expensive block in the Las Virgenes Municipal Water District.[22]

[22]Prices currently include only those for water service, not wastewater service. Wastewater charges will be incorporated into the analysis so that price represents the effective marginal price of water – the price of the flow into the household and out of the household. Many of the utilities in our data use complicated pricing systems for wastewater service that require special care to be incorporated into the model. For example, many utilities benchmark water use during the winter, and use average winter consumption for the previous year, rather than current consumption, as the basis for the wastewater charge. When we observe households during these benchmarking periods, the effective price of water includes both the marginal price of water consumption, and some cost of future wastewater service, as current consumption contributes to average winter monthly consumption. This "outflow" portion of the effective marginal price of water would be the present value of the future stream of costs associated with current water use.

Table 2 lists descriptive statistics for the variables included in our basic daily water demand model.

Table 2. Variable Descriptions and Summary Statistics

Variable	Description	Units	Mean	Std. Dev.	Min.	Max.
w	Daily household water demand	kgal/day	0.40	0.58	0.00	9.78
lnw	Natural log, daily water demand	ln(kgal)	-1.57	1.25	-11.51	2.29
p1	Marginal price in block 1	$/kgal	1.45	0.54	0.50	3.70
p2	Marginal price in block 2	$/kgal	1.84	0.40	0.84	4.06
p3	Marginal price in block 3	$/kgal	2.43	0.87	0.93	4.96
p4	Marginal price in block 4	$/kgal	3.28	1.30	0.99	5.98
y	Gross annual household income	$000/yr	69.81	67.67	5.00	388.64
yd2	Virtual income, block 2 + y	$000/yr	77.20	78.45	5.00	388.71
yd3	Virtual income, block 3 + y	$000/yr	121.63	107.48	5.01	388.71
yd4	Virtual income, block 4 + y	$000/yr	122.15	107.62	5.02	389.52
w1	Water quantity at kink 1	kgal/day	0.21	0.08	0.06	0.37
w2	Water quantity at kink 2	kgal/day	0.36	0.09	0.30	0.50
w3	Water quantity at kink 3	kgal/day	1.82	0.80	0.75	2.49
seas	Season: 1 if irrigation season, 0 if not	binary	0.51	0.50	0	1
weath	Evapotranspiration less effective rainfall	mm	5.06	8.42	-46.15	19.37
maxt	Maximum daily temperature	ºC	24.12	8.78	0	42.78
famsz	Number of residents in household	integer	2.79	1.34	1	9
bthrm	Number of bathrooms in household	integer	2.58	1.30	1	7
sqft	Approximate area of home	000 ft^2	2.02	0.82	0.40	4.37
lotsz	Approximate area of lot	000 ft^2	10.87	9.22	1.00	45.77
age	Approximate age of home	yrs/10	2.88	1.62	0.07	5
age2	Square of home age	yrs/100	10.92	9.60	0.01	25
evap	Evaporative cooling: 1 if yes, 0 if no	binary	0.09	0.28	0	1
lasv	Indicator –Las Virgenes MWD	binary	0.10	0.29	0	1
seat	Indicator –Seattle	binary	0.09	0.28	0	1
sandg	Indicator –San Diego	binary	0.09	0.28	0	1
tampa	Indicator –Tampa	binary	0.09	0.29	0	1
phx	Indicator –Phoenix	binary	0.09	0.29	0	1
tscot	Indicator –Tempe, Scottsdale	binary	0.09	0.29	0	1
wcamb	Indicator –Waterloo, Cambridge	binary	0.08	0.28	0	1
wvall	Indicator –Walnut Valley Water District	binary	0.10	0.29	0	1
lomp	Indicator –Lompoc	binary	0.09	0.29	0	1

5.2. Econometric Model of Water Demand

We use a log-log functional form for demand in our analysis, described by equations (5) and (6).[23] We chose this demand function because specifying the dependent variable as the natural log of water demand, rather than water demand itself, allows for substantial skewness in the data. Figure 5 illustrates the right-skewness in the distribution of water demand and symmetry in the distribution of its natural log. Second, we use the same functional form as Hewitt and Hanemann (1995) because we wish to be able to compare our results to theirs.

$$w = \exp(Z\delta) p^{\alpha} \widetilde{Y}^{\mu} \exp(\eta) \exp(\epsilon) \tag{5}$$

or taking logs,

$$\ln w = Z\delta + \alpha \ln p + \mu \ln \widetilde{Y} + \eta + \epsilon \tag{6}$$

We have some priors on the factors that affect household water demand. Most importantly, economic theory predicts downward-sloping demand curves, requiring a negative relationship between price (p) and quantity (w).[24] In addition, income ($\widetilde{Y}$) and quantity should be positively correlated.

The matrix Z comprises observations on the weather, sociodemographic and housing variables in our model. Most of household water demand, with the exception of the small fraction used for drinking water, is actually derived demand, in which the primary demand is for water-consuming items and services, such as clean laundry, indoor bathroom use, and green lawns. As a result, household water demand depends on characteristics that represent the household's tastes for water consumption in such services.

As we have specified the daily weather variables, each should be positively correlated with demand. Maximum daily temperature is represented by *maxt*, and *weath* represents the moisture requirements of green lawns not met by precipitation, or evapotranspiration less effective rainfall. In addition, given the very different distributions

[23]For an explanation of how this demand function can be derived from the underlying utility function, see [39].

[24]In the IV and OLS models, for households facing block prices, the price variable is marginal price within the observed consumption block. Establishing this price involves making an important assumption that the consumption observed during two weeks of each season is a good predictor of consumption during the entire billing period. Marginal water prices are based on monthly or bimonthly use, not daily use, so we multiplied average daily use over two weeks by the average number of days in a billing period for the household's utility in order to place the household in a consumption block. This assumption is made implicitly in the discrete-continuous choice model when we divide the monthly block cutoffs by the number of days in the month to obtain daily cutoffs to use in the model.

of water demand in each of the two seasons portrayed in Figure 5 – irrigation and non-irrigation seasons – we expect that the influence of season (*seas*), a dummy variable set equal to unity during the outdoor watering season, will be positive.

