Demand Specification for Municipal Water Management: Evaluation of the Stone-Geary Form

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ABSTRACT. *To specify demand in most water allocation problems, researchers face a tradeoff between flexibility and parsimony. Flexible forms are less constraining on elasticity estimates, but require large parameter sets that tend to cause poor out-of-sample forecasts and computational difficulties. Using a five-year panel of Texas municipalities, the parsimonious Stone-Geary form yields estimated demand functions that are comparable to flexible form results. The Stone-Geary specification also provides an estimate of the portion of water use that may not be responsive to price, and is useful in analysing price structures and designing conservation policies.* (JEL Q25, C23)

I. INTRODUCTION

Most applications of water demand emphasize the need for accurate and unconstrained price elasticity estimates as well as parsimony in parameters. The combination of these two features is particularly important in dynamic simulation models of water planning and management where water demand estimates are used to evaluate the welfare implications of different water allocations over time. Whether it is to evaluate water supply enhancement projects, water conservation measures, rate changes, or the conjunctive use of ground and surface water, dynamics are involved and the choice of a functional form is paramount. The need for dynamic water management models has become more pronounced, especially for the development of municipal water plans. For example, in Texas, the focus of our empirical analysis, rapid urban growth in the last thirty years has caused large transfers of water from agriculture to municipalities, and the trend is expected to continue in the future.[1] Many municipalities are depleting their ground water reserves, causing increased pumping costs for all future periods, land subsidence, and quality degradation. At the same time, surface water is becoming scarce and cities must decide whether to use ground water, surface water, or both (Hultberg 1999). Similar problems are commonly found elsewhere and it has become clear that the sustainability of economic development in many cities depends largely on improved long-run planning and management of scarce resources such as water.

Water demand estimation involves a tradeoff between achieving parsimony and global regularity of the preference structure on the one hand, and flexibility on the other.[2] Most of the earlier studies in water demand have chosen simplicity, using linear and/or log-linear specifications.[3] The resulting restrictions on elasticities are not problematic as long as price variation is small and predictions are made within a similar price range. Because there is evidence that price elasticity

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[1] The Texas Water Development Board estimates that in the year 2040, municipalities will be the main consumers of water in Texas (TWDB 1990).

[2] Flexibility usually refers to the ability of a functional form to approximate a twice continuously differentiable function to the second order. The number of free parameters required for this purpose can be large. In particular, if the number of exogenous variables is N, a flexible consumer demand function requires $(N^2 + 3N - 4)/2$ free parameters (Diewert and Wales 1988).

[3] A summary of these studies up to 1979 is given by Danielson (1979). Later studies include Cochran and Cotton (1985) and Hansen (1996).

is neither constant nor increasing with the price level, we need a functional form that allows elasticity to decrease with price.[4] Except for cases where different regressions are performed on subsamples of the data,[5] nonconstant elasticity results have been obtained using flexible functional forms, but flexible forms are not well suited for specification of benefits in dynamic programming simulations for reasons explained below.

Although flexibility often provides good sample fits, out-of-sample forecasts suffer if the values of variables trend away from within-sample values. Global curvature restrictions can be imposed on these flexible forms but, unless flexibility is greatly restricted, the number of parameters needed is still large (Diewert and Wales 1987). Some methods address the concavity problem by only imposing restrictions locally "over a set of prices where inference will be drawn" (Terrell 1996), but this does not solve the out-of-sample problem.

Hausman and Newey (1995) use nonparametric methods to estimate exact consumer surplus. Dynamic optimization models usually employ consumer surplus, but the consumer surplus must be expressed as a function of control variables that change over time. A nonparametric estimation with numerical approximation of a demand function cannot be used for this purpose. The main problem is one of parameter parsimony. None of these functions are parsimonious enough to be used in dynamic simulations where the full form of the demand function is required.

In addition, in most flexible form estimations, parameter estimates are functional approximations and often do not have any straightforward economic interpretation. To get better insights on results of dynamic optimization models and their sensitivity to parameterization, it can be important to be able to interpret the demand parameters with reference to an underlying structural model.

The present paper suggests and estimates a functional form that is simple, interpretable, and generates nonconstant price elasticities. We propose the use of a Stone-Geary demand function and compare its performance to a flexible functional form, previously used in water demand estimation, the Generalized Cobb-Douglas (GCD).[6] The comparison is based on the estimation of water demand using five years of monthly data from a large number of Texas communities. We find that the elasticities obtained for the Stone-Geary have seasonality patterns similar to the estimates obtained for the GCD, as long as Stone-Geary parameters are allowed to be linear functions of the exogenous variables used in the GCD regressions. Also, the estimated function does not break down at high levels of prices and provides insight into the determinants of threshold effects on water use.

The paper is organized as follows: Section 2 contains a brief description of the data, variables, and functional forms. Improvements provided by a random effect estimation of the GCD functional form are presented in Section 3. In Section 4, results of the Stone-Geary estimations are reported and compared to the GCD results and some caveats in parameter interpretation are discussed.

