



An annual quasidifference approach to water price elasticity

David R. Bell¹ and Ronald C. Griffin¹

Received 5 June 2007; revised 24 February 2008; accepted 2 April 2008; published 14 August 2008.

[1] The preferred price specification for retail water demand estimation has not been fully settled by prior literature. Empirical consistency of price indices is necessary to enable testing of competing specifications. Available methods of unbiasing the price index are summarized here. Using original rate information from several hundred Texas utilities, new indices of marginal and average price change are constructed. Marginal water price change is shown to explain consumption variation better than average water price change, based on standard information criteria. Annual change in quantity consumed per month is estimated with differences in climate variables and the new quasidifference marginal price index. As expected, the annual price elasticity of demand is found to vary with daily high and low temperatures and the frequency of precipitation.

Citation: Bell, D. R., and R. C. Griffin (2008), An annual quasidifference approach to water price elasticity, *Water Resour. Res.*, 44, W08420, doi:10.1029/2007WR006233.

1. Introduction

[2] Economic views on water demand continue to gain attention as a result of the scarcity sensitivity that is intrinsic to a value-dependent vision of demand. The almost worldwide phenomenon of rising water scarcity makes the economic perspective useful in multiple ways. Among these is the policy significance of signaling scarcity to all water users through more informed rate-making, so as to motivate efficient consumption and conservation behavior. Another key advantage of understanding how water usage depends on water value is being able to perform *ex ante* appraisals of water projects' prospective benefits. Other policy-relevant advantages are also attributable to the economic view of demand or do not become tractable until demands have been estimated.

[3] To firm up these achievements and turn concepts into practice, economists have conducted many empirical investigations of water demand [Renzetti, 2002]. The study area of greatest concentration pertains to household demand for water in urbanized areas, which is also the subject of this study [Arbués *et al.*, 2003; Dalhuisen *et al.*, 2003]. Undoubtedly, a strong contributing factor to this emphasis is the comparative availability of reasonably reliable data. As compared to agricultural, industrial, and heavy commercial water usage, residential/urban water use is more likely to occur in settings where many water users are active, water use is reasonably well metered and not self-reported, and a variety of consumption circumstances can be observed. The latter factor is important for producing an acceptable degree of variation in statistically exogenous variables, so as to permit analysis of potentially influential factors. In all such studies, fundamental requirements are that consumers have the freedom to determine their water use, and that researchers

can observe water use and water price(s), as well as other demand-driving factors.

[4] Utility-maximizing consumer behavior is straightforward to model when price and quantity demanded are well known to the consumer, and standard modeling practice is that consumers are presumed to be rationally advancing their own welfares in the data they generate for us. These assumptions are not well met, however, when the good in question is retail water service. Unlike most goods households buy, water costs are fully revealed to the consumer well after the consumption decision is made, when the monthly or bimonthly bill arrives. When this bill does come, it typically does not transparently communicate water price to consumers. Thus, discerning the prospective expenditure effects of behavioral modifications can be a challenge for consumers, given that bills are functionally dependent on some or all of the following elements: a flat fee per period billing, uniform or block rates, seasonal rates, metered-water-dependent sewerage fees, and often fees for the provision of nonwater services such as garbage disposal and energy.

[5] Even water quantity information is elusive from the consumer's vantage, since water-consuming taps and appliances hardly ever provide volumetric usage information. Nor does a water bill provide the consumer with a fully satisfactory alternative. A water bill does not itemize the array of water use activities conducted by the consumer; instead they are lumped into a single water usage quantity. Bills provided by some water utilities do not even indicate units of measurement, compounding the complexities of consumer price information.

[6] Consumer perception of water's marginal price is especially dim. Evidence suggests that fewer than 10% of customers invest in marginal price knowledge [Carter and Milon, 2005]. In a recent survey of water utility systems, only 2.9% provided customers with the price schedule on their water bills [Gaudin, 2006]. Cognizant of the bounds of consumer rationality under costly information, water (and electricity) demand modelers have turned their attention from the price to which consumers allegedly should re-

¹Department of Agricultural Economics, Texas A&M University, College Station, Texas, USA.

spond, to ask which price do consumers respond to [Shin, 1985]. In econometric terms, this requires formal testing of alternate price specifications.

[7] Unfortunately, the gathering of evidence to settle this empirical question has been confounded by the difficulty of producing any price index that conforms to the OLS assumption of a random error term uncorrelated with the independent variable. Competing specifications cannot be fairly compared unless they are measured accurately. Some previous attempts to construct an exogenous price index are reviewed in this article. None has been entirely satisfactory. An alternative index is proposed that incorporates rate information in a hypothetical price difference between rate regimes. The new index is a quasidifference operation: the difference between the observed lagged price and the unobserved contemporaneous price net of demand-side influences. Since it is based on the published (deterministic) supply decisions of the water provider, this price quasidifference does not vary simultaneously with demand and therefore provides a theoretically unbiased estimate of supply price change. From this basis, the relative behavioral influence of alternate theoretical specifications can be compared. It is hoped that this procedure will open the door to a more active generation of behavior-based price hypotheses. We limit ourselves here to consideration of marginal price and average price specifications only.

[8] Once an unbiased and behaviorally descriptive price index is selected, an equation of annual demand elasticity is calculated. Community-level rate and usage data are obtained for a sample of 385 utility systems in Texas. The breadth of the data may be unprecedented among studies of this kind. The wide range of observed prices in these data may provide a wider applicability for the estimated parameters than previous research. The aggregate character of the data is respected by weighting the quasidifference estimators by the presumed standard lognormal distribution of households across total quantity demanded. A semiflexible functional form is employed that allows price elasticity to vary linearly with the climatic parameters, resulting in a rejection of the hypothesis of constant elasticity. Unlike the preponderance of demand analyses which are static, this elasticity in differences provides a time-rate of adjustment (one year) rather than an assumed re-equilibrium adjustment. This distinction makes the results especially useful for projecting the repercussions of a change in pricing policy over the near future, or in planning successive rate changes.