In addition to weather, the composition of the household should affect daily demand. Larger houses with larger outdoor watering areas, more water-using fixtures, and more family members to use them should exhibit higher demand. Thus we expect positive correlations between the variables that represent these characteristics (*lotsz*, *sqft*, *bthrms*, and *famsz*) and daily demand. We include one idiosyncratic variable in the models– the presence or absence of an evaporative cooler (*evap*). Many of our sample cities are arid, and low-income households in such cities frequently have evaporative coolers, rather than traditional air conditioning. These appliances are profligate water users and can consume up to 500 gallons per day, more than the mean total daily household consumption in our sample, 399 gallons. We include this variable in order to avoid biasing the income coefficient estimate in our models downward.[25]

This is the first study to include the age of the home in a residential water demand equation using appropriate treatment of block pricing. We believe that home vintage may be responsible for 5 to 10 percent of the variation in residential water demand.[26] More specifically, very old homes are likely to have smaller connections to their city water system, and also fewer water-using fixtures such as dishwashers and jacuzzis than do newer homes. The very newest homes are those built after the passage of local ordinances in the 1980s and 1990s requiring low-flow toilets and other water-conserving fixtures to be installed.[27] Middle-aged homes should be the largest water users, as they

[25] While less than 10 percent of sample households have evaporative coolers, they are quite common in the arid cities. Forty-three percent of sample households in Phoenix have evaporative coolers, as do one-third of households in Tempe and Scottsdale, higher-income suburbs of Phoenix. In Denver, 14 percent of sample households have these appliances, as do small percentages in San Diego, Walnut Valley and Las Virgenes. Mean annual income among households with evaporative coolers is $56,000, compared to $71,000 among households without them. The t-statistic in a test of the significance of this difference in means is 9.94; the difference is highly significant.

[26] When we run a simple panel random effects regression of the natural log of water demand on home age, the square of home age and two variables that account for the size of a home (square footage and number of bathrooms), we obtain significant coefficients on both home age variables and explain approximately 17 percent of the variation in water demand across households.

Vintage models are frequently used to study energy conservation, in order to account for the fact that it is not economic for households or firms to scrap existing capital in response to every change in relative prices [43][51]. We know of only one example of existing work on the role of construction vintage in water demand, or in the effectiveness of water conservation policies. A model of the impact of vintage on demand for water used for toilets indicates that homes built before 1960 or after 1990 used less water for flushing, all else equal, than homes built between 1960 and 1990 [52].

[27] The Energy Policy Act of 1992 established a national manufacturing standard of 1.6 gallons per flush for most toilets. Initial implementation occurred on January 1, 1994. All of the cities in our study have ordinances on the books requiring low-flow plumbing fixtures in newly constructed and renovated residential structures, some of which were also required by state law.

were built with a taste for high water use in mind and before water-conserving fixtures were required by law. We therefore expect the relationship between demand and home age to be non-monotonic – water demand may be positively correlated with the age of a home, and negatively correlated with age squared.

Finally, we include a set of indicator variables that represent the 11 urban areas included in the study: Denver, Eugene, Seattle, San Diego, Tampa, Phoenix, Tempe/Scottsdale, Waterloo/Cambridge (Ontario), and Lompoc. These variables are included to account for variation in geography, conservation programs, regulations and culture not included within the other independent variables. These variables will be less important when we estimate models that account explicitly for non-price conservation programs, but for now that information is included within these city dummies.

We estimate three models of daily household water demand – the two-error discrete/continuous choice (DCC) model described above, and for comparison purposes, a GLS random-effects model, and an instrumental variables (IV) model. The GLS model, as explained earlier, generates estimates that will be biased and inconsistent because it does not account for the fact that marginal price and the choice of block are simultaneously determined. (It does, however, account for the panel nature of the data.) We include it here to demonstrate that the GLS price coefficients reflect the upward-sloping price structure rather than the downward-sloping demand curve.

The IV model is similar to the 2SLS model estimated in Hewitt and Hanemann (1995), which was originally due to Wilder and Willenborg (1975). In this model, the first stage equation is a regression of observed marginal price on the characteristics of the price structure (fixed charges and the full set of marginal prices), as well as all of the exogenous covariates. The second stage equation uses predicted values of price, which unlike observed price are uncorrelated with water demand, and the exogenous covariates to generate parameter estimates. While this model does not account for all of the theoretical and econometric issues associated with block pricing, it does account for the simultaneous determination of price and quantity, or more precisely of price and the block in which to consume. Because the estimated demand curve is downward-sloping, price elasticities generated by IV models can serve as an interesting point of comparison with the DCC model.

There are two important differences, however, between our IV model and those implemented in earlier papers. First, because there are 26 price structures represented in our data, we create instruments for marginal price that do not depend on specific block quantity cutoffs, which vary widely among price structures. Here we borrow an idea from the labor economics literature and create a set of variables representing the marginal price of consuming certain quantities of water (the marginal price of 1,000 gallons, 2,000 gallons, and so on) [33].[28] Like the earlier papers, we also use the fixed

[28]Our method is similar to that used by Gruber and Saez (2000) to estimate the elasticity of taxable

charges and exogenous covariates to complete the set of instruments.

A second important difference is that we account for the fact that observations are correlated across households. Our IV model is a two-stage GLS random-effects model specifically constructed for panel data.[29] This is important not solely because of the efficiency gain anticipated from recognizing the panel structure, but also because failing to do so may bias standard error estimates substantially downward if the error terms are positively correlated [61][59]. This is particularly true when estimation of the coefficients of interest relies on between-group variation more than within-group variation, which is the case for the price coefficient in our sample [61].[30]

The DCC model we implement is the model described above, with the likelihood function as described in Appendix A. To construct and program the model, we used information in Hewitt (1993), Hewitt and Hanemann (1995), Pint (1999) and Waldman (2000).[31] As many who have applied these models have noted previously, convergence is difficult to achieve if the maximization algorithm is started at initial parameter values that are far from the maximized values [40][68][76]. We used parameter estimates from the IV models as starting values in the DCC model, with reasonable success and without encountering other possible local maxima. Note that the DCC model does not account for the panel nature of the data. All observations are treated as if they are independent, and each makes an equally-weighted contribution to the value of the maximized likelihood function. Testing the extent to which the standard error estimates may be biased by this and eventually estimating a model that recognizes the panel nature of the data is an important future extension of this work.

6. Basic Model Results

Model results bear out our expectations, in large part. Table 3 reports coefficient estimates, standard errors, and significance levels for the three models – GLS, IV and DCC. Standard errors are presented in parentheses beneath parameter estimates.[32]

income.

[29] We use Stata 7.0 to estimate the IV model. The version of Stata's instrumental variables panel data model that we use is G2SLS due to Balestra and Varadharajan-Krishnakumar (1987). Baltagi (1995) offers a review of this and other panel simultaneous equation methods.

[30] The clustering of the data by households is not the only level of grouping in our data. Households can be grouped by city or utility district, as well. This is an additional and important reason to include the city fixed effects in our model. Antweiler terms this approach "mixed effects," in which the lower level of grouping (here households) is accounted for with random effects, and the higher level with fixed effects [5].

