

**DO CONSUMERS REACT TO THE SHAPE OF SUPPLY?
WATER DEMAND UNDER
HETEROGENEOUS PRICE STRUCTURES**

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ABSTRACT

Urban water pricing provides an opportunity to examine whether consumers react to the shape of supply functions. We carry out an empirical analysis of the influence of price and price structure on residential water demand, using the most price-diverse, detailed, household-level water demand data yet available for this purpose. We adapt the Hausman model of labor supply under progressive income taxation to estimate water demand under non-linear prices. Ours is the first analysis to address both the simultaneous determination of marginal price and water demand under block pricing and the possibility of endogenous price structures in the cross section. In order to examine the possibility that consumers facing block prices are more price-responsive, all else equal, we test for price elasticity differences across price structures. We find that households facing block prices are more sensitive to price increases than households facing uniform marginal prices. Tests for endogenous price structures cannot rule out a behavioral response to the shape of supply, but suggest that observed differences in price elasticity under supply curves of varying shapes may result, in part, from underlying heterogeneity among utility service areas.

Keywords: Non-linear pricing, water demand, price elasticity

JEL Codes: D12, Q21, Q25, Q28, L95

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1. INTRODUCTION

Nonlinear prices appear with increasing frequency in a variety of markets, including those for water, energy, and cellular phone service. In 2000, approximately one-third of U.S. urban residential water customers faced increasing block prices, in which marginal prices increase with the quantity consumed, up from four percent of customers in 1982 (OECD 1999; Raftelis 1999). In water markets, the price elasticity of demand is a key policy variable of interest, because: (1) regulators may use price to manage demand during periods of scarcity; and (2) utilities often face zero-profit constraints, so the impact of price changes on total revenues must be predictable.

Economists have encouraged water utilities' adoption of increasing block prices to expand the fraction of consumption that is priced at the long-run marginal cost (LRMC) of water supply, the efficient price. LRMC can be greater than average cost, because LRMC reflects the cost of new supply acquisition, and new supplies are typically more costly to develop than current supplies (Hanemann 1997). Thus, pricing all units at LRMC may cause utility revenues to exceed expenses, sometimes substantially (Moncur and Pollack 1988; Hall 2000). Increasing-block pricing allows utilities to charge LRMC for the "marginal" uses (lawn-watering and the like), while adjusting block cutoffs and infra-marginal prices to meet zero-profit constraints.

Water utility managers traditionally have maintained that consumers do not respond to price signals, and so demand management has occurred most frequently through restrictions on specific water uses and requirements for the adoption of specific technologies. In theory, raising prices to bring about a given level of water conservation is less costly than implementing a command-and-control approach, even if the prices in question are inefficient.¹ As water utilities increasingly hear this message and respond, in many cases by implementing increasing block prices (IBPs), unbiased estimates of the price elasticity of water demand become more important.

Consumer responses to IBPs in the market for water are unclear, at best.² Estimating water demand functions under non-linear price regimes requires econometric techniques that can separate demand from supply. Under IBPs, this problem is twofold. First, marginal prices rise as consumption increases. Thus, even though price schedules are set by regulators, the upward-sloping nature of IBPs means that the price and choice of “block” in which to consume are simultaneously determined. Second, when estimating water demand functions using data in which most of the price variation occurs in the cross-section (water price schedules vary little over time), a utility’s choice of price schedule, itself, may be endogenous, potentially biasing cross-sectional elasticity estimates and casting doubt on cross-city comparisons.

Ours is the first analysis to address both the simultaneous determination of marginal price

¹The comparison of market-based and command-and-control approaches to environmental policy has a long history (Pigou 1920; Crocker 1966; Dales 1968; Montgomery 1972; Baumol and Oates 1988), but few studies have addressed water conservation policies in this framework (Michelsen et al. 1998; Corral 1997).

²Responses to IBPs in other markets are also unclear (Reiss and White 2001; Iyengar 2005).

and water demand under block pricing and the possibility of endogenous price structures. Some previous studies tackled the first problem but not the second, generating results that suggest that price elasticity is higher under IBPs than under a linear marginal price.³ Thus, a one percent price increase under IBPs would result in a greater reduction in water consumption than a one percent price increase under a uniform marginal price, all else equal. If this is true, it implies that consumers exhibit a demand response to the shape of the supply curve, and not simply its height (the magnitude of marginal price).

Using the most price-diverse, detailed, household-level water demand data yet available, we exploit substantial cross-sectional and time-series variation in the price incentives faced by households to estimate price elasticities under heterogeneous price structures. We then examine how the price elasticity of demand varies between linear and non-linear pricing regimes and explore possible explanations for these differences.

We estimate a full-sample price elasticity of water demand of approximately $-.33$.⁴ Models that split our sample by price structure suggest that demand is more price-elastic under IBPs, implying either a demand response to price structure, or underlying heterogeneity among the two sub-samples. We explore the possibility of underlying heterogeneity, with mixed results,

³A causal link has been posited in Dalhuisen et al. (2003) and Hewitt (2000). In addition, price elasticity estimates of water demand under increasing block prices have been on the high end of elasticity estimates as a whole, controlling for other factors (Espey et al. 1997; Hewitt and Hanemann 1995; Rietveld et al. 1997; Pint 1999).

⁴Our elasticity estimates are a mixture of short-run and long-run. Much of the variation in price comes from the cross-section. But there is also substantial variation within individual households over time, due to IBPs. There is also a small amount of variation in price over time due to utility price changes.

but we cannot rule out a behavioral response to the shape of supply curves. Evidence of endogenous price structures is suggestive enough, however, to discourage the application of IBPs for the purpose of increasing consumers' price sensitivity. Their justification on efficiency grounds, in an era of scarcity of both water resources and the potential market-based approaches that might result in prices reflecting economic value, certainly stands.

The questions we examine bring to mind an earlier debate in the labor economics literature with respect to the Hausman model of labor supply under progressive income taxation. We adapt the Hausman model for the estimation of water demand functions. However, we demonstrate why this debate is very different, and explain why the use of this model should not result in dramatic changes in how economists think about the price elasticity of water demand, as it did in how economists think about the wage elasticity of labor supply. The contrast with applications from tax policy is relevant to IBPs for commodities other than water, and must be considered carefully as analysts import the Hausman model in other markets.

The paper is organized as follows. In Section 2, we review the literature on the price elasticity of residential water demand, possible explanations for variation in price elasticity, and the economic theory and econometrics of piecewise linear budget constraints. In Section 3 we describe the data, and in Section 4 we describe our models. In Section 5, we describe the results, and in Section 6, we conclude.