2. Sources of and Responses to Price Endogeneity

[9] Charges for residential water service are set administratively, typically only at the beginning of the fiscal year. Consumers experience the rate schedule as they would a market supply correspondence, except that the household supply function is nonconstant when the marginal price of water varies with household usage. In contemporary rate structures the most common form of water price discrimination is the increasing block rate (IBR) structure, which is found in 47% of the present data (with less than 1% exhibiting decreasing block rates). Under IBR or any other rate regime where price is determined simultaneously with the quantity decision, identification issues analogous to those familiar to market demand analysts must be addressed [Working, 1927]. It is also possible that the choice to adopt

IBR is itself endogenous [Hewitt, 2000b; Reynaud et al., 2005].

[10] In choosing a consumption quantity, consumers subjected to block rates implicitly select a marginal price, even if they are unaware of the choice. If an entire community is modeled as a single representative consumer, this price endogeneity can be exaggerated, spuriously influencing elasticity estimates [Shin, 1985]. The low-information average price specification is further biased by the algebraic simultaneity of division by the dependent variable when a flat fee is included [Taylor et al., 2004]. This problem exists for uniform rates (constant marginal price) as well as for variable block rates. Given these inconvenient properties of observed price measures, research has tried to derive a price variable that more adequately captures the ceteris paribus effect of changing fee schedules. Previous strategies to properly identify the price signal may be generally grouped into reduced form, instrumental variable (IV), and maximum likelihood (ML) techniques [Herriges and King, 1994].

2.1. Reduced Form Price

[11] The reduced form strategy involves creating a price index of known fee schedule parameters that is independent of observed volume. An early example is provided by Taylor [1975], who proposed regressing on each block of multiblock rates. Since nonlinear fee schedules are multidimensional, this technique incorporates more price information, while eliminating quantity consumed as an argument of price charged. The disadvantages of the approach are the lack of theoretical support, additional complexity [Herriges and King, 1994], and misspecification bias. The latter arises from the inaccurate assumption that any given price index will be equally representative across the range of observed consumption quantities.

2.2. Instrumental Price

[12] The IV approach [Nieswiadomy, 1991] allows price to vary across the observed range, at the cost of additional complexity, by identifying a linear proxy to the theoretical supply curve. Although widespread in studies of competitive markets, IV applied to public utilities suffers a number of disadvantages. One is the problem of estimating a censored variable as a line. IV price estimates evaluated at the extrema are not necessarily a combination of experienced prices or even necessarily greater than zero. The result is a correlation between the IV price and the regression error [Terza, 1986]. When this problem is addressed with the use of limited dependent variable techniques, the method is equivalent to ML price estimation.

[13] The demand price, that ideal scalar employed by the model consumer's decision process, is ultimately unknown. Demand modeling depends upon parameterizing the demand price in terms of the supply price, i.e., the rate schedule. An IV price is therefore an instrumental estimate of an instrument. Problematically, the IV price correspondence predicts intra-annual price changes that are neither observed nor institutionally feasible. Nevertheless, IV may be necessary if the data used are spot prices at arbitrary consumption levels. If the timing and magnitude of fee schedule changes are known, however, the IV approach is a distant second-best solution, as it is inefficient to reconstruct perfectly known price policies into a stochastic estimate of

pricing policy. In Texas as elsewhere, price schedules are available data, so an instrumental estimation of price is unnecessary. Even though household perception of price remains mysterious, the supplier's signal is known to researchers.

2.3. Maximum Likelihood Price

[14] ML estimation can be used to probabilistically assign a marginal price to a representative consumer either based on an IV inverse supply function or as a two-stage procedure simultaneously estimating price and quantity demanded [Burtless and Hausman, 1978; Herriges and King, 1994]. The "discrete/continuous" [Hanemann, 1984] or "endogenous sorting" [Reiss and White, 2005] model is a ML model brought to the arena of water demand by Hewitt and Hanemann [1995]. The story behind endogenous sorting is that consumers select the price region (block) in which their consumption will lie, then an exact quantity within the block [Hewitt and Hanemann, 1995]. The method adds a degree of rationality to the price specification dilemma, but perhaps too much. The information demand on the consumer under this model is intense [Martinez-Espiñeira, 2003], and some studies have experienced difficulty deriving a probability estimate that is positive in the neighborhood of price kinks [Cavanagh et al., 2002]. That is, observed aggregate quantity decisions may be assigned negative probabilities, implying that the representative consumer is irrational. Ensuring the existence of a cumulative distribution function under such circumstances is nontrivial. Furthermore, repeated application of ML in a dynamic model is computationally demanding [Reiss and White, 2005].

[15] More fundamentally, when aggregate data are modeled with a ML price, the distinction is lost between the representative consumer and representative consumption. If the individual makes a ML consumption decision, the community consumes across the whole probability distribution. Whether the average consumer enjoys average consumption depends heavily upon the normality assumption [Hewitt, 2000a]. Although the ML approach is unsupportably utility theoretic under incomplete information, it does offer a helpful framework that will be exploited in a forthcoming section addressing aggregation issues.