[31] We programmed the DCC model in GAUSS 3.6, using the application MAXLIK 5.0 to maximize the likelihood function and generate parameter and standard error estimates. Pint and Hewitt provided GAUSS code that served as starting points for our programming effort.

[32] All city effects are relative to households in Denver, Colorado. Asterisks represent significance levels: ***at $\alpha = .01$, **at $\alpha = .05$, and * at $\alpha = .10$.

Table 3. Water Demand Model Estimates

Variable	GLS	IV	DCC
lnprice	1.4019 (.0483)***	-.6336 (.1235)***	-.3408 (.0298)***
lnincome	.1257 (.0305)***	.1490 (.0323)***	.1305 (.0118)***
seas	.2579 (.0205)***	.3272 (.0215) ***	.3070 (.0247)***
weath	.0075 (.0010)***	.0083 (.0011) ***	.0079 (.0013)***
maxt	.0146 (.0015)***	.0207 (.0016) ***	.0196 (.0018)***
famsz	.1694 (.0144)***	.1973 (.0153) ***	.1961 (.0056)***
bthrm	.0325 (.0240)	.0533 (.0254)**	.0585 (.0093)***
sqft	.0713 (.0362)**	.1390 (.0385) ***	.1257 (.0140)***
lotsz	.0041 (.0023)*	.0067 (.0025) ***	.0065 (.0009)***
age	.0778 (.0565)	.0908 (.0598)	.0867 (.0219)***
age2	-.0150 (.0094)	-.0154 (.0099)	-.0137 (.0036)***
evap	.1922 (.0787)**	.2477 (.0833) ***	.2277 (.0300)***
lasv	-.7523 (.0971)***	.3925 (.1206) ***	.2592 (.0409)***
seat	-1.0216 (.0914)***	.0510 (.1133)	-.1231 (.0380)***
sandg	-.6722 (.0894)***	.0786 (.1032)	.0136 (.0366)
tampa	-.6098 (.0893)***	-.3406 (.0956) ***	-.3881 (.0373)***
phx	-.0734 (.0927)	.0482 (.0983)	-.0043 (.0385)
tscot	.0377 (.0915)	-.1508 (.0974)	-.1032 (.0360)***
eug	.9175 (.0931)***	-.1598 (.1150)	.0050 (.0388)
wcamb	-.6669 (.0909)***	-.1416 (.1004)	-.1938 (.0362)***
wvall	-.3842 (.0921)***	.2862 (.1042) ***	.1785 (.0388)***
lomp	-.9395 (.0915)***	.0627 (.1115)	-.0646 (.0373)*
constant	-3.7236 (.1539) ***	-3.7198 (.1627) ***	-3.6993 (.0653)***
σ_η	---	---	1.0768 (.0103)***
σ_ε	---	---	.3554 (.0277)***

Beginning with the panel GLS model, the first thing to notice is the large positive and statistically significant price coefficient, which represents the slope of the increasing block price structures in our data, rather than the demand curve. We do not attempt to directly interpret any of the other coefficients in the GLS model, because they are known to be biased and inconsistent. Instead, we turn to the IV and DCC estimation results.

6.1. Effects of Price and Income on Water Demand

Due to the non-linear budget constraint, the price and income coefficients in the IV and DCC models cannot be interpreted directly as elasticities, because they do not reflect the probability that a household switches blocks in response to a change in price or income. In effect, the coefficients are conditional price and income elasticities of demand given consumption within a certain block. Changes in price and income also affect the probabilities of each discrete choice, and these probability changes must be accounted for in a precise elasticity. We interpret these coefficients, therefore, as measures of household sensitivity to price and income increases within blocks rather than precise elasticities.

The price and income coefficients in the IV model are the best we can do in terms of estimating elasticities, given that the discrete portion of the consumption choice is not modeled directly. For the DCC model we can do somewhat better, however. Given that the DCC model reflects both the discrete and continuous portions of a household's choice, we can generate price and income elasticities by taking expectations of the exponential form of the conditional demand function, simulating a price or income change, and then calculating the resulting change in expected demand. Implementing this process is an area of current work, so here we use the reported coefficients as proxies for price and income elasticity in the DCC model.[33]

The effect of price on daily water demand is small in our analysis, in keeping with most results in the literature for price elasticity of residential of water demand. It is, however, negative and highly significant. As expected, in the IV model, the use of instruments to generate predicted values of the natural log of marginal price addressed the endogeneity of price and quantity, resulting in the estimation of a downward-sloping demand curve.[34] The price coefficient of -0.63 is estimated at a very high level of

[33]Elasticities calculated by taking expectations of the conditional demand function were 14-17 percent lower than the price coefficient estimated by Hewitt and Hanemann (1995). No other examples of these calculations exist in the literature, so we do not speculate about the magnitude of the differences we will find.

[34]As mentioned earlier, instruments included the price structures themselves (fixed charges and marginal prices at varying quantities of consumption), as well as all of the exogenous covariates. The

significance ($\alpha = .01$) and is well within the range of estimates in the literature.[35]

The price coefficient we estimate with the DCC model is -0.34, substantially lower than that estimated by the IV model. The two previous applications of the DCC model to water demand do not give us strong points of comparison for interpreting the relative results of our DCC and IV models for price elasticity. The first previous application fails to find a statistically significant price effect in two different IV models, yet it finds the largest price elasticity in the literature (-1.90) with the DCC model [40]. In the other previous application to water demand, the DCC model is the only model estimated that accounts for the endogeneity of price and quantity; no IV model was estimated [68].[36]

In absolute terms, the difference between our DCC estimate and that of Hewitt and Hanemann (1995) is substantial; their coefficient is almost six times the magnitude of ours. Some difference in estimates is expected due to differences in data. For example, we exclude marginal wastewater charges from the present analysis, and we include a variety of household-level variables that were not available to previous analysts. However, it would be surprising if the entire disparity in price coefficients were due to these differences. We suggest that the most important determinants of this difference are: (1) our estimation of a short-run, rather than a long-run elasticity; and (2) the fact that 40 percent of households in our sample face uniform marginal prices, rather than block prices.

First, as mentioned earlier, both previous applications of the DCC model to water demand estimated long-run price elasticities for household water demand over a period of 3 to 10 years. We observe households over a period of less than one year, and our model results confirm the expectation that short-run sensitivity to price is lower than long-run sensitivity, which can reflect substituting away from water through the adoption of water-conserving appliances. As in studies of the price elasticity of demand for electricity, long-run estimates of price elasticity for water demand tend to be higher than short-run estimates [26].