2. THE LITERATURE AND THE ECONOMIC CONTEXT

2.1 Price Elasticity of Water Demand

Previous analyses suggest that water demand is inelastic. In a meta-analysis of 124 estimates generated between 1963 and 1993, accounting for the precision of estimates, Espey et al. (1997) obtain a mean price elasticity of -0.51, a short-run median estimate of -0.38, and a long-run median estimate of -0.64, with 90 percent of estimates between 0 and -0.75.⁵

Some of the largest price elasticity estimates — in the range of -1 to -2 — have been obtained with structural analyses that model directly the piecewise-linear budget constraint created by block pricing (Hewitt and Hanemann 1995; Rietveld et al. 1997; Pint 1999), drawing upon an approach developed to estimate labor supply effects of progressive income taxation.⁶ In addition, two meta-analyses have found that consumers facing IBPs are more price-elastic than consumers facing linear marginal prices (Espey et al. 1997; Dalhuisen et al. 2003). In comparing elasticities across different studies, the meta-analyses face many confounding factors that differentiate the studies in their samples. They control for some, but not all, of these factors. These results have caused some to suspect that previous studies had underestimated price elasticity through incorrect modeling, or that IBPs themselves are responsible for greater sensitivity of demand to price.

2.2 Sources of Variation in Price Elasticity

⁵Dalhuisen et al. (2003) obtain a mean price elasticity of -0.41, in a meta-analysis of almost 300 price elasticity studies, 1963-1998.

⁶ Prior to Hewitt and Hanemann (1995), only three published studies had estimated price elasticities in the elastic range (Howe and Lineweaver 1967; Danielson 1979; Deller et al. 1986).

In water demand estimation, higher elasticity estimates are associated with long-run analyses, data restricted to summer observations, and areas with increasing block rates (Hanemann 1997; Espey et al. 1997). Greater elasticities for summer use (which includes a higher irrigation component) and long-run analyses are reasonable on the basis of economic theory; but higher elasticities for areas facing IBPs are more difficult to understand. If consumers react to price structure, as well as the magnitude of marginal price, there may be a behavioral explanation (Liebman and Zeckhauser 2004).

An alternative explanation is unobserved heterogeneity among cities implementing different price structures. Higher observed price elasticities among block-price cities could be explained by higher average magnitude of marginal prices, or a higher fraction of income devoted to water expenditures. In fact, any utility service area heterogeneity that is systematically correlated with price structure choice might explain the higher observed demand elasticities in IBP cities.

2.3 Block Pricing and Piecewise Linear Budget Constraints

Urban residential water service pricing typically takes one of three forms: (1) a uniform marginal price; (2) increasing block prices; or (3) decreasing block prices. Each of these price structures is typically accompanied by a fixed water service fee. Under constant or uniform rates, households pay 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.

2.3.1 Theory of piecewise linear budget constraints

Under block pricing, consumers face a piecewise-linear budget constraint. Figure 2 depicts the budget constraint in a two-tier increasing block price system with a set of hypothetical indifference curves. 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.⁷

The use of IBPs creates a wedge between average and marginal price and makes these prices endogenous to the consumer's water use decision. The water demand literature has focused mainly on the former; the labor supply literature handled both aspects within the framework of the discrete-continuous choice model of Hausman. The econometric complications caused by these features have been discussed in the literature (Burtless and Hausman 1978; Moffitt 1986, 1990).

Regarding the wedge between average and marginal price, for households consuming anywhere above the first linear segment on a piecewise linear budget constraint, the marginal price is not the price paid for every unit consumed. We account for the implicit subsidy that

⁷Under decreasing-block structures, budget sets are non-convex, enabling multiple tangencies between consumer indifference curves and the budget constraint. The theory and empirics of the non-convex case are straightforward extensions of the convex case described here. The decreasing block case has been developed generally (Moffitt 1986, 1990); in the literature on labor supply and taxation (Burtless and Hausman 1978; Hausman 1985); and for the case of water supply (Hewitt 1993; Hewitt and Hanemann 1995).

derives from the infra-marginal rates by adding to income the difference between what a household would pay if all units were charged at the marginal price, and what they actually pay. This income supplement for a household consuming in the second block of a two-tier price structure would be equal to the shaded region in Figure 1. Following standard practice, we refer to this as “virtual income”.⁸

2.3.2 Econometric Modeling of Demand Under Block Pricing

Regarding the simultaneous determination of block and consumption, if a typical single-error stochastic specification were employed, the size of the error term, marginal price, and virtual income (a function of marginal price) would be systematically correlated. Thus, ordinary least squares (OLS) estimates of the parameters of the demand function will be biased and inconsistent.

This problem has been addressed by estimating instrumental variables (IV) models, such as two-stage least squares, for both labor supply and water and energy demand (Hausman et al. 1979; Agthe et al. 1986; Deller et al. 1986; Nieswiadomy and Molina 1988, 1989). While such models can estimate downward-sloping demand curves, they exhibit three key limitations. First, simultaneous equations models can be used only to estimate elasticities conditional on remaining within the observed block of consumption. Second, the IV methods disregard the fact that some households consume within the neighborhood of a kink point, where it is unclear which value of

⁸The treatment of infra-marginal price changes as lump-sum changes in household income was developed in the labor supply literature (Hall 1973; Burtless and Hausman 1978), and in the electricity demand literature (Nordin 1976; Taylor 1975). The first application to water demand was by Billings and Agthe (1980).

marginal price should be assigned (in an econometric model that includes one or more error terms). Arbitrary treatment of these observations, such as assigning them to one block or another or dropping them from the sample, cannot be reconciled with utility theory. Third, the effect of changes in the price structure, such as a shift from two blocks to three, or a change in block quantity thresholds, cannot be assessed, as these elements of the price structure do not enter IV models.

The discrete-continuous choice (DCC) model, a maximum likelihood model, addresses these issues. The DCC model is a stochastic expression in which each observation is treated as if it could have occurred at any kink or along any linear portion of the household's budget constraint. The probability statement for an individual observation is the sum of joint probability statements, one for each kink and linear block in the budget constraint. Each joint probability includes the probability of the continuous choice of quantity consumed and the conditional probability that consumption occurred at that kink or block, given the choice of quantity. The form of the likelihood function differs depending on the nature of the supply curve faced by each household.⁹

2.4 Piecewise Linear Budgets: Water Demand vs. Labor Supply

⁹A critique of this approach in labor supply analysis has been that the locations of consumers' budget constraint kink points are uncertain – they depend on information about income tax itemizations and deductions, typically unknown – creating measurement error presumed to bias estimates (Heckman 1983; Gan and Stahl 2002). In water demand analysis, the critique is irrelevant because budget constraint kink points correspond to administratively-set block cutoffs and, thus, are known with certainty. This makes the DCC model particularly attractive for estimating water demand functions. A further critique of the DCC model in labor supply has been that results are sensitive to assumptions about the functional form of demand and distribution of error terms (Heckman 1983; Blomquist et al. 2001). This may be true in water demand, as well.