2.4. Quasidifference Price

[16] Assuming that demand for water service is functionally related to price and other exogenous variables, the typical under-identified demand function is

$$w = \omega(p(w), z), \quad (1)$$

where w , quantity demanded in a given period, is functionally related to $p(w)$, the price index calculated at w , and other variables, z . Net price changes may fruitfully be seen as composed of a policy price change and possibly an endogenous change resultant from a change in quantity demanded. Although the price faced by any particular consumer varies with the level of consumption, the nominal price schedule varies exogenously only when the water provider decides to vary it. Changes in price due to the purchasing power of money are also exogenous, but are withheld from the following discussion for clarity.

[17] Though a price level net of demand-side influences has proven elusive, price change is separable in the derivative,

$$\frac{dp}{dt} = \frac{\partial p}{\partial t} + \frac{\partial p}{\partial w} \frac{\partial w}{\partial t}, \quad (2)$$

$$\text{where } \frac{\partial p}{\partial t} = \Delta p(\bar{w}) \quad (3)$$

is the exogenous price difference evaluated at some consumption level \bar{w} .

[18] The form of equation (1) to be estimated is the annual difference in demand:

$$\Delta w = w_t - w_{t-12} = \Delta \omega(\Delta p(\bar{w}), \Delta z) \quad (4)$$

[19] Choice of the point \bar{w} depends on the price change that is to be measured, because price changes are not generally uniform. A simple reduced form approach is to evaluate Δp at a single consumption level for all observations. The reduced form assignment of

$$\bar{w}_t = W^*, \text{ for all } t, \quad (5)$$

is too rigid, though, if consumption is not stationary about W^* . Whenever consumers migrate their consumption out of the rate block containing W^* , $\Delta p(W^*)$ will cease to be a good estimator of Δp . If instead,

$$\bar{w}_t = w_{t-12}, \quad (6)$$

Δp may be interpreted as the price change that would have obtained if consumption had remained constant from the same month of the year before. The interpretation conforms to both the behavioral model of households reacting to pricing policy and to the ceteris paribus principle of statistical inference. The quasidifference estimator is defined as

$$\Delta p = p_t(w_{t-12}) - p_{t-12}(w_{t-12}) \quad (7)$$

in the linear model, or

$$\Delta \ln p = \ln \left(\frac{p_t(w_{t-12})}{p_{t-12}(w_{t-12})} \right) \quad (8)$$

in the logarithmic models used in this paper.

[20] The necessity of adopting an annual lag when monthly data are available follows from the dominance of seasonal behavior in water consumption patterns. Seasonality has been modeled with climatic variables [Griffin and Chang, 1991] and with Fourier harmonics [Renwick and Green, 2000], but neither method has completely captured the persistent demand characteristics unique to each month of the year.

[21] This dynamic form dictates a specific interpretation of estimated parameters. The implied consumption response occurs within a single community over the span of 1 year. Comparisons across communities are no longer applicable, including the common interpretation of cross-sectional

variation as a measure of long run adjustment [Kennedy, 2003, p. 211]. Because the differential form implies a price elasticity of demand for water to pricing policy (and inflationary) changes within a given community, its implications are more relevant to projecting and evaluating incremental local adjustments than basinwide projects with long horizons, which would benefit from the scope of a static model. The results of this estimation should not be used to prescribe an efficient equilibrium pricing policy because adjustment will commonly take longer than the 1-year time step emphasized here.

[22] On the other hand, standard structural estimation is not well suited to applications requiring a finite time horizon. The price response implied by such models may take an indefinitely long time to realize. Knowledge of the time-path of adjustment is necessary to describe optimal policies that achieve period-by-period utility system goals such as revenue sufficiency and stability. For example, in cases of acute capacity constraint such as drought, timing is a factor, and a policy based on a structural elasticity may not achieve the desired demand management goal (i.e., a temporary reallocation) before the drought dissipates. An elasticity derived from the approach introduced here is recommended for such applications.

3. Aggregation

[23] The ML endogenous sorting model recognizes that different consumers make choices that place them in different rate blocks [Hanemann, 1984], but the implications for aggregation have not been well explored. The probability that a consumer consumes within a rate block is equal to the proportion of consumers in an aggregate who consume within that block. This interpretation allows the usual point estimate of aggregate consumption to be replaced with a consumption distribution in the formulation of price indices. When block rates are present in the data, this alternative can greatly improve the explanatory power of price.

[24] Because all consumers do not simultaneously move from block to block, a point estimate of representative consumption and price exaggerates block effects [Shin, 1985]. Schefter and David [1985] observe that the price faced by the mean consumer may estimate mean price with bias, especially if the variance of consumption is high. The distributional symmetry assumption that justifies point estimates of marginal price is tenuous and has been empirically rejected [Hewitt, 2000a; Schefter and David, 1985]. Distribution of water consumption over households is asymmetrical (with median < mean) and truncated at zero, conforming to a possible gamma or lognormal distribution, as a small number of households consumes a relatively large amount of water. Martínez-Españeira [2003] corrects this bias using additional information about customer types to weight marginal price across the community aggregate.

[25] The least precise representation of aggregate marginal price under block rates is a point-mass centered at the mean of consumption multiplied by the price effective at that consumption level. The most precise is a weighting of prices by the actual proportion of consumers whose marginal consumption falls in each block. Lacking agent-level data, the model employed here uses a distributional assumption in lieu of customer type data. Since the standard

lognormal distribution is asymmetrical, truncated at zero, and uniquely determined by a single parameter that is conveniently related to mean consumption, \bar{w} , the distribution of individual consumption levels for each community in each period is modeled as standard lognormal. A lognormal distribution of w is consistent with OLS assumptions on

$$\ln w = \beta \ln X + \varepsilon, \quad (9)$$

which is the general form on which the present analysis is based. The aggregate quasidifference price variable is therefore a quasidifference operation on a linear combination of prices weighted by a block consumption probability function assumed to be standard lognormal with a mean at the data point \bar{w}_t . The assumption of lognormality is much cruder than the sorting devices proposed in the ML models, suggesting that even more precision could be achieved by refinements of the weighting function.