II. EXPLANATORY VARIABLES, DATA, AND FUNCTIONAL FORMS

Variables and Data

The data set provides information for 221 Texas communities during the period 1981–1985.[7] Summary statistics for all variables are given in Table 1. Out of 12,050 observa-

[4] Foster and Beattie (1979) obtain nonconstant price elasticities using a price exponential model. Griffin and Chang (1990 and 1991) compare linear, log linear, Generalized Cobb-Douglas, Translog, and Fourier functional forms. They find price elasticities that increase with price when a flexible form is used.

[5] For example Dandy et al. (1997) use winter evaporation for the "winter model" and summer moisture for the "summer model" to obtain different winter and summer price elasticities.

[6] In their comparison of several demand specifications, Griffin and Chang (1991) find that the Generalized Cobb-Douglas form (GCD) provides flexibility in the parameters while preserving a relatively nicely behaved demand function.

[7] The data set was developed by Ron Griffin and Chan Chang. A more detailed description of the data as well as thorough justification for data manipulation and choice of variables can be obtained from Griffin and Chang (1989, 1990, 1991).

TABLE 1

SUMMARY STATISTICS, SAMPLES OF 12,050 AND 9,430 OBSERVATIONS

Variable	Description	Frequency	Units
Q	Quantity of water produced	Monthly	Gallons/capita/day
AP	Average Price	Monthly	US$/1000 gallon
I	Income (1980 Census)	Time invariant	1000 US dollars/capita/year
SP	Spanish Population (1980 Census)	Time invariant	Percent of population
C	Days with rainfall <.25 in × Avg. temp.	Monthly	Degrees F. × days
AAP	60-year average annual precipitation	Time invariant	Inches/year

		Full Sample (years not identified)					Reduced Samples (years identified)			
	N	Mean	St. Dev.	Min	Max	*N*	Mean	St. Dev.	Min	Max
All	12,050					9,430				
Q		1.69	67.8	21.0	731		168	67.2	21.0	731
AP		1.72	0.70	0.17	6.21		1.75	0.73	0.17	6.21
I		6.40	1.68	2.30	14.5		6.50	1.69	2.30	14.5
SP		6.07	6.47	0.00	35.3		5.83	6.33	0.00	35.3
C		1801	418	644	2764		1790	412	680	2757
AAP		32.5	10.8	7.82	59.2		32.9	10.7	7.82	54.5
January	997					750				
Q		138	41.6	35.6	387		136	41.0	35.6	387
AP		1.78	0.69	0.32	6.21		1.84	0.73	0.59	6.21
I		6.39	1.67	2.30	14.5		6.49	1.62	2.30	14.5
SP		6.06	6.41	0.00	35.3		5.63	5.83	0.00	23.3
C		1287	174	871	1941		1286	161	871	1941
AAP		32.5	10.8	7.82	59.2		33.1	10.5	7.82	54.5
July	969					715				
Q		228	84.7	34.2	548		227	86.9	59.2	548
AP		1.56	0.67	0.19	5.14		1.58	0.71	0.19	5.14
I		6.44	1.69	2.30	14.5		6.64	1.76	2.93	14.5
SP		6.04	6.51	0.00	35.3		5.69	6.33	0.00	35.3
C		2359	177	1632	2764		2355	181	1632	2694
AAP		32.6	10.9	7.82	59.2		33.1	10.9	7.82	54.5

tions in the original sample, 2,620 are dropped to identify years and use the data set as a panel. Table 1 also gives summary statistics for the resulting 9,340 observations (186 communities).[8]

We use five variables that have been shown to have a significant effect on per capita water consumption (Q) across different functional forms. These five variables are the average price of water (AP), per capita income (I), percentage of the population of Spanish origin (SP), a climate variable (C), and average annual precipitation (AAP).[9]

AP was statistically shown to be the price variable on which individual decisions on water consumption are made, as opposed to the marginal price or a Taylor-Nordin specification for multipart tariff structures (Griffin and Chang 1990). Although economic theory without transaction costs suggests that con-

[8] Years could only be identified when the full 5 years of a given month were reported. Consequently, the municipalities dropped were those with the most irregular reporting. The new sample is more homogeneous and is less likely to contain measurement errors. The most noticeable difference between the two samples is the drop in percentage of population of Spanish origin (see Table 1).

[9] Foster and Beattie (1979) justify the exclusion of other goods in the estimation arguing that water has no direct substitutes and is a complement only with durable items such as appliances, the price of which does not affect water consumption once they have been purchased. Cross price effects are therefore normally assumed negligible in water demand. We will discuss the implications of this restriction in the context of interpreting the "threshold water use" parameter obtained from the Stone-Geary estimation.

sumer behavior is guided by marginal prices, in a world where the costs of obtaining specific information on complicated rate structures is high relative to the cost of water, it is likely that consumers will react to a transparent average price (Foster and Beattie 1981).[10]

The inclusion of *SP* as explanatory variable is based on a 1986 statistical study performed by demographers (Murdock et al. 1988) where Spanish origin was found to have a significant negative impact on per capita water use. It has not been tested whether this might be due to the larger average family size of Hispanics (thus spreading outdoor and other "common" household water uses over more people), different cultural norms regarding the use of water-consuming durables (e.g. pools, lawns, appliances), or some other factors.