Labor supply under progressive income taxation and water demand under IBPs share the theoretical structure implied by piecewise linear budget constraints, but differ in important ways. A controversial result of Hausman's labor supply models is his estimation of a significant negative compensated wage elasticity of labor supply, implying substantial deadweight losses from income taxation (Hausman 1981). Earlier studies had found uncompensated wage elasticities close to zero and thus concluded that income taxation had negligible effects on desired work hours. Applications of Hausman's model accounting for piecewise linear budget constraints established that the uncompensated effect was, in fact, close to zero because the income and substitution effects of a tax increase could effectively cancel each other out in the data (Hausman 1981; Blundell and MaCurdy 1999; Heim and Meyer 2001). Hausman's result is, in large part, attributable to virtual income – the implicit subsidies from infra-marginal tax rates are relatively large in labor supply analysis (Burtless 1981).

In the case of water demand, we typically measure a small, negative uncompensated price elasticity. In contrast with the labor supply case, the income and substitution effects of a water price increase operate in the same direction: water is relatively more expensive, and real income decreases, so consumers purchase less for both reasons. One would, therefore, expect the compensated price effect to be smaller than the uncompensated effect—not larger as in the case of labor supply. The increase in real income from the (very small) implicit lump-sum transfer due to the water price schedule could, in theory, also diminish the compensated price effect relative to the uncompensated effect. But attempts to measure effects of these small infra-marginal rate income transfers in isolation have been unsuccessful, both in electricity and water

demand (Hausman et al. 1979; Deller et al. 1986; Nieswiadomy and Molina 1989).¹⁰

Without the substantial “compensation” through virtual income from the progressive tax rate analysis, and without competing income and substitution effects, one would not expect price elasticities of water demand to be larger, on average, where DCC models are employed to estimate them. Yet, this is, in fact, what has previously been found.

3. THE DATA

The data comprise 1,082 households in 11 urban areas in the United States and Canada, served by 16 water utilities.¹¹ The sample is notable for its geographic and climatic diversity. Table 1 provides descriptive statistics.

Daily household water demand and weather conditions are observed over two periods of two weeks each, one in the lawn-watering season and one in a season in which irrigation is not required. Daily demand data were gathered by automated data loggers, attached to magnetic household water meters by utility staff.¹²

¹⁰Even in the fourth block in the sample cities analyzed here, where implicit lump-sum transfers reach a maximum, their average contribution to virtual income is less than \$584 per year.

¹¹The household-level data were gathered by Mayer et al. (1998) for a study sponsored by the American Waterworks Association Research Foundation. Sample utilities include Denver Water (CO); Eugene Water and Electric Board (OR); Seattle Public Utilities (WA); City of Bellevue Utilities Department (WA); Highline Water District (WA); Northshore Utility District (WA); City of San Diego Water Department (CA); Tampa Water Department (FL); Phoenix Water Department (AZ); City of Tempe Water Utilities (AZ); City of Scottsdale Water Department (AZ); Regional Water Services, Municipality of Waterloo (ONT); City of Cambridge (ONT); Walnut Valley Water District (CA); City of Lompoc Utilities Department (CA); and Las Virgenes Municipal Water District (CA).

¹²These devices were hidden from sight during most, if not all, uses of water.

Each household faces one price structure throughout each season of observation, but some price structures changed between the two periods. As a result, the data include 26 price structures: eight two-tier IBP structures, ten four-tier IBP structures, and eight uniform structures. Marginal prices exhibit substantial variation, from \$0 to \$4.96/kgal.

Household demographic data were collected by a one-time household survey.¹³ Water demand, with the exception of the small fraction used for drinking, is derived demand in which the primary demand is for water-consuming goods and services, such as clean laundry, indoor bathroom use, and green lawns. Thus, in addition to price and income, the demand models also include characteristics such as lot size, square footage of homes, number of bathrooms, and family size, that represent household taste for water consumption in various services. Home age is included in the water demand equation, and we expect that both very old and new homes may use less water than “middle aged” homes.¹⁴ We include one idiosyncratic housing variable in the models—the presence or absence of an evaporative cooler, which essentially substitutes water for electricity in air conditioning.¹⁵

We include a set of daily weather variables. Maximum daily temperature is represented

¹³Households chosen for the study were randomly sampled from a subset of utilities’ customer databases: residential single-family households. Sampling procedures, response rates, and statistical tests for selection bias are described in Mayer et al. (1998) and Cavanagh (Olmstead) (2002).

¹⁴Very old homes are likely to have smaller connections to their city water system, and also fewer water-using appliances, such as dishwashers and jacuzzis, than do newer homes. The newest homes were built after the passage of local ordinances in the 1980s and 1990s requiring various water-conserving fixtures.

¹⁵In our sample, households with evaporative coolers use on average 40 percent more water per day. We include this variable to avoid biasing the other parameter estimates, particularly the income coefficient estimate, since evaporative cooling is relatively more common in low-income households.

by $maxt$, $weath$ represents the moisture requirements of green lawns not met by precipitation, and $seas$ is a dummy variable set equal to one during the outdoor watering season.¹⁶

Finally, the models include a set of dummy variables that represent the 11 urban areas included in the study: Denver, Eugene, Seattle, San Diego, Tampa, Phoenix, Tempe/Scottsdale, Waterloo/Cambridge (Ontario), Walnut Valley, Las Virgenes, and Lompoc. These city fixed effects account for variations in geography, regulations and culture not addressed by the other variables.

4. THE MODELS

4.1 Demand Models

We use a log-log demand function in all of the models in this analysis, described by equation (1).

$$\ln w = Z\delta + \alpha \ln p + \mu \ln \tilde{Y} + \eta + \varepsilon \quad (1)$$

The dependent variable, w , is daily household water demand. The matrix Z comprises daily weather observations varying both within and across cities over time; as well as time-invariant, household-level observations of socio-demographic and housing characteristics and city fixed effects. Marginal prices enter the demand equation as p , and virtual income as \tilde{Y} .

¹⁶Lawn moisture needs are captured through estimated evapotranspiration (ET), less effective rainfall (equal to 0.6* measured precipitation). We use Hargreaves' approximation to the Penman-Monteith evapotranspiration equation, which requires mean, minimum, and maximum daily temperature, degrees latitude (to estimate a solar radiation parameter), and a readily-available constant associated with the crop of interest – green grass. For information on our ET calculation, see Cavanagh (Olmstead) (2002), Appendix C.

The model has two error terms. The first source of error (η) represents heterogeneous water consumption preferences among households. The second source of error (ε) reflects the fact that actual use may not coincide with optimal use. We assume that $\eta \sim N(0, \sigma_\eta^2)$ and $\varepsilon \sim N(0, \sigma_\varepsilon^2)$, and that the two error terms are independent.