[26] Let $F(w)$ be the cumulative distribution of a standard lognormal function whose mean is \bar{w}_t . Given block rate function $P(w) = \{p_i : x_{i-1} < w < x_i\}$, where w is partitioned into N blocks by x ($x_0 = 0$, $x_N = \infty$), the aggregate price index is defined as

$$p = \sum_{j=1}^N p_j [F(x_j) - F(x_{j-1})]. \quad (10)$$

[27] The procedure is analogous to probability weighting of time-of-day electricity prices [Hausman et al., 1979]. Choice of the partition x is straightforward for the calculation of marginal price. All consumers in the same rate block do not share a common average price, however. In the calculation of aggregate average price, x is defined in increments of 500 gallons up to 50,000 gallons, and a mean average price is calculated for each interval. To construct the aggregate quasidifference price, both the contemporaneous and the lagged price functions are weighted by the same distribution and then differenced.

4. Empirical Model

4.1. Dynamic Specification

[28] Most empirically estimated water demand equations have been static. Unfortunately, dynamic studies that have tested the significance of the contemporaneous price variable have found its effect to be insignificant during non-summer months [Lyman, 1992], inconsistent across models [Agthe and Billings, 1980], and insignificant or unexpectedly close to zero [Carver and Boland, 1980]. Investigations of natural gas [Balestra and Nerlove, 1966] and electricity [Bushnell and Mansur, 2005] have also suffered from weak results. Low significance levels in contemporaneous price are consistent with the hypothesis of incomplete information, which would imply a learning process over time [Carver and Boland, 1980].

[29] Nauges and Thomas [2003] provide a more revealing dynamic analysis that estimates a statistically significant short-term elasticity of -0.26. Although their study is focused on cross-sectional heterogeneity, an issue set aside in the current research, it is exemplary in the sense of

incorporating additional information on pricing practice unique to the region under study.

[30] The price elasticity actually measured by static equations is typically cross-sectional elasticity [Balestra and Nerlove, 1966]. It can be argued that this is a measure of the longest adjustment term, over which habits and stocks of water-demanding capital have tended more completely to evolve to equilibria. Such a horizon is too long to serve all types of policy analysis, however, as suggested above. In contrast, an annual elasticity is sought here. Although a wider range of results are obtained, the central question are, "What is the percent change in consumption over 1 year following a uniform 1% rate change or its equivalent?"

4.2. Flexibility

[31] Quantity-dependent pricing implies highly informed consumers would perceive a nonlinear budget set, then inferring idiosyncratic hypotheses about the resulting price elasticity. In particular, price elasticity is expected to vary with income level, especially for a subsistence good [Dalhuisen *et al.*, 2003]. The limited available evidence suggests that price elasticity is also sensitive to climatic conditions in nontrivial ways [Griffin and Chang, 1991]. Nevertheless, many empirical estimates use the simple log-linear functional form (equation (9)), which imposes constant elasticity. In this instance, a generalization of equation (9) is employed that allows a second-order interaction among the covariates (X_j), based on the translog functional form [Christensen *et al.*, 1973]:

$$\ln w = \sum_{i=1}^I \beta_i \ln x_i + \sum_{i=1}^I \sum_{j=1}^I \frac{\gamma_{ij}}{2} \ln x_i \ln x_j + \varepsilon. \quad (11)$$

[32] Note that the quadratic terms of the full translog model are excluded. While the model indicated by equation (11) is more flexible than that of equation (9), it is not a globally or even locally flexible form.

4.3. Price Elasticity

[33] To distinguish price effects, equation (11) may be rewritten as

$$\begin{aligned} \ln w = & \beta_p \ln p + \sum_{i=2}^I \beta_i \ln x_i + \sum_{i=2}^I \gamma_{pi} \ln p \ln x_i \\ & + \sum_{i=2}^I \sum_{j=2}^I \frac{\gamma_{ij}}{2} \ln x_i \ln x_j + \varepsilon. \end{aligned} \quad (12)$$

[34] Introducing a temporal element and taking the first difference produces

$$\begin{aligned} \Delta \ln w = & \beta_p \Delta \ln p + \sum_{i=2}^I \beta_i \Delta \ln x_i + \sum_{i=2}^I \gamma_{pi} \Delta (\ln p \ln x_i) \\ & + \sum_{i=2}^I \sum_{j=2}^I \frac{\gamma_{ij}}{2} \Delta (\ln x_i \ln x_j) + \nu. \end{aligned} \quad (13)$$

[35] Equation (13) is the estimating equation for the empirical analysis of the next section. Since an expression for the ceteris paribus price effect on the quantity of water demanded is sought, $\Delta \ln x_i = 0$ is stipulated for each i -th

covariate when calculating price elasticity. Note that, for each term in the second summation,

$$\begin{aligned} \gamma_{pi} \Delta (\ln p \ln x_i) &= \gamma_{pi} [\ln p_t \ln x_{it} - \ln p_{t-1} (\ln x_{it} - \Delta \ln x_i)] \\ &= \gamma_{pi} (\Delta \ln p_t \ln x_{it} + \ln p_{t-1} \Delta \ln x_i). \end{aligned} \quad (14)$$

[36] Thus (13) reduces to,

$$\frac{\Delta \ln w}{\Delta \ln p} = \beta_p + \sum_{i=2}^I \gamma_{pi} \ln x_i + \nu. \quad (15)$$

[37] In the limit, for small changes,

$$\eta = \beta_p + \sum_{i=2}^I \gamma_{pi} \ln x_i \quad (16)$$

is the own-price elasticity of demand. Constant elasticity is confirmed if $\gamma_{pi} = 0$ for every $i \in I$.