Second, our sample comprises households facing three general types of price structures – uniform prices, two-tier increasing block structures, and four-tier increasing block structures. Water demand among households facing uniform marginal prices appears to be significantly less elastic than among households facing block prices, according to

correlation between the predicted natural log of price and observed natural log of price is 0.90; the correlation between predicted natural log of price and natural log of water demand, the dependent variable, is 0.09.

[35]The IV model in Hewitt and Hanemann (1995) did not identify a significant price effect. We have a good deal more price variation in our data, as well as a significantly greater number of households (1,082 compared to 121 in that study), so it is not surprising to find an effect where they did not.

[36]In the labor literature, however, the discrete-continuous choice model, often called the "Hausman model," has estimated greater labor supply distortions from taxation than competing models. Our results are somewhat surprising in that light, but we do not take this difference very seriously, given the substantial contextual differences in estimating water demand and labor supply functions.

one meta-analysis of selected water demand studies from 1963-1993 [26]. If a household knows that higher levels of use result in higher prices, it will be more sensitive to price. In fact, when we estimate our DCC model on households facing two-tier block prices alone, we obtain a price coefficient of approximately -1.00. For households facing uniform marginal prices alone, we obtain a coefficient of -0.19. This suggests that price sensitivity is higher for households facing block pricing.[37]

The results of the IV and DCC models for the effect of income on water demand are straightforward. The estimated income coefficient in the IV model is 0.15 and in the DCC model is 0.13.[38] Our income estimates and those of others who have applied the DCC model (using indirect measures of income) are somewhat low compared with other models in the literature. The range of income elasticity estimates from 1951-1991 was 0.18 to 2.14, with most estimates falling in the range of 0.2 to 0.6 [36]. But most of these studies did not include household-level information on housing characteristics (which are strongly positively correlated with income). The omission of these variables would have overestimated the influence of income itself on water demand.

6.2. Effect of Weather and Household Characteristics on Water Demand

The household and housing characteristics that serve as proxies for the determinants of primary water demand have the expected signs in both the IV and DCC models. In addition, estimates of the components of δ in these models are very close. It is tempting to interpret the vector of estimates, δ, as the marginal effects of the columns of Z on water demand, but this is not the case due to the functional form of demand we employ in the model. Because the weather, sociodemographic and housing characteristics enter the model exponentially, the effects listed in Table 4 can be interpreted as "multipliers"

[37] In addition, one of the previous applications of the DCC model to water demand combined households facing uniform prices with those facing a four-tier price structure, with resultant price elasticity estimates much closer to our coefficients than those of Hewitt and Hanemann [68]. On average, households facing block prices in our sample have larger homes and lots, more bathrooms, higher incomes, and smaller families. Due to these differences in mean values of important independent variables, we cannot rule out the chance that the difference in estimated price coefficients is due to selection bias or some other confounding factor, rather than true consumer response to the different price structures.

[38] Note that although income, $\widetilde{Y}$, includes the virtual income "rebate" from paying less than the marginal price for initial units when a household consumes beyond the first block, we do not instrument for $\widetilde{Y}$ in the IV model. This is true even though the value of virtual income depends on price, which is the endogenous variable. We do not instrument for income because the fraction of income represented by virtual income is exceptionally small – on average it is $25 per year. (This is quite different from the labor supply literature, where the values of virtual income that result from the marginal tax structure reach into the many thousands of dollars per year.) In order to be able to compare the IV and DCC results, we leave un-instrumented income+virtual income ($\widetilde{Y}$) in the equation. When we estimate IV models with separate coefficients for income and virtual income, with virtual income instrumented, they result in statistically insignificant results for virtual income and an estimated income coefficient of 0.149, identical to three decimal places to the result in the IV model reported here.

of daily demand associated with a one-unit increase in the component of Z, at any values of the other independent variables[39] If the multiplier is greater than one, it represents an increase in demand associated with an increase in the component of Z. A multiplier less than one represents a decrease in demand associated with an increase in the component of Z, and a multiplier equal to one represents the absence of a statistically detectable effect.[40]

Table 4. Effects of Variables in Z on Water Demand

Component of Z	**GLS**	**IV**	**DCC**
Season	1.294*	1.387*	1.359*
Evapotranspiration less rainfall, mm	1.008*	1.008*	1.008*
Maximum daily temperature, °C	1.015*	1.021*	1.020*
Number of household members	1.185*	1.218*	1.217*
Number of bathrooms	1.033	1.055*	1.060*
Area of home, ft^2	1.074*	1.149*	1.134*
Area of lot, ft^2	1.004*	1.007*	1.007*
Age of home, yrs./10	1.081	1.095	1.091*
Age of home squared	0.985	0.985	0.986*
Evaporative cooler	1.212*	1.281*	1.256*
Las Virgenes MWD	0.471*	1.481*	1.296*
Seattle	0.360*	1.052	0.884*
San Diego	0.511*	1.082	1.014
Tampa	0.543*	0.711*	0.678*
Phoenix	0.929	1.049	0.996
Tempe/Scottsdale	1.038	0.860	0.902*
Eugene	2.503*	0.852	1.005
Waterloo/Cambridge	0.513*	0.868	0.824*
Walnut Valley Water District	0.681*	1.331*	1.195*
Lompoc	0.391*	1.065	0.937*

In interpreting the numbers in Table 4, we refer to the IV and DCC models; the estimates of these two models of the effects of weather and household structure and composition are remarkably close. In the irrigation season, households use 35 to 40

[39]While the marginal effects of independent variables in a linear model would be expressed as effects at some specific value of the other covariates, usually the means, the exponentiated coefficients in this model are constant elasticities at *any* value of the other covariates. (The magnitude of the change in the dependent variable will, of course, depend on the values of the other covariates because the function is multiplicative.) Like the price and income coefficients, these effects should be interpreted as effects conditional on staying within a given block.

[40]Significance levels are reported again here, copied from Table 4 for reference. They represent significance tests on the difference of the parameter estimates themselves from zero, not the difference of the exponentiated coefficients from one. An asterisk (*) represents significance at a level of $\alpha = .10$ or less.

percent more water per day, on average, than they do in the non-irrigation season, holding all other variables constant. For every centimeter of lawn moisture need not met by precipitation, daily water demand can be expected to rise by less than one percent.[41] An increase of ten degrees Celsius in maximum daily temperature can be expected to cause a two percent increase in daily water demand, *ceteris paribus*. Each additional household resident can be expected to increase daily water demand by approximately 22 percent, and each additional bathroom by approximately six percent. For every 1,000 square feet of home area, daily demand increases by 13 to 15 percent, and by much less for every 1,000 square feet of lot area (0.7 percent). The presence of an evaporative cooler increases household demand by 25 to 30 percent.[42]

While the variables incorporating the age of the home into the model were statistically significant only in the DCC model, their parameter estimates and resulting predicted effects are similar across the three models.[43] We conclude that there is an identifiable effect of home age on daily water demand, and that the character of the effect meets our expectations.