We estimate three demand models. A full-sample DCC model is our baseline model. Equation (2) describes conditional demand under increasing block prices, with K blocks and $K-1$ kinks, where W is observed consumption, $w_k^*(Z, p_k, \tilde{Y}_k; \delta, \alpha, \mu)$ is optimal consumption in the interior of block segment k , and w_k is equal to consumption at kink point k . Equation (3) is the likelihood function, in which Φ is the standard normal cumulative distribution function.¹⁷

¹⁷The full derivation of the likelihood function is described in Cavanagh (Olmstead) (2002).

$$\ln w = \begin{cases} \ln \underline{w}_1^*(Z, p_1, \tilde{Y}_1; \delta, \alpha, \mu) + \eta + \varepsilon & (2) \\ \quad \text{if } -\infty < \eta < \ln w_1 - \ln \underline{w}_1^*(Z, p_1, \tilde{Y}_1; \delta, \alpha, \mu) \\ \ln w_1 + \varepsilon \\ \quad \text{if } \ln w_1 - \ln \underline{w}_1^*(Z, p_1, \tilde{Y}_1; \delta, \alpha, \mu) < \eta < \ln w_1 - \ln \underline{w}_2^*(Z, p_2, \tilde{Y}_2; \delta, \alpha, \mu) \\ \ln \underline{w}_2^*(Z, p_2, \tilde{Y}_2; \delta, \alpha, \mu) + \eta + \varepsilon \\ \quad \text{if } \ln w_1 - \ln \underline{w}_2^*(Z, p_2, \tilde{Y}_2; \delta, \alpha, \mu) < \eta < \ln w_2 - \ln \underline{w}_2^*(Z, p_2, \tilde{Y}_2; \delta, \alpha, \mu) \\ \dots \\ \ln w_{K-1} + \varepsilon \\ \quad \text{if } \ln w_{K-1} - \ln \underline{w}_{K-1}^*(Z, p_{K-1}, \tilde{Y}_{K-1}; \delta, \alpha, \mu) < \eta < \ln w_{K-1} - \ln \underline{w}_K^*(Z, p_K, \tilde{Y}_K; \delta, \alpha, \mu) \\ \ln \underline{w}_K^*(Z, p_K, \tilde{Y}_K; \delta, \alpha, \mu) + \eta + \varepsilon \\ \quad \text{if } \ln w_{K-1} - \ln \underline{w}_K^*(Z, p_K, \tilde{Y}_K; \delta, \alpha, \mu) < \eta < \infty \end{cases}$$

$$\begin{aligned}
\ln L = & \sum_{\text{uniform price households}} \ln \left(\frac{1}{\sqrt{2\pi}} * \frac{\exp-(s_1)^2 / 2}{\sigma_v} \right) + \\
& \sum_{\text{block price households}} \ln \left[\begin{aligned} & \sum_{k=1}^K \left(\frac{1}{\sqrt{2\pi}} * \frac{\exp-(s_k)^2 / 2}{\sigma_v} \right) * (\Phi(r_k) - \Phi(n_k)) \\ & + \sum_{k=1}^{K-1} \left(\frac{1}{\sqrt{2\pi}} * \frac{\exp-(u_k)^2 / 2}{\sigma_\varepsilon} \right) * (\Phi(m_k) - \Phi(t_k)) \end{aligned} \right]
\end{aligned} \tag{3}$$

$$v = \eta + \varepsilon$$

$$\rho = \text{corr}(v, \eta)$$

$$s_k = (\ln w_i - \ln \underline{w}_k^*(.)) / \sigma_v$$

$$u_k = (\ln w_i - \ln w_k) / \sigma_\varepsilon$$

Where :

$$t_k = (\ln w_k - \ln \underline{w}_k^*(.)) / \sigma_\eta$$

$$r_k = (t_k - \rho s_k) / \sqrt{1 - \rho^2}$$

$$m_k = (\ln w_k - \ln \underline{w}_{k+1}^*(.)) / \sigma_\eta$$

$$n_k = (m_{k-1} - \rho s_k) / \sqrt{1 - \rho^2}$$

We explore the possibility of variation in demand and price elasticity with the shape of supply by estimating two further demand models: (1) the baseline DCC model, for IBP households only; and (2) a panel random-effects model for UP households only. Results are reported in Table 2.

Due to the non-linear nature of the DCC model, parameter estimates are not marginal effects. To simulate elasticities, we take expectations of the exponential form of the conditional demand function, simulate a percentage change in the explanatory variable, and calculate the resulting change in expected demand. We obtain standard errors for simulated elasticities through Monte Carlo simulation. Simulated price and income elasticities are reported in Table 3. Appendix A describes the simulations in detail.

4.2 Model Testing for Endogenous Price Structures

Ideally, to test for the possibility of endogenous price structures, we would estimate a two-stage model, first predicting price structure at the utility level, then estimating elasticity, given the predicted price structure. With the appropriate choice of instruments, this would presumably give us unbiased estimates of price elasticity, free of the effects of underlying heterogeneity in “supply curve design” among utilities. However, the data include only 16 water utilities, a sample too small to support the first stage of such an analysis. Even with a sufficient number of utilities, given a set of predicted types of price structure (uniform vs. IBP), how would we construct the actual schedules of prices? For example, if the first-stage model were to predict block pricing in Eugene, Oregon, when Eugene actually had implemented a uniform marginal

price, the choice of number of blocks, consumption cutoffs marking block divisions, and price levels at each block would involve too many parameters for which to instrument convincingly and would, in the end, be arbitrary.

A second-best approach would be to test our full-sample models, allowing the price elasticity parameter to vary with the shape of supply, controlling perfectly for the utility-level characteristics we believe to be correlated with the choice of price structure and with price elasticity. It is unlikely, however, that we could specify a model that controls for all of these omitted variables and leaves no endogenous variation in price structure choice remaining. In addition, while our data are the best known to us for this purpose, there is not enough price variation within the uniform price cities, alone, to allow the necessary loss of degrees of freedom that would accompany this approach and jointly estimate a pair of price elasticities.¹⁸

Thus, we take a third-best approach. We estimate a new full-sample DCC demand model, including a larger set of fixed effects for the uniform price cities. This larger set of fixed effects (13 of them) absorbs all of the price variation from the uniform price utilities over time and space. The parameter estimates for these fixed effects can be interpreted as average daily water consumption among households within each uniform-price utility service area, within each season, controlling for all of the remaining covariates in the full-sample models. We place these fixed effects, devoid of any household-level variation in home characteristics and socio-

¹⁸Taking into account the variation in uniform prices, alone, over time and space, we have 13 degrees of freedom. Variation in block prices (both across utilities and within the individual price structures, themselves) is much more extensive.

demographics, and devoid of any sub-city-level variation in daily weather, on the left-hand side of a simple second-stage model. This left-hand-side variable contains only utility-level variation in price and characteristics omitted from the main model, some of which we believe to be correlated with price elasticity. We run ordinary least squares (OLS) regressions of these fixed effects on marginal price and utility-level characteristics that may be driving the observed difference in price elasticity among price structures. Results are reported in Table 4.