5. Data

[38] The original data for this application consists of monthly water supply series for 385 Texas communities (serving 5.6 million Texas residents). Water use data are provided by the Texas Water Development Board, and corresponding water and sewer service rates are provided by the communities themselves per request. Of 1406 community water providers considered, 734 responded to mailed inquiries seeking water and sewerage rate structures for a 5-year period. Raw data expressed in nominal dollars are corrected for inflation in the analysis.

[39] Due to the lag structure of the proposed model, only those communities for which supply and price series are complete from January 1999 to December 2003 are considered further. The 385×60 panel contains 23,100 elements of which 20% are expended in support of the lag structure. Twelve additional observations are excluded because the marginal price changed from zero to a positive quantity over the year, resulting in an undefined log difference. In other cases (<1% of data) where price remained at zero in both periods, log price difference is redefined to be zero. On the basis of comparisons of community size and monthly usage, the sample is representative of the targeted population although the high variance of both of these measures reduces their ability to verify sample selection bias.

[40] Personal income statistics from the Bureau of Economic Analysis (www.bea.gov/regional/reis/) and climate data from the National Climatic Data Center (NCDC; www.ncdc.noaa.gov/) augment the data. Personal income is aggregated at the county level, with 156 counties represented, or at the metropolitan level of larger cities for which income data are available. Daily temperature and precipitation data are matched by proximity to the nearest NCDC cooperative weather station, usually in the same county as the system observation. All dollar amounts are normalized to December 2003, using the Urban South CPI measurement (www.bls.gov/data/). Data are summarized in Table 1. The log difference transformations of the data are summarized in Table 2.

[41] Figures 1 and 2 illustrate the variation in water price over the sample. The wide variation in price measures

Table 1. Summary Statistics, N = 23100

Variable	Units	Mean	Standard Deviation
Volume per capita per day	liters	540.3645	267.2517
Marginal water price	2003 USD/kliter	0.6607	0.2966
Marginal sewer price	2003 USD/kliter	0.1466	0.2314
Average water price	2003 USD/kliter	1.1242	0.5506
Average sewer price	2003 USD/kliter	0.4356	0.4215
Monthly personal Income	2003 USD	2158.2780	499.6223
Average minimum temperature	°F	55.3835	14.0675
Average maximum temperature	°F	78.2141	13.2448
Days in month with no precipitation	days	27.1997	2.7631

provides an advantage in estimation over more geographically limited studies, in that the estimated expression for price elasticity may be confidently generalized over a wider range of price levels. The degree of variation in the other regressors supports the maintained hypothesis that individual (cross-sectional) effects are random across the sample.

6. Results

6.1. Log-Linear Model

[42] The centerpiece of this econometric investigation is estimation of a multidimensional elasticity function. However, simple log-linear regressions are performed ahead of the more flexible central regression to guide the selection of independent variables. Additional findings are consequently generated. Variables included in the preliminary regressions are average water price, marginal water price, average sewer price, marginal sewer price, monthly income, mean minimum daily temperature, mean maximum daily temperature, and number of days in the month with less than 0.25 inches of precipitation. The regressed values in each case are the annual differences in logarithms of variable levels.

[43] It has been argued that the nonlinear price schedule creates a secondary income effect that ought to be measured [Nordin, 1976]. The “Nordin difference” expenditure variable (which is not in any way related to the quasidifference introduced here) has not been included, primarily because the assumptive base for identifying such a variable in aggregate data is too tenuous. This choice is also justified ex post by the insignificance of the primary income variable, as will be seen below.

[44] Final selection of price variable is determined by comparing a marginal price model with an average price model using the Akaike Information Criterion or the Schwarz Criterion, both of which are in this case equivalent to finding the specification with the lowest sum of squared errors. Additionally, since parsimony is improved if water and sewer prices can be combined or if minimum and maximum temperatures can be averaged prior to estimation, both of these hypotheses are tested.

[45] Results of the log-linear estimations are shown in Table 3, with marginal price variables included in Model 1 and average price variables in Model 2. The lower information criteria corresponding to Model 1 indicate the

slightly better fit. On this comparative basis, marginal price is adopted as the price index of the central analysis. The marginal sewer price index, however, is insignificant. For many systems in the sample, marginal price for sewer service is zero in nonwinter months due to many utilities’ policies of setting sewer cost ceilings or applying “winter averages”. The insignificant coefficient may indicate that consumers are not aware of these practices. Even considering months where marginal sewer price is strictly positive, the t-statistic for the corresponding coefficient is only -0.35. Consumption is apparently unresponsive to marginal sewer pricing. This variable is not included in the central regression.

[46] An alternative, nested test of water price specification is proposed by Shin [1985]. Here both average price and marginal price variables are included in the same regression. Interpretation of the marginal price and average price coefficients as $(1-k)\beta$ and $k\beta$, respectively, allows a measure of the relative influence of marginal and average price on the consumption decision [Shin, 1985]. Parameter estimates for this regression are not reported, though we apply Shin’s procedure. For water, we obtain $k = -0.76$. On the basis of $k < 0.5$ for water service, marginal price is indicated as more influential than average price. The corresponding value of $k = 2.89$ for sewer service supports the average price specification for sewerage. Bearing in mind that $0 < k < 1$ in a well-specified Shin test, these results are curious.

[47] The hypothesis that the effect of an increase in daily low temperature is equivalent to the effect of an increase in daily high temperature is rejected. Both variables are included in the more flexible regression.