The relationship between the age of the home and water demand, presented in Figure 7, is nonlinear. When vintage is considered in isolation, the highest water demand occurs among homes in the range of 20 to 40 years old; both newer homes and older homes use less water.[44] According to the DCC model, the highest combined effect of home age and its square occurs at an age of approximately 32 years – homes built in the early 1960s.[45]

[41] This is not surprising, given that many homes have timed automatic sprinkling systems or less technical but still systematic patterns of watering on certain days or over certain intervals of time. These patterns may be largely uncorrelated with the actual moisture needs of lawns. One survey of 515 single-family households in the Metropolitan Water District of Southern California estimated that only 11 percent watered landscaping within 10 percent of actual moisture requirements; 39 percent over-irrigated by more than 10 percent, and 50 percent under-irrigated by more than 10 percent [47].

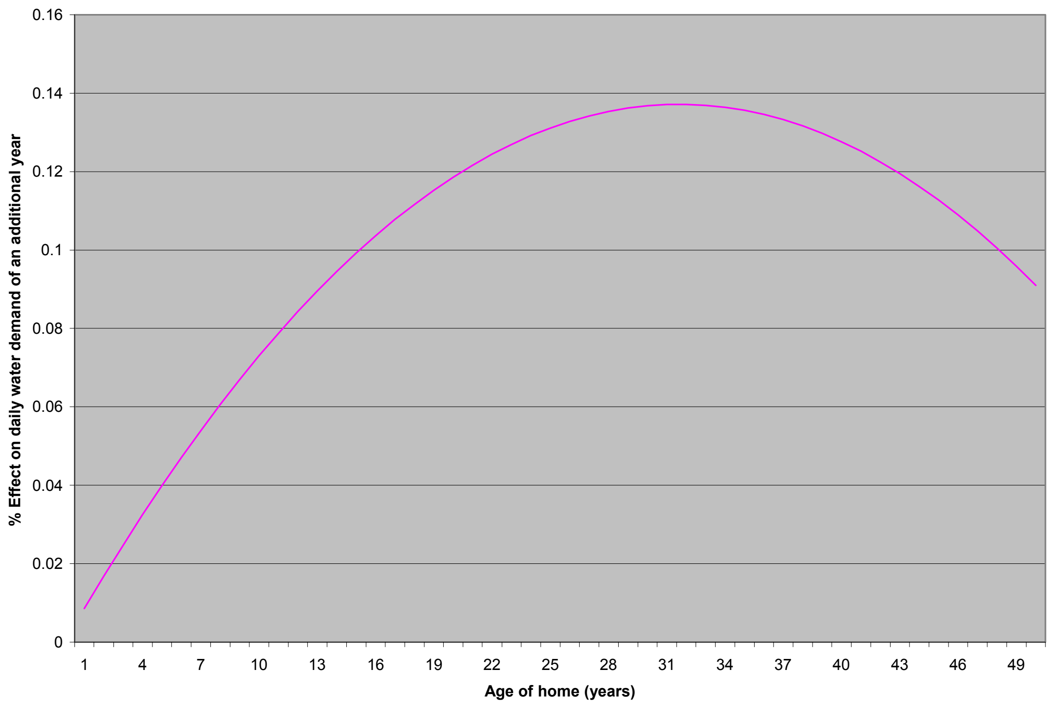
[42] In our sample, without controlling for other variables, households with evaporative coolers use on average 40 percent more water per day than households without them. Households with evaporative coolers effectively substitute water for electricity to satisfy their demand for air conditioning.

[43] The p-values for these variables were in most cases very close to 0.10, but below 0.10 only in the DCC model.

[44] The variable home age counts backward in time from the year of observation, 1995 or 1996 depending on the household.

[45] The effect of home age on water demand is relatively small compared with the effects of other factors in the model. First, many sample cities are sunbelt cities like Phoenix, Tempe/Scottsdale, Denver, Tampa, and the southern California cities, in which the housing stock is fairly young. Recall that the average age of a home in our data is 28 years. In addition, the data on home age are top-censored. We have no information on the distribution of home age for homes built prior to 1960. In order to estimate an age for these oldest homes in the sample, we fit a distribution to home age observations prior to 1960 and use the parameters of that distribution to predict a mean age of approximately 50 years, meaning that they appear in the data to have been built around 1945.

Figure 6: Effect of Home Age on Daily Water Demand Predicted by DCC Model



6.3. Between-city Variation in Water Demand

Results for the city dummy variables represent city-level variation not otherwise accounted for in the model. The figures in Table 4 associated with the city dummies should be interpreted as the percentage increase or decrease in daily water demand associated with residence in a given city, in comparison with residence in Denver, Colorado. If we rank the cities according to their mean daily water demands, the ranking comes close to a ranking of the city dummy multipliers from the DCC model (Table 5).[46] We hope to identify the sources of some of this city-level variation when we analyze the effects of non-price residential water demand management policies.

[46] For three of the four cities in which the ranking seems "out of order"–those in the middle of the distribution, the DCC model did not detect a significant difference from the effect of residence in Denver. Means for all cities are calculated for households without evaporative coolers; means are substantially different with and without evaporative cooling in Phoenix, Tempe/Scottsdale, Denver and Walnut Valley Water District in southern California.

Table 5. Mean Water Demand by City vs. City Demand Multiplier Predicted by DCC Model

City or Utility District	Mean Daily Household Water Demand (gals.)	Estimated Multiplier Effect of Residence in City Predicted by DCC Model
Las Virgenes MWD	683	1.296
Walnut Valley WD	501	1.195
Denver	484	1.000
Phoenix	474	0.996
Tempe/Scottsdale	390	0.902
Eugene	384	1.005
San Diego	344	1.014
Lompoc	280	0.937
Seattle	259	0.884
Waterloo/Cambridge	236	0.824
Tampa	225	0.678

In addition, of all the components of δ, the city dummy coefficient estimates are the only ones that differ markedly between the IV and the DCC models. We believe this is due to the fact that the characteristics of the price structures, including block cutoffs and the magnitude of marginal price differences between blocks, are incorporated within the city dummies in the IV and GLS models. In the DCC model, these characteristics of the price structure are accounted for in the probability statement for each observation. These types of differences, because they do not enter directly into the GLS and IV models, are absorbed into the between-city variation represented by the city dummy coefficients.