5. EMPIRICAL RESULTS

5.1 Full-Sample Discrete-Continuous Choice Model

Weather, income and the other household-level characteristics affect demand in expected ways. Results regarding the age of homes are weak, but the effect is as expected: the highest water demand occurs among homes aged 20 to 40 years; both newer homes and older homes use less water. Our income elasticity estimate is low compared with previous studies. 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 (Hanemann 1997). Most previous studies, however, have not included household-level information on housing characteristics, which are strongly correlated with income. The omission of these variables may have overestimated the influence of income on water demand.

The variable of greatest interest, price elasticity, indicates that a one percent price increase will reduce demand by 0.33 percent, all else equal.¹⁹ Our simulated price elasticity,

¹⁹Price elasticity in our DCC models is a percent change in quantity demanded for a one percent increase in all prices in a household's price structure.

produced by exploiting the widest variation yet available in price, price structure, and individual household characteristics, is comparable to the central tendency of estimates over the past 40 years, but much smaller than those previously estimated using the DCC approach. Hewitt and Hanemann (1995), for example, obtain an elasticity almost six times the magnitude of ours.

5.2 Models Exploring Elasticity Magnitude and Price Structure

When we estimate the DCC model for households facing IBPs only, we obtain a simulated price elasticity of approximately -0.64. When we estimate a panel random-effects model for households facing uniform marginal prices only, we obtain an elasticity estimate of -0.33, and the effect is statistically insignificant, even with about 400 households in this group. This pattern is similar to what we see in the existing literature. In comparisons of studies using different samples, we observe greater price elasticities among block-price samples than among uniform-price samples. Does price elasticity vary with price structure, all else equal, or is something else going on?

5.2.1 Tests of simple theoretical explanations

To examine the question of a causal link between price elasticity and the shape of supply, we return to basics and investigate whether the observed difference can be explained by theory. First, we would expect price elasticities to be larger in the long run than in the short run. While it is possible that this explains the differences seen in the previous literature, it does not explain the difference we see in our data, since all households (IBP and uniform-price) were observed over approximately the same time period.

Second, if the average magnitude of prices were higher in IBP cities than in uniform-price cities, this could explain the observed difference in the magnitude of price elasticity. In our sample, the average magnitude of marginal price in uniform-price cities is \$1.72 per kgal, while in block-price cities it is \$1.78 (assuming that marginal price for IBP households is price in the block of observed consumption). With a difference this small, it is unlikely that heterogeneity in the average magnitude of prices is responsible for the different elasticities we observe.

Third, if the percentage of total income devoted to water consumption were lower among households in uniform price cities, on average, than among households facing IBPs, this might explain the observed difference in elasticities. Estimated annual expenditures on water consumption (including fixed charges) in our sample are approximately 0.5 percent of annual income; we observe no statistically significant difference in the budget share for water across price structures.

We have eliminated some likely candidates from the list of potential explanations for the observed variation in price elasticity with the shape of supply. There are two remaining possibilities. First, it is conceivable that part of the observed difference in price elasticity of demand across price structures is, indeed, driven by the shape of the supply curves themselves. But correlation does not demonstrate causality. The second possibility is that price structures, themselves, are endogenous.

5.2.2 Tests for endogenous price structures

Long-term aridity and long growing seasons may lead utilities to adopt IBPs, seen as a tool to reduce peak demand (chiefly summer lawn watering), and may also cause consumers to be more responsive to water price changes. IBP cities may also have implemented more extensive residential non-price conservation programs, which may increase consumers' attention to water consumption and price. We test some of these hypotheses in our final model.

This model comprises only 13 observations, so we lack the degrees of freedom required to include more than two regressors at a time, and our conclusions are necessarily limited. In general, there are no surprises regarding the impact of these city-level characteristics on average water consumption (devoid of household-level variation and daily weather impacts). To the extent that these variables have statistically significant effects, water consumption is increasing in long-run average July and January temperatures, and decreasing in both long-run average precipitation and utility expenditures per account on water conservation programming.²⁰

The price coefficient estimates in these models can be considered price elasticities for the uniform-price households. Price elasticities vary greatly in magnitude and precision with model specification. Elasticity estimates for these uniform-price cities as a group range from -.01 (indistinguishable from zero) in a model controlling for long-run average July temperature to -.96 in a model controlling for per-connection expenditures on water conservation programming.

²⁰The conservation budget variable is likely endogenous (utilities with higher overall water demand may be more likely to implement conservation policies and programs). We expect that the true relationship of *cbudget* to water demand is negative. Endogeneity would tend to drive the parameter estimate toward zero, shrinking the measured effect in an OLS model like this one. This implies that the true coefficient would be larger in magnitude than the estimate we report here.

Even with no variation in the shape of supply, price elasticity appears to be very sensitive to omitted cross-sectional variables.

These results do not rule out the possibility of a behavioral reaction to the shape of the supply curve. But they lend support to the hypothesis that underlying city-level heterogeneity in characteristics such as aridity and conservation programs, which may be correlated with both consumers' price elasticity and utilities' price schedule choice, explains part of the observed pattern of higher price elasticity under IBPs.

6. CONCLUSION

We explore the issue of water demand under non-linear price structures, an area of great practical importance given that: (1) non-linear prices are implemented in water supply, energy, cellular phone pricing, and other markets with increasing frequency; and (2) there is little work on the implications of such prices for demand in these markets. The empirical problems with demand estimation under IBPs are usually thought to have been adequately treated in the tax literature, but importing tax models to the markets for water and other commodities with similar price structures requires careful exploration of the differences in these applications.

This is the first study to address both aspects of the separation of demand and supply under non-linear pricing – simultaneous choice of price block and quantity consumed at the household level, and endogenous price structure at the utility level. We estimate price elasticity of water demand among urban households facing a variety of price structures, including

increasing block pricing and uniform marginal prices, using a structural model that accommodates piecewise-linear budget constraints. We exploit the most price-diverse, detailed, household-level water demand data yet available to obtain elasticity estimates more representative of U.S. urban areas than those of previous studies using such models.

In response to a literature that suggests that price elasticity varies with the shape of administratively-determined supply curves, we estimate separate price elasticities for two subsamples of households — those facing IBPs and those facing uniform marginal prices. We observe a substantial difference in elasticity (indeed, we fail to identify a price elasticity significantly different from zero for the uniform-price households, alone), and posit a set of potential explanations for these differences. We eliminate a number of possibilities that would be consistent with economic theory. We then test for the remaining suspect among empirical explanations — the possibility of endogenous price structures. Results from our tests for endogenous price structures do not eliminate the possibility of some kind of behavioral response to the shape of supply, in addition to the magnitude of marginal price, but they cast doubt on this possibility as the sole explanation.

Even if our results indicate that water utilities should not adopt IBPs with the sole intention of increasing the potential “bang for the buck” (water demand reductions for a given price increase) from price-based conservation policies, an important efficiency justification for the implementation of IBPs remains. To the extent that IBPs increase the portion of consumers facing efficient prices on the margin, they may well be welfare-improving. Exploration of the

efficiency advantages of IBPs, and of consumer responses to non-linear prices, is an important area for further research.