[48] The existence of an income effect is rejected. An unfortunate characteristic of the income data is that the variation is cross-sectional except for the CPI normalization, and is therefore unnoticed by this procedure. It is plausible that income is insignificant because of slow aggregate response to income change, but it is more likely in this case that the income measure is simply too broadly aggregated to identify accurately the spending power of a single community. Perhaps a refined monthly income measure would produce better results. Income is not included in the following regression.

6.2. Log-Nonlinear Model

[49] The final regressors are differences in logs of marginal water price, average low temperature, average high temperature, and number of days without precipitation, as well as the differences in products of each pair of indepen-

Table 2. Summary of Differences in Logs, N = 18468

Variable	Mean	Standard Deviation
$d\ln w$	-0.0141	0.2658
$d\ln MP$ (water)	0.0066	0.0980
$d\ln MP$ (sewer)	0.0012	0.0691
$d\ln AP$ (water)	0.0041	0.0776
$d\ln AP$ (sewer)	0.0084	0.0936
$d\ln PI$	0.0010	0.0276
$d\ln T_{min}$	-0.0057	0.0916
$d\ln T_{max}$	-0.0086	0.0775
$d\ln dry$	-0.0020	0.1862

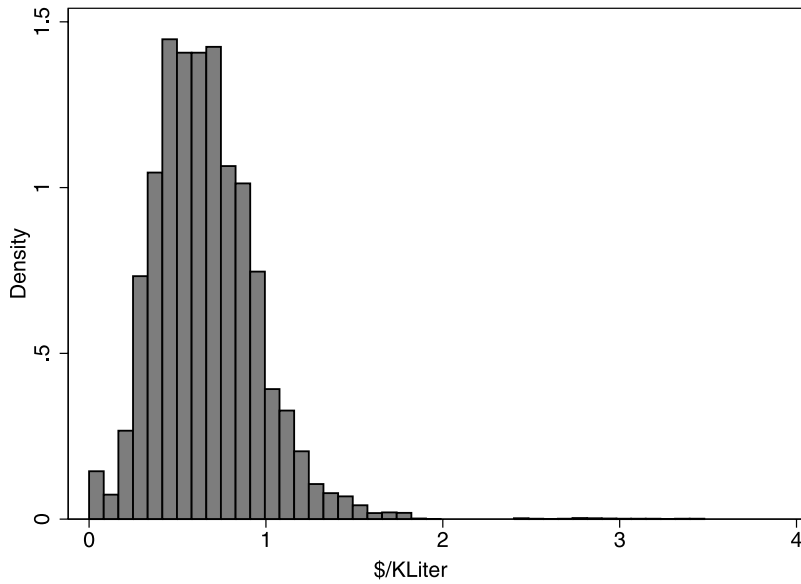


Figure 1. Distribution of observed marginal water prices.

dent variables' logarithms. The results of this central regression are summarized in Table 4. Because of the inclusion of the interactive product regressors, the intuitive value of Table 4 is limited, although the strong significance of these interactive terms justifies the use of the more flexible functional form. In particular, the significance of the price interactions allows the rejection of the hypothesis of constant price elasticity across the sample. The Breusch-Pagan statistic of 1.51 for this regression ($p = 0.219$) fails to reject the null hypothesis of homoskedasticity.

[50] Applying the coefficients in Table 4 to equation (16) results in the elasticity equation,

$$\eta = 1.290 + 0.190 \log t_{\min} - 0.439 \log t_{\max} - 0.081 \log d \quad (17)$$

Each of the individual coefficients is significant at the 99% level. Demand for water service is more elastic when daily

high temperature is higher or when more days of the month pass without precipitation. Demand is less elastic when daily low temperatures are higher. The magnitude of the coefficient on high temperature is higher than that on low temperature, implying that hotter months see an increase in price elasticity (more elastic demand).

[51] Price elasticity evaluated as a linear combination of variable levels and regression coefficients is found to have a mean of -0.127 . The standard deviation of η , estimated using the regression standard errors and variance-covariance matrix is 0.0188, implying that demand is inelastic but significantly downsloping at the mean. The estimate is consistent with other recent research on short term elasticity [Martínez-Españeira, 2004; Renwick and Green, 2000]. It is somewhat lower in absolute value than most cross-sectional static models [Dalhuisen et al.,

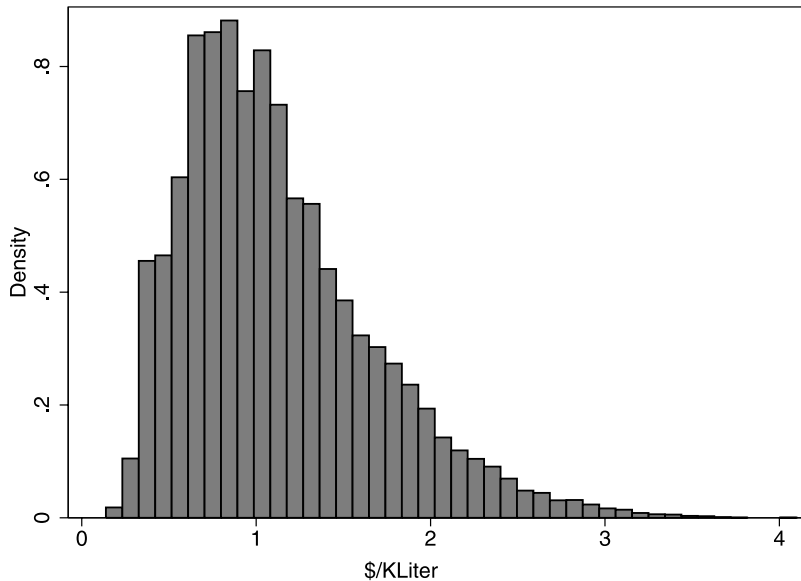


Figure 2. Distribution of observed average water prices.