Variables' specifications are as follows. Q is measured in gallons per capita per day. Water production per day is obtained from the Texas Water Development Board (TWDB).[11] The data generally excludes industrial and heavy commercial use so municipal water use can be considered mostly residential.[12] 1980 Census data on population is used to calculate per capita use.

AP is calculated as the average household's water and sewer bill divided by the average household's water use. The climate variable C is constructed using the number of days without significant rainfall in the community ($\leq$0.25 inches) multiplied by the month's average temperature in degrees Fahrenheit. This information was obtained from daily National Weather Service data. C is intended to capture the sensitivity of outdoor water demand to climate variations. I, in thousand dollars per capita, and *SP* are obtained from the 1980 census. *AAP* is average annual precipitation in inches from 1951 to 1980, obtained from the National Oceanic and Atmospheric Administration. Q, *AP*, and C are time variant, whereas I, *SP*, and *AAP* vary only cross-sectionally.

Figure 1 shows the distribution of the price variable in the sample of 9,430 observations. The bulk of the data is within the \$1 to \$3 price range, with a mean price of \$1.75. Applications of estimated flexible form demand functions should be particularly mindful of this range.

Functional Forms

The Generalized Cobb-Douglas (GCD) demand function. The GCD specification contains features similar to a double logarithmic model in that the demand function is asymptotic to the price axis, has a positive quantity intercept and does not assume constant elasticity. The GCD form was originally proposed by Diewert (1973).[13] Its logarithmic transformation is

$$\ln Q = \delta_0 + \sum_i \sum_{j \neq i} \delta_{ij} \frac{\ln(x_i + x_j)}{2} + \sum_i \delta_i \ln x_i,$$

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[10] An economic theory endogenizing transaction costs would recognize the high household cost of determining MP relative to AP. AP can be identified from typical water bills, whereas MP requires knowledge of the typical rate structure. As Foster and Beattie point out in their 1981 paper, at low water values, households will not be motivated to spend the resources needed to determine MP. We concur with the Foster and Beattie position that the choice of a price variable for water is properly a matter of explanatory ability. It must be noted, however, that as water becomes more scarce, the empirical superiority of AP might not persist.

[11] This feature is a weakness specific to water demand estimation. Two problems arise. First, the presence of storage tanks allows for monthly variations in production that may not reflect monthly variation in consumption. Some of the data had to be discarded because of high variation that canceled out in the next month. Second, losses to the system are included. These losses constitute 15 to 20 percent of water supply in Texas municipalities (TWDB 1990, 2–8).

[12] It must be noted that the burden is on communities to report this properly and we cannot be confident about their care. However, because larger water users have larger diameter service and meters (which are accompanied by higher monthly flat fees), it is relatively easy for communities to report industrial water use separately as requested by the TWDB.

[13] The GCD form has been more commonly used in production analysis. See for example Guilkey, Lovell, and Sickles (1983) for a comparison of the performance of different functional forms for cost estimation. They use an extended version of the GCD form (EGCD) which does not restrict the coefficients on cross products to equal 1/2. They find that in almost every comparison they conducted, the Translog (TL) systems estimator and the EGCD estimator outperform all other estimators, typically by a wide margin. However, each of these flexible forms always performs better when the production function exhibits some features of the underlying restricted form.