This is the first study to apply the DCC model to water demand across multiple cities over time. We note that the confounding of the effects of price structure with other city-level variation in the GLS and IV models provides another reason to account for the price structure directly in the econometric model. Estimating models such as the DCC model may be the only way to separate the effects of price structure from other city-level effects of interest, particularly the effects of water conservation policies.

As a final note, we mention that the DCC model estimates separately the variance of the two error terms. As described in Appendix A, heterogeneous preferences among households are represented by the error term η. Optimization error on the part of the household and perception error on the part of the econometrician are represented by ε. In keeping with the literature on water demand and labor supply, household heterogeneity accounts for a greater portion of the unexplained variance in water demand than does optimization or perception error[56][40][68]. The ratio of the two error standard deviations, heterogeneity to measurement error, is a common measure of the relative importance of the two types of error. This ratio is larger than in previous studies, due to the larger variation in our data. Recall that previous water demand DCC models were estimated for households in one city – our households are far more heterogeneous.[47]

7. Conclusions

In many areas of the world, including large parts of the United States, scarce water supplies are a serious resource and environmental concern. The possibility exists that water is being used at rates that exceed what would be dictated by efficiency criteria, particularly when externalities are taken into account. Because of this, much attention has been paid by policy makers and others to the use of demand management techniques, including requirements for the adoption of specific technologies and restrictions on particular uses. A natural question for economists to ask is whether price would be a more effective instrument to facilitate efficient management of water resources. As a first step in such an investigation, this paper draws upon a newly-available set of detailed data to estimate the demand function for household use of urban water supplies, using appropriate econometric treatment of block pricing.

Our results generate four categories of conclusions for urban water management, and two conclusions for the theory and estimation of water demand. Conclusions for the practice of urban water management include those with respect to the effects of the following on residential water demand: (1) price and price structure; (2) housing characteristics; (3) weather and season; and (4) city or utility of residence. The analysis described in this paper is a work in progress. As we conclude, we note areas in which we plan extensions of the model.

7.1. Price and Price Structure

With respect to price and price structure, at current prices the sensitivity of household water demand to price is small, but it is significantly larger for households facing block prices than for those facing uniform prices. This suggests that price structure may be a more important influence on water demand than the magnitude of marginal price itself. We generate the first estimate of the short-run sensitivity of demand to marginal price, using appropriate econometric treatment of block pricing. These results are

[47]Moffitt (1986) lists the variance ratio: heterogeneity to optimation/perception error (which he calls measurement error) from 21 labor supply applications of the Hausman model, 1980-1985. Of these, all were either greater than or statistically indistinguishable from zero. The ratio here is 3.03; of the two existing applications of the DCC model to water demand, Hewitt and Hanemann (1995) obtains a ratio of 2.32 and Pint (1999) a ratio of 1.17.

better indicators than previous long-run estimates of how households will respond to policies such as drought management pricing or other short-term price changes. The fact that our short-run estimates are closer to the range of historical estimates in the literature is important, because initial applications of the DCC model to water demand resulted in surprisingly high price elasticity estimates, and could have been interpreted as indications that earlier, smaller effects were due to inadequate econometric treatment of block pricing. While our initial results will not put that debate to rest, they provide plausible explanations for the higher elasticities estimated by previous applications of the DCC model – block pricing itself, and the difference between short- and long-run sensitivity to price.

Putting the estimated price and income coefficient estimates in context, a ten-percent price increase in our data amounts to an increase of about 15 cents per thousand gallons, when we consider the marginal price for households facing uniform prices and only the first-block price for households facing block structures. For an average household in our sample, this would represent an increase of less than $2.00 per month in volumetric water consumption charges, were there no income or substitution affects associated with the price increase. We mention this to emphasize, again, the very small fraction of household expenditures accounted for by water consumption, which makes it unlikely that any analysis will find demand to be highly responsive to price or to income.

7.2. Household and Housing Characteristics

The unique household-level data made available for this analysis allows a more precise look than ever before at the effect of household and housing characteristics on residential water demand. Several of the explanatory variables that have the greatest influence over daily demand are not variables that can be affected by utility water conservation policies or programs – here we refer especially to the size of a home, number of bathrooms, and number of residents in a household, and to a smaller extent, lot size and home age.

The fact that water use varies substantially with household and housing characteristics indicates that there is substantial "cost heterogeneity" for water use reduction across households. Household and housing factors are indicators of preferences for consumptive residential water use. Utility policies have typically sought to reduce water in specific uses, especially outdoor lawn-watering and indoor use of water for showering and flushing toilets. However, such policies that restrict water use reductions to specific uses are similar to command-and-control policies for pollution control; they are not cost-effective because they do not allow households to determine their own least-cost water reduction options.[48]

For example, our results regarding the influence of home vintage on demand, the first such estimates for the residential sector, indicate that some households may be more

[48] We refer to opportunity cost, not necessarily out-of-pocket financial cost.

constrained than others in their ability to respond to utility conservation programs. If it is relatively more costly for consumers in "middle-aged" homes to reduce water consumption in certain uses, then policies that establish one target for homes of all ages are clearly not cost-effective. Evidence of cost heterogeneity across households in this study provides a good reason to believe that price increases and changes in price structure may be more cost-effective in practice than non-price utility demand management programs.

7.3. Weather and Season

While the incidence of a growing season for green grass is an important determinant of water demand in this study, other weather variables have relatively small effects on daily demand. This is not surprising; day-to-day household lawn-watering practices may have little to do with scientific calculations of the moisture needs of landscaped properties. However, given that irrigation constitutes such a large portion of residential water demand, especially during arid peak seasons when the true marginal cost of water supply is likely to increase, the small correlation between watering needs and water demand is notable from a policy standpoint.

7.4. City or Utility of Residence

This study is the first application of the DCC model of water demand to households in multiple cities; the variation in price and price structure in our sample is unprecedented. After accounting for all of the variables typically included in a water demand function, as well as several new ones including home age and family size, we still see substantial variation in daily water demand across cities. This is suggests that an analysis of city water conservation programs and policies may be informative if we are able to construct a model that accounts for the endogeneity of these programs. This study provides evidence that one type of utility conservation policy–price structure–matters in determining how sensitive residential water customers are to changes in price. Further work is needed to understand the causes of the variation in water demand across cities.

The most important next step in that process is to estimate more precise price and income elasticities for the DCC model across ranges of water demand. When we calculate these, we will generate values for each observation, not just for the sample as a whole. That information will allow us to assess the impacts of specific utility conservation policies and programs by looking at their impact on household price elasticity itself, rather than simply on water demand. For example, we will assess whether households are more responsive to the price of water if the price is printed on their utility bill, if the bill includes information that allows them to compare their current level of use to that of the same period in the previous year, or if the utility bills once per month rather than once every two months. In addition, we will use these models to analyze the effects of utility demand management programs, such as the distribution of low-flow fixtures and conservation education material, on household water demand.