2003], consistent with the hypothesis of adjustment lags greater than 1 year.

7. Summary

[52] Fully informed and rational consumers will use water until the monetized marginal benefit of the next unit is equal to its marginal price. Yet, price and quantity information is dimly available to water customers, and these consumers cannot improve their information conditions without experiencing costs. Imperfectly informed consumption behavior is therefore the norm. Less informed consumers may be expected to optimize with respect to a lower information price index, for example average price. Although *Shin* [1985] provides a test of relative explanatory power between two proposed price indices, the test results are only meaningful if both indices consistently represent the theoretical quantities they purport to represent. Prices based on observation or on the usage of a representative consumer are endogenous and not necessarily unbiased.

[53] Prices constructed as instrumental variables can be a poor fit because strong instruments are generally lacking. Continuous, linear pricing is characteristic of IV prices but not of the actual price-setting process. Maximum likelihood prices are not guaranteed to be fully defined throughout the range and do not aggregate well to the community level. If a complete rate history is known, an alternative strategy is to calculate the difference in a defined price index for each consumption level before and after a rate change. In the case of aggregate data, these hypothetical differences should be weighted by the probability density of each consumption level. We assume that consumption is distributed standard lognormally and weight the prices corresponding to each block by the probability density of consumption in the block. A tradeoff of operating in differences is that cross-sectional variation in variable levels disappears, limiting application of the results to annual adjustments. This idiosyncrasy can be put to good use, however, given the thinner water demand literature on adjustment over time.

[54] A comparison of information criteria for log-linear regressions on quasidifferenced marginal and average prices indicates that marginal price change is more influential than average price change. Sewer price changes are not shown to be significant, nor are income changes. An equation of marginal price elasticity of demand is derived from a more

Table 4. Log-Nonlinear Regression, N = 18468

Variable	Dependent Variable is $d\ln W$	
	Coefficient (t-Scores)	
$d\ln MP$	1.2901 (6.15)	
$d\ln T_{min}$	-1.8966 (-3.25)	
$d\ln T_{max}$	-15.8700 (-19.30)	
$d\ln dry$	-7.7871 (-17.96)	
$d\ln MP \cdot d\ln T_{min}$	0.1904 (3.57)	
$d\ln MP \cdot d\ln T_{max}$	-0.4392 (-6.13)	
$d\ln MP \cdot d\ln dry$	-0.0809 (-3.05)	
$d\ln T_{min} \cdot d\ln T_{max}$	1.6405 (23.47)	
$d\ln T_{min} \cdot d\ln dry$	-1.6420 (-10.42)	
$d\ln T_{max} \cdot d\ln dry$	3.3590 (14.48)	
Constant	-0.0053 (-2.85)	
Adjusted R^2	0.1172	
$F(10, 18457)$	246.21	

$p < 0.01$ for all estimated coefficients.

flexible regression of annual change in monthly water use on changes in marginal price, mean low temperature, mean high temperature, and number of days without significant precipitation.

[55] The data are an original set of system-level price, quantity, income, and climate observations for 385 systems in the state of Texas, USA. The data set is remarkable due to its volume and the variety of systems polled, water providers for millions of Texans. Own-price elasticity is shown to vary with climatic conditions. The derived mean price elasticity of -0.127 in the first year is plausible in relation to previous research. It is less elastic than most structural estimates of long-run elasticity, implying an adjustment period longer than 1 year.

[56] As water demand adjustment behavior remains incompletely understood, further research that demonstrates both shorter and longer demand patterns in an integrated way would contribute significantly to modeling and policy-setting efforts. A fundamentally elusive element is the decision mechanism of the retail water consumer. Since neither marginal price nor average price appears to capture this mechanism fully, developing and testing of new price indices is to be anticipated. In further research on aggregate demand under block pricing, more consistent and representative price indices could be developed by incorporating probabilistic methods from endogenous sorting models previously applied only to microdata.

[57] **Acknowledgments.** This research was supported by the Texas Water Development Board (contract 2004-483-023) and the United States Geological Survey (grant 06HQGR0188). The Texas Water Development Board also supplied data critical to the analysis. We thank the many community water professionals who responded to our rate survey, and also David Bessler and three anonymous referees whose valuable remarks improved the quality of this paper.

References

Agthe, D., and R. Billings (1980), Dynamic models of residential water demand, *Water Resour. Res.*, 16, 476–480.
 Arbués, F., M. Á. García-Valiñas, and R. Martínez-Espineira (2003), Estimation of residential water demand: A state-of-the-art review, *J. Socio-Econ.*, 32, 81–102.
 Balestra, P., and M. Nerlove (1966), Pooling cross section and time series data in the estimation of a dynamic model: The demand for natural gas, *Econometrica*, 34, 585–612.
 Burtless, G., and J. A. Hausman (1978), The effect of taxation on labor supply: Evaluating the Gary negative income tax experiment, *J. Polit. Econ.*, 86, 1103–1130.

Table 3. Log Linear Regression, N = 18468

Variable	Dependent Variable is $d\ln W$ (t-scores in parentheses)	
	Model 1	Model 2
$d\ln MP$ (water)	-0.1423 (-7.20) ^a	
$d\ln MP$ (sewer)	0.0077 (0.28)	
$d\ln AP$ (water)		-0.1124 (-4.47) ^a
$d\ln AP$ (sewer)		-0.0462 (-2.21)
$d\ln PI$	-0.0662 (-0.96)	-0.0738 (-1.07)
$d\ln T_{min}$	-0.3238 (-12.14) ^a	-0.3220 (-12.06) ^a
$d\ln T_{max}$	0.9062 (26.78) ^a	0.9051 (26.73) ^a
$d\ln dry$	0.0947 (8.49) ^a	0.0952 (8.53) ^a
Constant	-0.0069 (-3.63) ^a	-0.0070 (-3.66) ^a
Akaike criterion	2267.3	2289.3
Schwarz criterion	2322.1	2344.0
$F(6, 18461)$	208.84	204.94

^a $p < 0.01$.