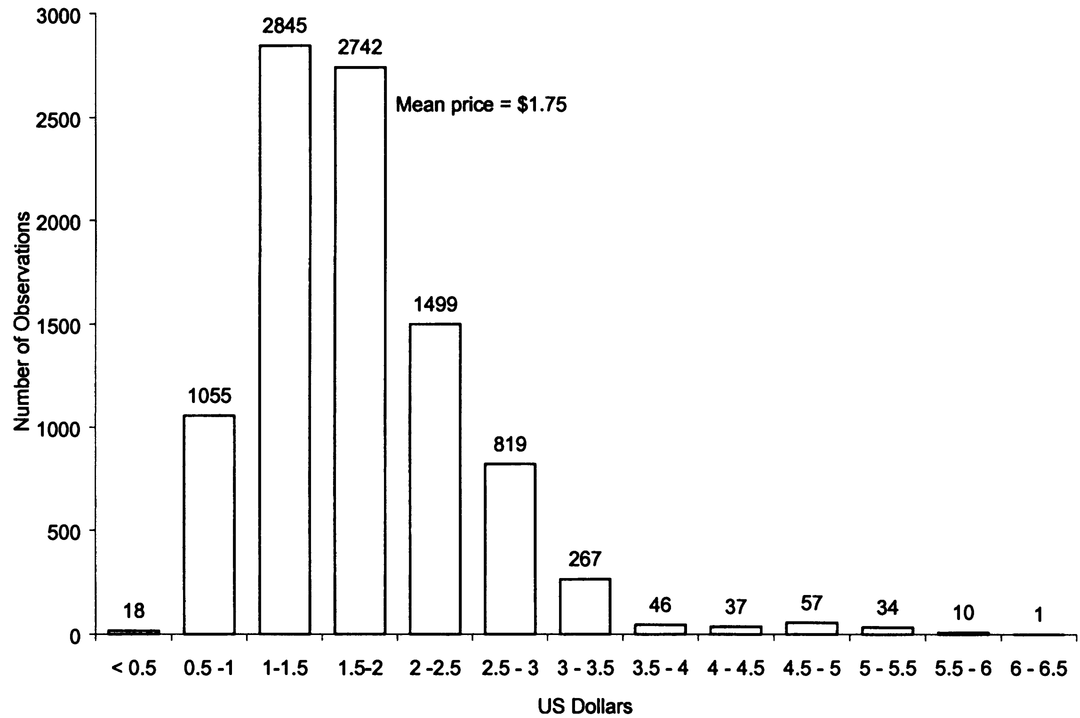

FIGURE 1
FREQUENCY DISTRIBUTION OF THE AVERAGE PRICE VARIABLE

where x_i, x_j are the exogenous explanatory variables (in our estimation, *AP*, *I*, *SP*, *C*, and *AAP*) and where $\delta_{ij} = \delta_{ji}$ for all i, j.

The GCD form is able to provide nonconstant elasticity estimates over the sample.[14] However, the number of parameters involved in the functional form is large[15] and raw parameters are not readily interpretable. This complexity limits the use of estimation results to applications requiring only elasticity estimates.

The Stone-Geary demand function. Because most structural dynamic models require more than just elasticity estimates, we look for a functional form that involves fewer parameters but still allows price elasticity to vary seasonally and with the levels of price, income, and quantity variables. The Stone-Geary form is interesting in these respects.[16] The function has been commonly used for food products, durable goods, and in the study of grants-in-aid, but it has not been investigated in the water demand literature. The main advantage of the Stone-Geary specification is its use of only two parameters while allowing for nonconstant elasticities

[14] Elasticities are calculated as, $(\partial \ln Q/\partial x_i)x_i$, so the elasticity of Q with respect to the variable x_i is

$$\delta_i + \sum_{j \neq i} \delta_{ij} \frac{x_i}{x_i + x_j}.$$

[15] The form uses $K + K!/(K - 2)!2$ parameters, where K is the number of exogenous variables. In our estimation where five explanatory variables are used, the number of parameter excluding the intercept is 15.

[16] For a clear description of the theoretical features of the Stone-Geary demand function, see Deaton and Muellbauer (1980a), Powell (1974), and/or Chung (1994). Stone-Geary demand and its linear expenditure system have been widely used in the study of private consumption patterns starting with the extensive study of British consumption data by Stone (1954). The system seems well suited for analyzing the demand for food products (Deaton and Muellbauer 1980b). It has also been used in the study of public sector consumption patterns (McGuire 1979; Johnson 1979).

that may increase with price. Another nice feature is that both parameters have economic meaning. One of the parameters can be interpreted as a threshold below which water consumption is not affected by prices, at least not in the short run. The magnitude of this parameter is potentially informative for investment and pricing decisions of water utilities in growing communities.

The Stone-Geary demand function can be derived from a utility function of the form: $\ln U = \sum_{i=1}^{n} \beta_i \ln(q_i - \gamma_i)$ with $\sum_i \beta_i = 1$. The function assumes that utilities are additive but does not require homotheticity. Two parameters with straightforward economic interpretation highlight the function: the "marginal budget share" (β) and the "subsistence level" (γ). The consumer is faced with a given level of income and a set of prices. The consumer first purchases a minimum acceptable level of each good (the γ_i's). The leftover income, also called "supernumerary income," is then allocated in fixed proportions to each good according to their respective preference parameter (the β_i's).

Because we are only interested in water consumption, we can look at a utility function where the consumer derives utility from water and some aggregate of all other goods used as the numeraire. Such a utility function generates the following demand function:

$$Q_w = \gamma_w + \beta \frac{I^* - P_w \gamma_w - \gamma_z}{P_w},$$

where the subscripts w and z indicate respectively parameters pertaining to water and to all other goods. We use I^* for income and P for price in this specification to distinguish them from I and AP used in the GCD specification. Some minor transformations of the variables have to be made so that the measurement of price and income corresponds to the units used for Q (per capita and per day).[17]

Price elasticity is given by $-\beta(I^* - \gamma_z)(P_w Q_w)$. The Stone-Geary function only allows for inelastic demand. This feature is not a problem for water given overwhelming support for low price elasticity in the literature.[18] Another feature of this price elasticity is that it is not constrained to increase with price, which distinguishes it from the linear form and makes it more appropriate for expected long-run elasticity changes. Income elasticity is $\beta I^*/(P_w Q_w)$. This result implies that only normal goods can be analyzed with the Stone-Geary functional form. Water fits into this category.