APPENDIX A. DCC MODEL ELASTICITY SIMULATIONS

The non-linearity of the discrete-continuous choice model requires that simulations be used to determine the marginal effects of changes in the independent variables on water demand. We take expectations of the exponential form of the conditional demand function (A.1), simulate changes in price and income, and calculate elasticities from the resulting changes in predicted daily water demand.

$$w = \begin{cases} \underline{w}_1^*(.) \exp(\eta) \exp(\varepsilon) & \text{if } 0 < \exp(\eta) < w_1 / \underline{w}_1^*(.) \\ w_1 \exp(\eta) & \text{if } w_1 / \underline{w}_1^*(.) < \exp(\eta) < w_1 / \underline{w}_2^*(.) \\ \underline{w}_2^*(.) \exp(\eta) \exp(\varepsilon) & \text{if } w_1 / \underline{w}_2^*(.) < \exp(\eta) < w_2 / \underline{w}_2^*(.) \\ \dots & \\ w_{K-1} \exp(\eta) & \text{if } w_{K-1} / \underline{w}_{K-1}^*(.) < \exp(\eta) < w_{K-1} / \underline{w}_K^*(.) \\ \underline{w}_K^*(.) \exp(\eta) \exp(\varepsilon) & \text{if } w_{K-1} / \underline{w}_K^*(.) < \exp(\eta) < \infty \end{cases} \quad (\text{A.1})$$

In the paragraphs that follow, we first develop the general case of the expectation of conditional demand for a household facing K blocks and $K-1$ kinks. Second, we describe a computationally attractive alternative to the techniques typically used to calculate these expectations, using the assumption of independence of ε and η to replace double integrals in the expectation calculation with closed-form expressions.

Calculating expectations in the general case

To take the expectation of w in A.1, recall that $\underline{w}_k^*(.) = \exp(Z\delta) p_k^\alpha \tilde{Y}_k^\mu$, a function of the data and DCC model parameter estimates. For all k , then, $\underline{w}_k^*(.)$ and w_k are known constants. In addition, the discrete choice is affected only by the range of η , not ε . Let $\exp(\eta) = \eta^*$ and $\exp(\varepsilon) = \varepsilon^*$. The expectation of w can thus be represented for the general case as in A.2, where the first summation is attributable to the possibility of consumption on a linear segment in the budget constraint, and the second summation to the possibility of consumption at a kink point. In the limit expressions bounding the integrals, $w_0 = 0$ and $w_K = \infty$.

$$E(w) = \sum_{k=1}^K \underline{w}_k^*(.) \times \int_0^{\frac{w_k}{\underline{w}_k^*(.)}} \int_{\frac{w_{k-1}}{\underline{w}_k^*(.)}}^{\frac{w_k}{\underline{w}_k^*(.)}} \varepsilon^* \eta^* f(\varepsilon^*, \eta^*) d\eta^* d\varepsilon^* + \sum_{k=1}^{K-1} w_k \times \int_0^{\frac{w_k}{\underline{w}_{k+1}^*(.)}} \int_{\frac{w_k}{\underline{w}_k^*(.)}}^{\frac{w_k}{\underline{w}_{k+1}^*(.)}} \varepsilon^* f(\varepsilon^*, \eta^*) d\eta^* d\varepsilon^* \quad (\text{A.2})$$

Given that the two error terms are assumed to be independent and normally distributed, their exponents are distributed lognormally, so that $f(\varepsilon^*, \eta^*)$ is the bivariate lognormal probability distribution function with $\rho = 0$, represented in A.3.

$$f(\varepsilon^*, \eta^*) = \frac{1}{2\pi\sigma_{\eta^*}\sigma_{\varepsilon^*}\varepsilon^*\eta^*} \exp\left(-\frac{1}{2}\left(\left(\frac{\ln(\eta^*) - \mu_{\eta^*}}{\sigma_{\eta^*}}\right)^2 + \left(\frac{\ln(\varepsilon^*) - \mu_{\varepsilon^*}}{\sigma_{\varepsilon^*}}\right)^2\right)\right) \quad (\text{A.3})$$

We use known transformations of the parameters of the error distributions to obtain the parameters of the distributions of their exponents (A.4-A.7). Recall that estimates of σ_{η} and σ_{ε} were obtained from the DCC model, and that μ_{η} and μ_{ε} are both zero.

$$E(\varepsilon^*) = \exp(\mu_{\varepsilon} + \sigma_{\varepsilon}^2 / 2) \quad (\text{A.4})$$

$$E(\eta^*) = \exp(\mu_{\eta} + \sigma_{\eta}^2 / 2) \quad (\text{A.5})$$

$$\text{Var}(\varepsilon^*) = \exp(2\mu_{\varepsilon} + 2\sigma_{\varepsilon}^2) + \exp(2\mu_{\varepsilon} + \sigma_{\varepsilon}^2) \quad (\text{A.6})$$

$$\text{Var}(\eta^*) = \exp(2\mu_{\eta} + 2\sigma_{\eta}^2) + \exp(2\mu_{\eta} + \sigma_{\eta}^2) \quad (\text{A.7})$$

The variance of heterogeneous preferences for water consumption (η) in our data was too large to allow numerical integration over $f(\eta^*)$, the univariate lognormal distribution of $\exp(\eta)$. As a result, we derived closed-form expressions for the expectation, using the independence of the two error terms.²¹

A computationally feasible alternative calculation of expectations

Where η and ε are independent and normally distributed with means zero and variances

²¹We are grateful to Todd Olmstead for the mathematical derivation of the two-block case described here.

σ_η and σ_ε and Φ is the standard normal cumulative distribution function, a closed-form expression equivalent to A.2 is given below as A.8, for the two-block case. The full derivation of the closed-form expression for the expectation of conditional demand is available from Cavanagh (Olmstead) (2002).

$$\begin{aligned}
 E(w) = & \underline{w}_1^*(.) \exp(\sigma_\varepsilon^2 / 2) \exp(\sigma_\eta^2 / 2) \left[1 - \Phi \left(\sigma_\eta - \frac{\ln\left(\frac{w_1}{\underline{w}_1^*(.)}\right)}{\sigma_\eta} \right) \right] + \quad (\text{A.8}) \\
 & w_1(.) \exp(\sigma_\varepsilon^2 / 2) \left[\Phi \left(\frac{\ln\left(\frac{w_1}{\underline{w}_2^*(.)}\right)}{\sigma_\eta} \right) - \Phi \left(\frac{\ln\left(\frac{w_1}{\underline{w}_1^*(.)}\right)}{\sigma_\eta} \right) \right] + \\
 & \underline{w}_1^*(.) \exp(\sigma_\varepsilon^2 / 2) \exp(\sigma_\eta^2 / 2) \Phi \left(\sigma_\eta - \frac{\ln\left(\frac{w_1}{\underline{w}_2^*(.)}\right)}{\sigma_\eta} \right)
 \end{aligned}$$

Equation A.8 is the form of $E(w)$, the expectation of daily water demand given the data, DCC parameter estimates, and known information about the error distributions, that we use to simulate elasticities from the DCC model in Table 3. The expression of expectations in terms of the data, parameter estimates, and Φ makes simulations especially tractable. We estimate expected demand at the observed values of price and income, perturb one variable holding all else constant, recalculate expected demand, and calculate the percentage change in demand for a change in the independent variable.