- Bushnell, J. B., and E. T. Mansur (2005), Consumption under noisy price signals: A study of electricity retail rate deregulation in San Diego, *J. Ind. Econ.*, 53(4), 493–514, doi:10.1111/j.1467-6451.2005.00267.x.
- Carter, D. W., and J. W. Milon (2005), Price knowledge in household demand for utility services, *Land Econ.*, 81, 265–283.
- Carver, P. H., and J. J. Boland (1980), Short-and long-run effects of price on municipal water use, *Water Resour. Res.*, 16, 609–616.
- Cavanagh, S. M., W. M. Hanemann, and R. N. Stavins (2002), *Muffled Price Signals: Household Water Demand Under Increasing-Block Prices*, pp. 1–45, Fondazione Eni Enrico Mattei, Trieste, Italy.
- Christensen, L. R., D. W. Jorgenson, and L. J. Lau (1973), Transcendental logarithmic production frontiers, *Rev. Econ. Stat.*, 28–45.
- Dalhuisen, J. M., R. Florax, H. L. F. de Groot, and P. Nijkamp (2003), Price and income elasticities of residential water demand: A meta analysis, *Land Econ.*, 79, 292–308.
- Gaudin, S. (2006), Effect of price information on residential water demand, *Appl. Econ.*, 38, 383–393.
- Griffin, R. C., and C. Chang (1991), Seasonality in community water demand, *Western J. Agric. Econ.*, 16, 207–217.
- Hanemann, W. M. (1984), Discrete/continuous models of consumer demand, *Econometrica*, 52, 541–561.
- Hausman, J. A., M. Kinnucan, and D. McFadden (1979), A two-level electricity demand model, *J. Econ.*, 10, 263–289.
- Herriges, J. A., and K. K. King (1994), Residential demand for electricity under inverted block rates: Evidence from a controlled experiment, *J. Bus. Econ. Stat.*, 12, 419–430.
- Hewitt, J. A. (2000a), A discrete/continuous choice approach to residential water demand under block rate pricing: Reply, *Land Econ.*, 76, 324–330.
- Hewitt, J. A. (2000b), An investigation into the reasons why water utilities choose particular residential rate structures, in *The Political Economy of Water Pricing Reforms*, edited by A. Dinar, pp. 259–277, Oxford Univ. Press, New York.
- Hewitt, J. A., and W. M. Hanemann (1995), A discrete/continuous choice approach to residential water demand under block rate pricing, *Land Econ.*, 71, 173–192.
- Kennedy, P. (2003), *A Guide to Econometrics*, 5th ed., MIT Press, Cambridge, Mass.
- Lyman, R. A. (1992), Peak and off-peak residential water demand, *Water Resour. Res.*, 28, 2159–2167.
- Martínez-Espiñeira, R. (2003), Estimating water demand under increasing-block tariffs using aggregate data and proportions of users per block, *Environ. Resour. Econ.*, 26, 5–23.
- Martínez-Espiñeira, R. (2004), An estimation of residential water demand using co-integration and error correction techniques, *J. Appl. Econ.*, 10, 161–184.
- Nauges, C., and A. Thomas (2003), Long run study of residential water consumption, *Environ. Resour. Econ.*, 26, 25–43.
- Nieswiadomy, M. L. (1991), A note on price perception in water demand models, *Land Econ.*, 67, 352–359.
- Nordin, J. A. (1976), A proposed modification of Taylor's demand analysis: Comment, *Bell J. Econ.*, 7, 719–721.
- Reiss, P. C., and M. W. White (2005), Household electricity demand revisited, *Rev. Econ. Stud.*, 72, 853–883.
- Renwick, M. E., and R. D. Green (2000), Do residential water demand side management policies measure up? An analysis of eight California water agencies, *J. Environ. Econ. Manage.*, 40, 37–55.
- Renzetti, S. (2002), *The Economics of Water Demands*, Springer, Boston, Mass.
- Reynaud, A., S. Renzetti, and M. Villeneuve (2005), Residential water demand with endogenous pricing: The Canadian case, *Water Resour. Res.*, 41, W11409, doi:10.1029/2005WR004195.
- Schefter, J. E., and E. L. David (1985), Estimating residential water demand under multi-part tariffs using aggregate data, *Land Econ.*, 61, 272–280.
- Shin, J.-S. (1985), Perception of price when price information is costly: Evidence from residential electricity demand, *Rev. Econ. Stat.*, 67, 591–598.
- Taylor, L. D. (1975), The demand for electricity: A survey, *Bell J. Econ.*, 6, 74–110.
- Taylor, R. G., J. R. McKean, and R. A. Young (2004), Alternate price specifications for estimating residential water demand with fixed fees, *Land Econ.*, 80, 463–475.
- Terza, J. V. (1986), Determinants of household electricity demand: A two-stage probit approach, *South. Econ. J.*, 52, 1131–1140.
- Working, E. J. (1927), What do statistical "demand curves" show?, *Q. J. Econ.*, 41, 212–235.

D. R. Bell and R. C. Griffin, Department of Agricultural Economics, Texas A&M University, 308C Blocker Building, College Station, TX 77843-2124, USA. (ron-griffin@tamu.edu)