Following McGuire (1979), we choose to abstract from γ_z, the general subsistence level, and treat I^* as the supernumerary income. This simplifies the function, leaving only two parameters β and γ, both pertaining directly to water demand. This simpler specification is preferred because γ_z provides no information relevant to the study. The remaining γ parameter is renamed as the *conditional water use threshold.* Indeed, the term "subsistence level" is misleading for water demand analysis. The γ parameter does not indicate how much water is needed to survive, but the amount of water that may not be responsive to prices. The term *conditional* emphasizes that this threshold is dependent on the available technology, the state of ownership, the pricing structure, and the price of water-consuming durable goods during the time period of the estimation. In the following we simply use the word *threshold* to refer to γ.

The parameters γ and β vary with the exogenous variables. γ is assumed to be a linear function of exogenous variables that have been shown to be of significance in water demand but are not directly included in the Stone-Geary formulation. These are the climate variable (C), the Spanish population variable (SP), and the average precipitation variable (AAP). Common sense indicates that the threshold should be sensitive to these variables. The impact of climate variables is intuitive. The impact of the SP variable could come from the fact that the variable may capture family size or cultural differences. The marginal budget share may also be sensitive to some exogenous variables, and there is no reason to assume that it is constant. Actually, a constant β would most likely generate un-

[17] $I^* = I\,(1000/365)$, and $P = AP/1000$.

[18] See Danielson (1979) where results from a large number of studies on water demand elasticities are summarized in a convenient table.

desirable results in terms of seasonality as the price elasticity varies inversely with quantity. Our simple formulation with other goods as the numeraire allows us to also specify β as a linear function of the same exogenous variables.[19]

III. GENERALIZED COBB-DOUGLAS ESTIMATION

Estimation Methods

We perform a simple OLS estimation,[20] add dummy variables for each month and year (OLSMYD), and compare the results to a random effect specification using Generalized Least Squares (GLS). The addition of time dummies is necessary to separate the seasonality and year effects from cross-sectional heterogeneity.[21] The one-way (cross-sectional) random effect model is intuitively appealing in this setup because the sample can be considered to be a random sample from a larger population of communities. Two features of the data make a fixed effect model impractical. First, the number of cross sections (N) is large and the loss of degrees of freedom caused by the addition of $N - 1$ dummy variables jeopardizes the stability of the coefficients. Second, and most important in our case, three of the variables used are time invariant, which makes a fixed effect model incapable of identifying coefficients on these variables.

The one-way random effect specification of the GCD form is

$$\ln Q_{it} = \delta_0 + Z_{it}\beta + u_i + \varepsilon_{it},$$

where Z consists of data for the right hand side variables to be used in the GCD form, ε_{it} is the classical error term, normally distributed and with zero mean, and u_i is a community-specific error term. This panel data formulation of the model uses the heterogeneity information contained in the data. The inclusion of a community-specific error term generates a nonstandard covariance structure. GLS is efficient and improves upon OLS as long as the effects are nonzero and uncorrelated with the regressors, which would make GLS inconsistent.[22] Hausman-Wu tests are carried out for all the random effect estimations. The results for all one-way random effect specifications (reported in Table 2) suggest that there is no problem of correlation between the effects and the exogenous variables when only cross-section random effects are used. F-tests calculated from fixed effects regressions and reported in Table 2 indicate the presence of cross-sectional sample heterogeneity. The GLS one-way random effect estimation should therefore be efficient and improve upon OLS.

GCD Results

OLS and GLS regressions are performed with and without time dummies.[23] The regression results in a raw form (i.e., with coefficients and standard errors pertaining to the regressors) are reported in Table 2. Because regressors in the GCD form are composites of the exogenous variables, raw results are not readily interpretable. To quantify the impact and significance of each exogenous variable separately, elasticities and their corre-

[19] Johnson (1979) also assumes that γ is a linear function of some exogenous variables. He argues that there is no theoretical reason to assume that β is not also a function of exogenous variables, but in his analysis with more than one β, it would have seriously complicated the analysis.

[20] The OLS results reproduce previously published results (Griffin and Chang 1991).

[21] First, only month dummies were added to capture seasonality but year effects were found to be highly significant. A simple OLS linear regression of Q on the exogenous variables, month dummies, and a year variable gave a highly significant coefficient of 4.82 on the year variable. Adding year dummies to our GCD regression takes care of this positive trend.

[22] For a theoretical discussion of one-way fixed and random effects models, see Greene (1997, 618–30) and Baltagi (1995, 9–18).

[23] Estimation of the GLS one-way unbalanced data random effects model is performed in SAS-ETS (1996) using the Baltagi and Chang (1994) specialization of the approach used by Wansbeek and Kapteyn (1989) for unbalanced two-way models. A two-way random effect estimation is also performed, but the Hausman-Wu test on this regression gives a poor result suggesting some correlation between the time effects and the exogenous variables (see Table 2).