We estimate standard errors for the simulated elasticities through Monte Carlo simulation. We draw 100 random samples of size N , with replacement, from our data. We then estimate the DCC model parameters for each Monte Carlo sample, and use the parameter estimates and the Monte Carlo data to simulate elasticities using the closed-form expression in A.8. Reported standard errors for the DCC elasticities (in Table 3) are the sample standard deviations of the 100 replications for each elasticity.

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Table 1. Descriptive Statistics

Variable	Description	Units	Mean	Std. Dev.	Min.	Max.
w	Daily household water demand	kgal/day	0.40	0.58	0.00	9.78
p ₁	Marginal price in block 1	\$/kgal	1.45	0.54	0.50	3.70
p ₂	Marginal price in block 2	\$/kgal	1.84	0.40	0.84	4.06
p ₃	Marginal price in block 3	\$/kgal	2.43	0.87	0.93	4.96
p ₄	Marginal price in block 4	\$/kgal	3.28	1.30	0.99	5.98
income	Gross annual household income	\$000/yr	69.81	67.67	5.00	388.64
w ₁	Water quantity at kink 1	kgal/day	0.21	0.08	0.06	0.37
w ₂	Water quantity at kink 2	kgal/day	0.36	0.09	0.30	0.50
w ₃	Water quantity at kink 3	kgal/day	1.82	0.80	0.75	2.49
blockp	Price structure: 1 if IBP; 0 if UP	0/1	0.61	0.49	0	1
seas	Season: 1 if irrigation season; 0 if not	0/1	0.51	0.50	0	1
weath	Evapotranspiration less effective rainfall	mm	5.06	8.42	-46.15	19.37
maxt	Maximum daily temperature	°C	24.12	8.78	0	42.78
famsz	Number of residents in household	number	2.79	1.34	1	9
bthrm	Number of bathrooms in household	number	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
evap	Evaporative cooling: 1 if yes; 0 if no	0/1	0.09	0.28	0	1

Notes: City fixed effects not summarized here. Approximately 10 percent of observations drawn from each city (Las Virgenes MWD, Seattle, San Diego, Tampa, Phoenix, Tempe/Scottsdale, Waterloo/Cambridge, Walnut Valley WD, Lompoc).

Table 2. Water Demand Model Estimates

VARIABLE	DISCRETE/CONTINUOUS CHOICE MODEL, FULL SAMPLE	SPLIT SAMPLE MODELS	
		DCC – IBP Households Only	Random Effects – UP Households Only
lnprice	-.3407* (.0298)	-.6411* (.0424)	-.3258 (.5644)
lnincome	.1306* (.0118)	.1959* (.0163)	.0432 (.0499)
seas	.3072* (.0247)	.3370* (.0330)	.2656* (.0331)
weath	.0079* (.0013)	.0094* (.0017)	.0054* (.0016)
maxt	.0196* (.0018)	.0238* (.0024)	.0193* (.0025)
famsz	.1960* (.0056)	.1959* (.0080)	.2095* (.0225)
bthrm	.0585* (.0093)	.0553* (.0127)	.0498 (.0393)
sqft	.1257* (.0140)	.2001* (.0191)	-.0066 (.0600)
lotsz	.0065* (.0009)	.0097* (.0011)	-.0010 (.0046)
age	.0869* (.0219)	.1814* (.0304)	-.0870 (.0940)
age2	-.0137* (.0036)	-.0252* (.0050)	.0109 (.0160)
evap	.2278* (.0300)	.2416* (.0334)	-.8139 (.6129)
lasv	.2590* (.0408)	.3391* (.0486)	
seat	-.1232* (.0379)	-.0482 (.0491)	
sandg	.0129 (.0365)	.1361* (.0416)	

VARIABLE	DISCRETE/CONTINUOUS CHOICE MODEL, FULL SAMPLE	SPLIT SAMPLE MODELS	
		DCC – IBP Households Only	Random Effects – UP Households Only
tampa	-.3879* (.0373)	-.3225* (.0427)	
phx	-.0044 (.0385)	-.0271 (.0444)	
tscot	-.1033* (.0359)	-.1436* (.0406)	
eug	.0050 (.0387)		-.0018 (.5846)
wcamb	-.1939* (.0362)		-.1646 (.1568)
wvall	.1784* (.0387)		.3272* (.1320)
lomp	-.0647 (.0373)		-.0440 (.1132)
constant	-3.6994* (.0652)	-4.3288* (.0888)	-3.1353* (.6854)
σ_{η}	1.0769* (.0103)	1.1493* (.0115)	
σ_{ϵ}	.3552* (.0277)	.4220* (.0227)	

Notes: *Significant at $\alpha=.05$. Standard errors in parentheses below estimates. Dependent variable is natural log of daily water demand. Models in columns 1 and 2 are discrete-continuous choice, estimated by maximum likelihood. Model in column 3 is random effects GLS regression for panel data. City fixed effects are relative to Denver, CO, except in column 3, where they are relative to Seattle, WA. For full-sample model (column 1), N=25,666. For IBP split-sample model (column 2), N=15,621; and for UP split-sample model (column 3), N=10,045.