7.5. Practice of Demand Estimation Across Cities

We find that the price sensitivity of water demand is different for households facing uniform prices and households facing block prices. The substantial diversity among the 26 price structures in our sample allow us to make this distinction. On the one hand, this is a promising result for the application of the DCC model to water demand; the DCC model was the only one of the three we estimated to separate the effects of price structure from other utility-level variation, which were confounded in the GLS and IV models. This implies that appropriate treatment of block pricing is a necessary component of a model that seeks to assess the effects of utility-level variables of interest, such as non-price water demand management programs.

However, the differential response that we note also calls into question the ability of any one model to estimate price elasticities across households facing disparate price structures. There have been many attempts in the literature at identifying such a common price elasticity. The magnitudes of elasticity estimates for water demand, including ours, are all small in an absolute sense. As a result, the differences we note among households facing various price structures are small for most purposes, with the exception of calculation of changes in utility revenues from a price increase, for which the distinction between elastic and inelastic demand is quite critical. Nonetheless, we interpret these results as a faint warning that the one-size-fits-all approach may be unwise, and that short-and long-run responses to changes in price may be more appropriately calculated at the local or regional level than at a higher level of aggregation.

Finally, we note that an important extension of this model is its adaptation to panel data. While previous applications of the DCC model to water demand used cross-sectional, time-series data, neither accounted for the panel nature of the data in estimation. Nor do we do so in the present analysis. Hence, we have greater confidence in our coefficient estimates, but less confidence in our standard error estimates for the DCC model than we do for the GLS and IV models. Non-parametric models may be promising avenues for appropriate treatment of block pricing with panel data, avenues that we will pursue in future work.

8. Appendix A. Derivation of Likelihood Function

This appendix describes the derivation of the likelihood function used to estimate the DCC model in this study. As mentioned in the text of this paper, the discrete-continuous choice model of water demand is based on the Hausman model of labor supply under increasing marginal tax rates [17][37], and the subsequent generalizations of Moffitt [56][55]. With respect to water demand, the likelihood function for the case of a two-tier increasing block price structure was described originally by Hewitt (1993). The general form for K blocks was solved by Waldman (2000), although it was essentially applied before then by Pint (1999). Our general model is that of Waldman (2000), with one substantive difference due to what we perceive to be a mistake in Waldman's original exposition, as well as differences in notation.

The model has two error terms, which complicates the derivation of the likelihood function. The first source of error is heterogeneity of preferences for water consumption among households. Household heterogeneity is represented by the term η, which incorporates characteristics known to the household, but not to the econometrician, that influence water use. The second source of error is usually called either optimization or perception error, ϵ. It is optimization error because we assume that a household's actual use is not always equal to intended use – perhaps the household contains some leaky fixtures, or teenagers who take long showers despite the plans of whomever manages the household budget. It is perception error because the econometrician fails to perceive these factors, as well. To summarize, η is error to the econometrician, but not to the household, and ϵ is error to both the household and the econometrician. We assume that both η and ϵ are normally distributed, with means zero and standard deviations σ_η and σ_ε, respectively. Given that we have no reason to believe there is a correlation between household heterogeneity and optimization or perception error, η and ϵ are also assumed to be independent.

Intended use is not necessarily equal to actual use, and observed use is not necessarily equal to either actual or intended use, so each observation is treated as if it could have occurred in any portion of the budget constraint, which has K blocks and $K-1$ kinks. (For this reason, we don't see the sample separation that is present in other types of discrete choice models, in which the log likelihood function sums separately over agents making each category of choice.)

The functional form that we use for demand in this paper is:

$$w = \exp(Z\delta) p^{\alpha} \widetilde{Y}^{\mu} \exp(\eta) \exp(\epsilon) \tag{7}$$

or taking logs,

$$\ln w = Z\delta + \alpha \ln p + \mu \ln \widetilde{Y} + \eta + \epsilon \tag{8}$$

Recall that $\widetilde{Y}$ reflects virtual income for households facing block prices. In equation (9) we describe conditional demand under increasing block prices, with K blocks and $K-1$ kinks, where $\ln w$ is the natural log of observed consumption, $\ln \underline{w}_k^*(Z, p_k, \widetilde{Y}_k; \delta, \alpha, \mu)$ is the natural log of optimal consumption in the interior of block segment k, and $\ln w_k$ is the natural log of consumption at kink point k.

$$
\ln w \begin{cases}
\ln \underline{w}_1^*(Z, p_1, \widetilde{Y}_1; \delta, \alpha, \mu) + \eta + \epsilon \qquad if \\
-\infty < \eta < \ln w_1 - \ln \underline{w}_1^*(Z, p_1, \widetilde{Y}_1; \delta, \alpha, \mu) \\
\ln w_1 + \epsilon \qquad if \\
\ln w_1 - \ln \underline{w}_1^*(Z, p_1, \widetilde{Y}_1; \delta, \alpha, \mu) < \eta < \ln w_1 - \ln \underline{w}_2^*(Z, p_2, \widetilde{Y}_2; \delta, \alpha, \mu) \\
\ln \underline{w}_2^*(Z, p_2, \widetilde{Y}_2; \delta, \alpha, \mu) + \eta + \epsilon \qquad if \\
\ln w_1 - \ln \underline{w}_2^*(Z, p_2, \widetilde{Y}_2; \delta, \alpha, \mu) < \eta < \ln w_2 - \ln \underline{w}_2^*(Z, p_2, \widetilde{Y}_2; \delta, \alpha, \mu) \\
... \\
\ln w_{K-1} + \epsilon \qquad if \quad \ln w_{K-1} - \ln \underline{w}_{K-1}^*(Z, p_{K-1}, \widetilde{Y}_{K-1}; \delta, \alpha, \mu) < \eta < \\
\ln w_{K-1} - \ln \underline{w}_K^*(Z, p_K, \widetilde{Y}_K; \delta, \alpha, \mu) \\
\ln \underline{w}_K^*(Z, p_K, \widetilde{Y}_K; \delta, \alpha, \mu) + \eta + \epsilon \qquad if \\
\ln w_{K-1} - \ln \underline{w}_K^*(Z, p_K, \widetilde{Y}_K; \delta, \alpha, \mu) < \eta < \infty
\end{cases} \tag{9}
$$

The probability of an individual observation of water demand, w_i, under a budget constraint with K blocks and $K-1$ kinks can be represented as in equation (10) below, where $\underline{w}_k^*(.)$ is shorthand for $\underline{w}_k^*(Z, p_k, \widetilde{Y}_k; \delta, \alpha, \mu)$ and $\nu = \eta + \epsilon$.