TABLE 2
GENERALIZED COBB-DOUGLAS REGRESSIONS

	OLS[a]	OLS	OLS	GLS1[b]	GLS1	GLS1	GLS2[b]
Sample Size	12,050	12,050	9,430	9,430	9,430	9,430	9,430
Dummies	—	Month/Year	Month/Year	—	Month	Month/Year	—
Intercept[c]	−5.08**	−1.72**	−2.80**	−6.31**	−2.84	−2.12	−1.95
	(0.39)	(0.34)	(0.39)	(1.88)	(2.22)	(2.95)	(2.77)
Ln(AP)	−0.58**	−0.60**	−0.60**	−0.41**	−0.40**	−0.51**	−0.50**
	(0.026)	(0.025)	(0.026)	(0.037)	(0.036)	(0.035)	(0.035)
Ln(AP + I)	0.48**	0.82**	0.58**	−0.92**	−0.74**	−0.87**	−0.78**
	(0.15)	(0.14)	(0.15)	(0.20)	(0.19)	(0.19)	(0.18)
Ln(AP + SP)	0.12**	0.10**	0.05**	0.058*	0.09**	0.13**	0.13**
	(0.016)	(0.015)	(0.016)	(0.035)**	(0.034)	(0.033)	(0.032)
Ln(AP + C)	124**	57.5**	42.6*	164**	108**	86.6**	80.0**
	(18.9)	(18.7)	(20.2)	(16.74)	(16.48)	(16.0)	(15.78)
Ln(AP + AAP)	−0.58	−0.30	1.40**	0.93*	1.17*	2.24**	2.06**
	(0.36)	(0.35)	(0.39)	(0.53)	(0.51)	(0.50)	(0.49)
Ln(I)	−0.10	−0.34**	−0.34**	1.03	1.01	1.23	1.21
	(0.11)	(0.11)	(0.12)	(0.71)	(0.76)	(1.11)	(1.04)
Ln(I + SP)	−0.36**	−0.27**	−0.063	−0.17	−0.18	−0.24	−0.27
	(0.044)	(0.04)	(0.048)	(0.46)	(0.50)	(0.73)	(0.68)
Ln(I + C)	71.3**	35.0**	50.2**	37.12**	−11.9	−23.7**	−40.0**
	(7.96)	(7.96)	(9.05)	(7.92)	(8.02)	(7.78)	(7.71)

Ln(I + AAP)	−0.96**	−0.74**	−0.91**	−1.08	−0.78	−0.82	−0.67
	(0.19)	(0.18)	(0.20)	(3.27)	(3.51)	(5.17)	(4.85)
SP	0.010**	0.012**	0.005	0.0071	0.010	0.012	0.016
	(0.0030)	(0.0030)	(0.0034)	(0.049)	(0.052)	(0.077)	(0.072)
Ln(SP + C)	18.0**	2.44	5.24	32.8**	19.4**	16.4**	9.95**
	(2.92)	(2.95)	(3.33)	(2.44)	(2.47)	(2.40)	(2.39)
Ln(SP + AAP)	−0.54**	−0.40**	−0.56**	−1.00	−0.92	−0.91	−0.85
	(0.061)	(0.060)	(0.066)	(0.99)	(1.06)	(1.56)	(1.46)
Ln(C)	−245**	−118**	−127**	−284**	−160**	−122**	−88.7**
	(19.7)	(20.1)	(22.1)	(17.14)	(17.66)	(17.2)	(17.3)
Ln(C + AAP)	32.3**	24.5**	30.2**	52.48**	46.44**	44.4**	40.0**
	(1.70)	(1.71)	(2.00)	(1.51)	(1.52)	(1.47)	(1.47)
Ln(AAP)	1.08**	0.67**	−0.81*	−0.24	−0.67	−1.59	−1.53
	(0.35)	(0.34)	(0.38)	(2.44)	(2.61)	(3.81)	(3.58)
$R^{2\,d}$	0.44	0.47	0.48	0.57	0.57	0.62	0.33
F-Test	633	355	294	—	—	—	—
Hausman-Wu: m	—	—	—	0.23	0.23	0.096	14.1
D.F.	—	—	—	9	20	24	9
prob. > m	—	—	—	(0.99)	(0.99)	(0.99)	(0.12)

[a] Replica of OLS results in Griffin and Chang (1991).
[b] GLS1 = One-way random effects; GLS2 = two-way random effects.
[c] Month dummy regressions intercept: December; Month/Year dummy regression intercept: December 1985.
[d] Adjusted R^2 are reported for OLS regressions. For GLS, a generalized version of the R^2 is used.
** Significant at the 1% level or better; * significant at the 10% level or better.