Table 3. Price and Income Elasticities of Demand

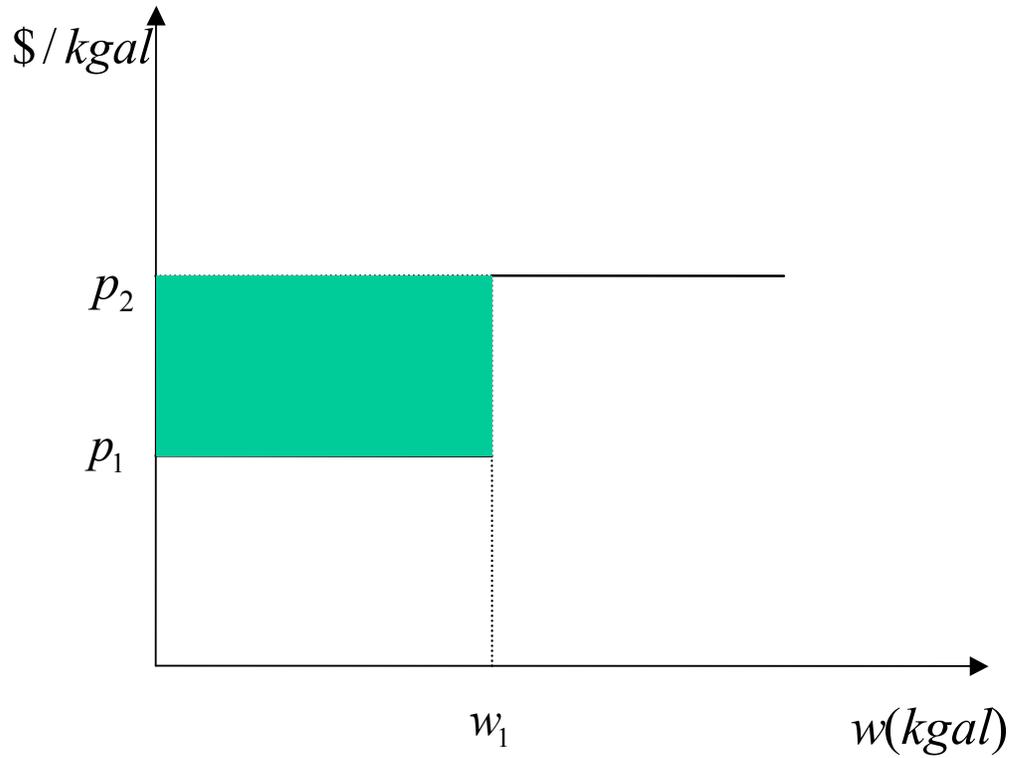
Model	Elasticity Estimates	
	Price	Income
Discrete / Continuous Choice – full sample	-.3319* (.0366)	.1273* (.0133)
Discrete / Continuous Choice – block-price households only	-.6090* (.0568)	.1865* (.0159)
Random Effects – uniform price households only	-.3258 (.5644)	.0432 (.0499)

Notes: *Significant at $\alpha=.05$. Elasticity estimates for discrete/continuous choice models (rows 1 and 2) calculated by taking expectation of conditional demand in exponential form, simulating a one percent change in the explanatory variable, and calculating resulting percent change in expected demand. Standard errors obtained by Monte Carlo simulation. See Appendix A for a detailed description of simulations and standard error calculations. Simulated DCC elasticity estimates for other independent variables do not vary appreciably from coefficient estimates, and are not reported here. Elasticity estimates for random effects model (row 3) are repeated from Table 2, for comparison purposes (no simulations necessary for this model).

Table 4. Tests for Endogenous Price Structures

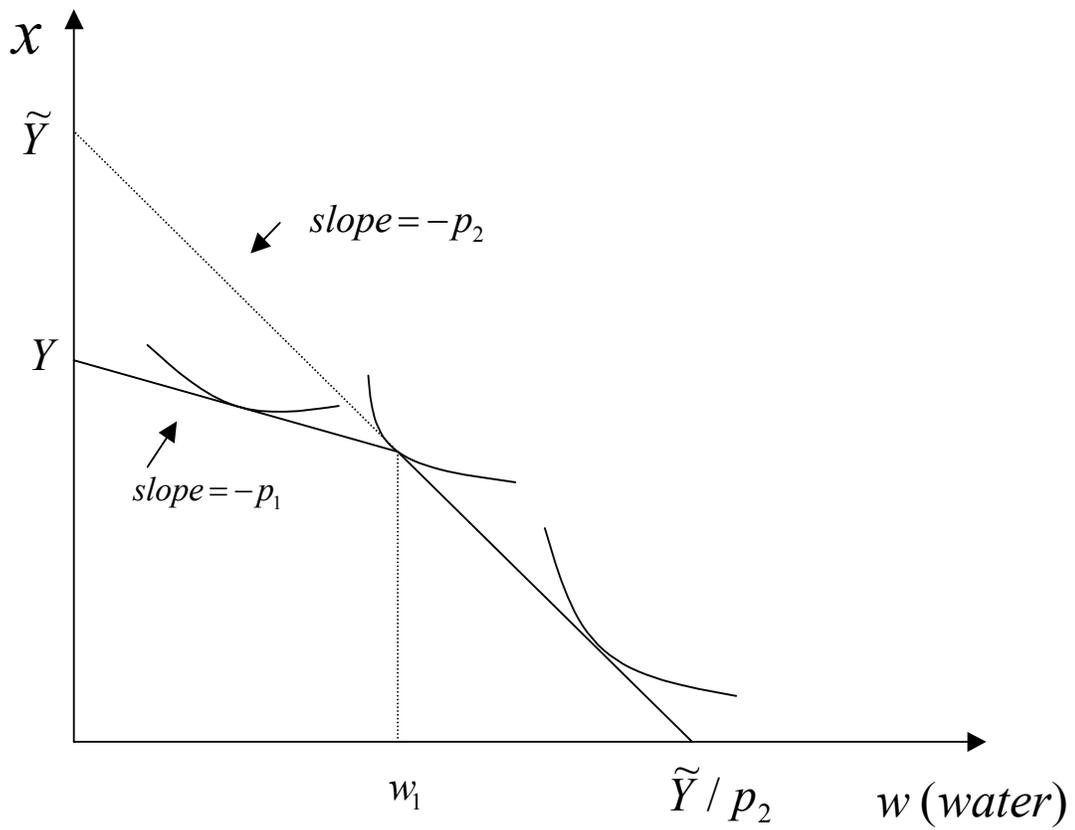
Variable	Parameter Estimates				
	Model A	Model B	Model C	Model D	Model E
Inprice	-.0695 (.0391)	-.0914* (.0466)	-.0120 (.0475)	-.2037* (.0867)	-.9632* (.3243)
long-run average January temperature		.0113* (.0043)			
long-run average July temperature			.0245* (.0103)		
long-run average precipitation				-.0032 (.0022)	
conservation budget per residential connection					-.0487* (.0111)
constant	.0199 (.0328)	-.0049 (.0252)	-.6513* (.2801)	.3110 (.2095)	.8906* (.2710)

Notes: *Significant at $\alpha=.05$. Standard errors, robust to clustering by utility, in parentheses. Dependent variable is set of city/season fixed effects for uniform price cities, estimated in first-stage equation (full-sample DCC model in which all price variation is absorbed by fixed effects). First-stage results are not reported here. The price coefficient in the first-stage model is -0.33 (t-statistic=-10.76). Models in Table 4 are all ordinary least squares regressions, with N=13, except for Model E (N=12), as conservation budget information was not available in Eugene, OR.



Where: w = water (units)
 p_1 = marginal price of water in block 1
 p_2 = marginal price of water in block 2
 w_1 = boundary quantity between block 1 and block 2

Figure 1. Two-tier increasing block price structure



Where: Y = income
 \tilde{Y} = virtual income
 p_1 = price of water in block 1
 p_2 = price of water in block 2
 w_1 = boundary quantity between block 1 and block 2

Figure 2. Utility Maximization under a Two-tier Increasing Block Price Structure