$$
\Pr(w_i) = \begin{array}{lllllll}
\Pr & (& \nu = \ln w_i - \ln \underline{w}_1^*(.) & , & -\infty < \eta < \ln w_1 - \ln \underline{w}_1^*(.) &) & + \\
\Pr & (& \epsilon = \ln w_i - \ln w_1 & , & \ln w_1 - \ln \underline{w}_1^*(.) < \eta < \ln w_1 - \ln \underline{w}_2^*(.) &) & + \\
\Pr & (& \nu = \ln w_i - \ln \underline{w}_2^*(.) & , & \ln w_1 - \ln \underline{w}_2^*(.) < \eta < \ln w_2 - \ln \underline{w}_2^*(.) &) & + \\
 & (& ... & , & ... &) & + \\
\Pr & (& \epsilon = \ln w_i - \ln w_{K-1} & , & \ln w_{K-1} - \ln \underline{w}_{K-1}^*(.) < \eta < \ln w_{K-1} - \ln \underline{w}_K^*(.) &) & + \\
\Pr & (& \nu = \ln w_i - \ln \underline{w}_K^*(.) & , & \ln w_{K-1} - \ln \underline{w}_K^*(.) < \eta < \infty &) &
\end{array} \tag{10}
$$

Note that the segment choices are based on particular values of (ν) and ranges of η, which requires specification of the joint distribution $f(\nu, \eta)$ in order to determine the probability of a segment observation. The kink point choices are based on particular values of ε and ranges of η, which requires specification of the joint distribution $g(\eta, \varepsilon)$. Because the two error terms are independent and normally distributed, $g(\eta, \varepsilon) = g(\eta) * g(\epsilon)$. However, $f(\nu, \eta)$ is a jointly dependent normal distribution. Let $corr(\nu, \eta) = \rho = \frac{cov(\nu,\eta)}{\sigma_\nu + \sigma_\eta}$, which reduces to σ_η / σ_ν.[49] The general form of the likelihood function can then be expressed as in equation (11), in which Φ is the normal cumulative distribution function.[50]

The first summation refers to households served by utilities that charge a constant marginal price for water consumption–the results of this part of the equation if estimated

[49]This is a nice result that derives from the facts that ε and η are independent, and that ν and η are both normal with means zero. The full simplification to σ_η / σ_ν is available from the authors.

[50]The full derivation of the likelihood function is available from the authors.

in isolation would be equivalent to OLS, because the budget constraint is linear. The second summation refers to households facing block prices and reflects both the discrete and the continuous choice. Within this portion of the equation, the first sub-summation represents the probability statement for consumption on K linear segments, and the second sub-summation represents the probability statement for consumption at the $K-1$ kink points.

$$\begin{aligned}
\ln L &= \sum_{uniform\ price\ hholds} \ln\left(\frac{1}{\sqrt{2\pi}} * \frac{\exp -(s_1)^2/2}{\sigma_\nu}\right) + \\
&\quad \sum_{block\ price\ hholds} \ln \left[\begin{array}{c} \sum_{k=1}^{K} \left(\frac{1}{\sqrt{2\pi}} * \frac{\exp -(s_k)^2/2}{\sigma_\nu}\right) * (\Phi(r_k) - \Phi(n_k)) \\ + \sum_{k=1}^{K-1} \left(\frac{1}{\sqrt{2\pi}} * \frac{\exp -(u_k)^2/2}{\sigma_\epsilon}\right) * (\Phi(m_k) - \Phi(t_k)) \end{array}\right]
\end{aligned} \tag{11}$$

$$Where\ : \begin{array}{l} s_k = \ln w_i - \ln \underline{w}_k^*(.)/\sigma_\nu \\ u_k = \ln w_i - \ln w_k/\sigma_\epsilon \\ t_k = \ln w_k - \ln \underline{w}_k^*(.)/\sigma_\eta \\ r_k = (t_k - \rho s_k)/\sqrt{1-\rho^2} \\ m_k = \ln w_k - \ln w_{k+1}^*(.)/\sigma_\eta \\ n_k = (m_{k-1} - \rho s_k)/\sqrt{1-\rho^2} \end{array}$$

9. Appendix B. Evapotranspiration Variable

This appendix describes the calculation of evapotranspiration less effective rainfall, one of the two weather variables in our demand models. The measure recommended by the Food and Agriculture Organization (FAO) for this purpose is calculated using the Penman-Monteith equation, which requires information on net solar radiation at the crop surface, soil heat flux density, mean daily air temperature and wind speed at 2m height, saturation vapor pressure, actual vapor pressure, the slope of the vapor pressure curve, and the psychometric constant, which is a function of atmospheric pressure [3]. This amount of daily weather information was available only for a very small sub-sample of our data, those households in Eugene and Tampa.

Due to data limitations, we have used Hargreaves' approximation to the Penman-Monteith equation, which requires only mean, minimum and maximum daily temperature, degrees latitude (to estimate a solar radiation parameter, Ra), and a readily-available constant (α) associated with the crop of interest – green grass. Hargreaves' formula is listed in equation (12).

$$ET_0 = \alpha(T_{avg} + 17.8) * (T_{\max} - T_{\min})^{1/2} * Ra \tag{12}$$

For the two cities in which the detailed data for Penman-Monteith could be obtained, we tested the predictions of the two alternative formulas to be sure that they would track closely. While the two formulae diverged somewhat in their predictions of evapotranspiration (ET) for Tampa, they tracked very closely in their predictions for Eugene. This is to be expected, given that results from the two equations tend to differ in humid areas. The Hargreaves' formula performed sufficiently well to be included in this study. In addition, we realize that policy makers interested in applying water demand models like the ones we estimate will rarely have access to the detailed data required for a more precise measure of ET than the one we have estimated.

Finally, we subtract effective rainfall from ET_0 in order to calculate the moisture needs of green grass *not* met by precipitation, the variable of interest for calculating household water demand [8]. The subtraction of effective rainfall, rather than total rainfall, from ET_0 accounts for the fact that a large portion of rainfall runs off and is not absorbed by soil. The California Irrigation Management Information System recommends an effective rainfall factor of 0.5 for such calculations in agricultural contexts, meaning that approximately half of measured precipitation reaches soil and contributes to plant growth [8]. We follow a convention established in a seminal urban residential water demand study, using an effective rainfall factor of 0.6 [42]. In summary, the variable *weath* in our models is equal to ET_0 as in equation (12), less 0.6*total measured precipitation, in millimeters. Information on the ET calculation and tests described above is available from the authors.

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