TABLE 3
ELASTICITIES FROM GCD ESTIMATIONS

	OLS	OLS	OLSMYD[a]	OLSMYD[a]	GLS	GLSMYD[a]
N	12,050	9,430	12,050	9,430	9,430	9,430
AP	−0.37**	−0.35**	−0.37**	−0.36**	−0.39**	−0.47**
	(0.007)	(0.009)	(0.007)	(0.009)	(0.012)	(0.012)
I	0.19**	0.12**	0.17**	0.11**	0.17	0.19
	(0.013)	(0.015)	(0.014)	(0.015)	(0.034)	(0.35)
SP	−0.04**	−0.04**	−0.03**	−0.03**	−0.04	−0.03
	(0.005)	(0.003)	(0.002)	(0.005)	(0.065)	(0.10)
C	0.72**	0.72**	0.53**	0.56**	0.74**	0.53**
	($<10^{-5}$)	(0.019)	(0.011)	($<10^{-5}$)	($<10^{-5}$)	(0.03)
AAP	−0.15**	−0.18**	−0.14**	−0.17**	−0.16	−0.12
	(0.010)	(0.012)	($<10^{-5}$)	(0.011)	(0.19)	(0.30)

[a] OLSMYD and GLSMYD correspond to OLS and GLS regressions with month and year dummies.
[b] Significant at the 1% level or better; * significant at the 10% level or better.

sponding standard errors are calculated.[24] Results are reported in Table 3.

To evaluate the effect of the change in sample size from 12,050 to 9,430 observations, the OLS results with and without time dummies for both samples are also reported. Finally, to investigate how the function performs in picking up seasonal variation in price elasticity, the parameters and elasticities are calculated at the January and July means. Table 4 presents these results.

Price elasticities obtained with OLS and evaluated at the sample mean range from 0.35 to 0.37. The GLS one-way random effect estimates of price elasticities are uniformly larger than their OLS counterparts, ranging from 0.39 to 0.47. As in the OLS estimation, the GLS estimate is a weighted average of the "within" estimate (which ignores variation between communities) and the "between" estimate (which ignores variation within communities). However, a nonzero variance of the u_i's increases the weight on the within estimate and decreases the weight on the between estimate when using GLS. Because the price (*AP*) and the climate variable (*C*) are the only variables that have nonzero within estimates, the GLS estimates on these variables are expected to be greater. In particular, since income is time invariant, the within estimate of price elasticity is likely to include the missing variation in income (which should increase price elasticity since water is a normal good). Finally, the use of GLS affects the significance levels of the estimates. Although the significance levels on price elasticities remain high, significance levels on elasticities with respect to *I*, *SP*, and *AAP* are reduced. Again, because the within variation is given more weight in the GLS regression and because these variables are invariant within communities (and therefore given a zero coefficient in the within estimation), this is not a surprising result.

We wish to evaluate how elasticities are likely to behave if this functional form and its estimates are used out of sample in long-run planning models (i.e., when higher values of variables such as price and income are used). To do so, elasticities are calculated at

[24] The price elasticity is calculated as

$$AP \times \left(\frac{\hat{b}[\ln(AP)]}{AP} + \frac{\hat{b}[\ln(AP + I)]}{AP + I} + \frac{\hat{b}[\ln(AP + SP)]}{AP + SP} + \frac{\hat{b}[\ln(AP + C)]}{AP + C} + \frac{\hat{b}[\ln(AP + AAP)]}{AP + AAP} \right)$$

where $\hat{b}[.]$ denotes the estimated coefficient on [.].

TABLE 4
ELASTICITIES FROM GCD ESTIMATIONS: SEASONALITY

	OLS	OLSMYD[a]	GLSMYD[a]	OLS	OLSMYD[a]	GLSMYD[a]
Month	January	January	January	July	July	July
N	997	750	750	969	715	715
AP	−0.31**	−0.33**	−0.43**	−0.41**	−0.39**	−0.49**
	(0.010)	(0.012	(0.014)	(0.009)	(0.010)	(0.013)
I	0.28**	0.18**	0.16	0.14**	0.08**	0.19
	(0.019)	(0.020)	(0.35)	(0.013)	(0.017)	(0.35)
SP	−0.02**	−0.02**	−0.01	−0.05**	−0.03**	−0.04
	(0.006)	(0.006)	(0.10)	(0.006)	(0.006)	(0.010)
C	0.32**	0.25**	0.19**	0.96**	0.74**	0.74**
	($<10^{-5}$)	(0.016)	(0.032)	($<10^{-5}$)	(0.017)	(0.032)
AAP	0.07*	0.03*	0.18	−0.29**	−0.29**	−0.30
	(0.016)	(0.017)	(0.30)	(0.013)	(0.015)	(0.29)

[a] OLSMYD and GLSMYD correspond to OLS and GLS regressions with month and year dummies.
** Significant at the 1% level or better; * significant at the 10% level or better.

the maximum sample values of price and income. Results are reported in Table 5. Elasticities are generally reduced except when evaluated at maximum income. One important feature is that in most cases, except for the random effect specification with dummies, price elasticities become positive. This indicates that the functions do not perform as well at the maximums. This problem is likely to worsen when the estimates are used out of sample.

Figures 2 and 3 provide a comparison between the OLS and GLS estimations of the GCD function with and without month and year dummies. As expected, the GCD function estimated with random effects (GLS) is better behaved than the OLS estimated function at higher prices, retaining its downward sloping shape. Figures 4 and 5 provide a comparison of the January and July functions using OLS and GLS with and without the use of month and year dummies. Again, the GLS estimated function retains its negative slope. The seasonal shifts are somewhat less pronounced at higher prices when using GLS. Finally, the use of dummy variables in the estimation seems to capture the shifts in a smoother way over a wider price range.

IV. STONE-GEARY ESTIMATION

The Stone-Geary functional form is estimated using OLS and GLS (one-way random effects) estimators. Although the function is always nonlinear in the variables, the regression equation can be written as linear or nonlinear in the parameters. Linear OLS can be used in the first case but nonlinear techniques are needed for the second formulation. The linear estimation focuses on the intercept and β, which are estimated as independent coefficients, γ is then calculated outside of the es-

TABLE 5
PRICE ELASTICITY AT HIGHEST SAMPLE VALUES OF PRICE AND INCOME

Variable at Maximum Value[a]	OLS	GLS	OLSMYD[b]	GLSMYD[b]
Price (AP)	0.13	−0.11	0.08	−0.21
Income (I)	−0.37	−0.29	−0.42	−0.38
AP and I	0.08	0.06	−0.03	−0.05

[a] All other variables are at their mean value.
[b] OLSMYD and GLSMYD correspond to OLS and GLS regressions with month and year dummies.

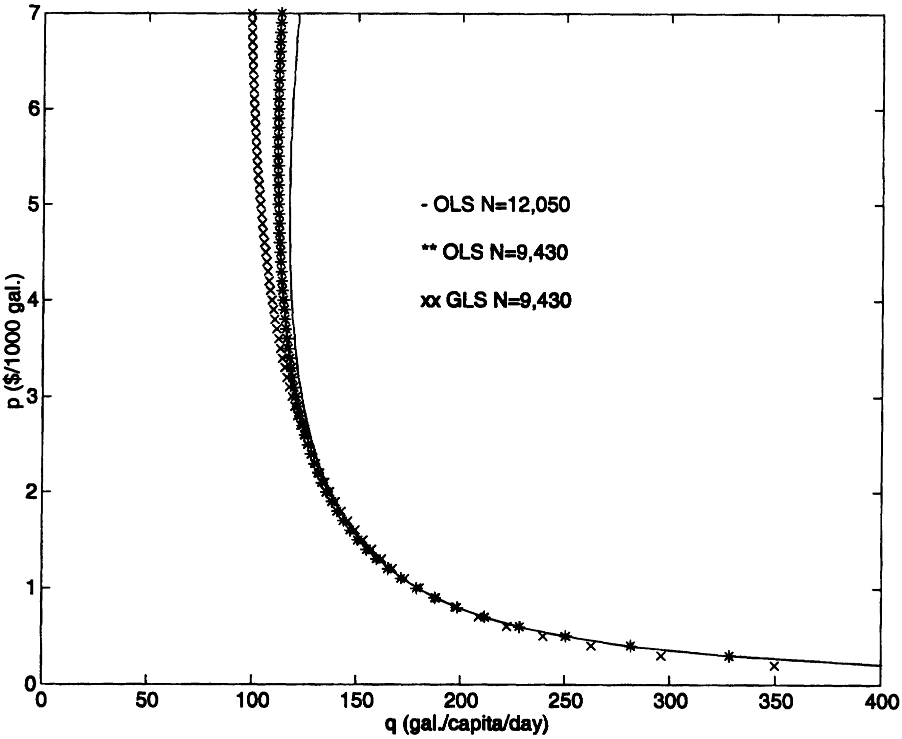

FIGURE 2
Plot of Estimated GCD Function

timation. The nonlinear technique estimates both β and γ simultaneously using iterative methods. Because the linear estimation is likely to lack efficiency, nonlinear OLS and nonlinear GLS are used to estimate the parameters. Nonlinear results are found to be very similar to linear results (only two iterations are needed to complete the estimation), but the nonlinear results have the advantage of providing a easy way to calculate approximate standard errors and significance levels on the estimates of γ and β, and therefore, on price elasticity. Linear regressions are used to report Hausman-Wu tests. Results on the threshold parameter and elasticities are discussed below. Results on elasticities and the shape of the estimated demand functions are compared to the GCD specification found best in the previous section, namely the random effect specification with month and year dummies.[25]

Estimated Equations

SGE(γ) refers to the estimation where γ is a linear combination of the exogenous variables but not β. The estimable Stone-Geary equation with fixed β is

$$Q = (1 - \beta)(\alpha_0 + \alpha_1 C + \alpha_2 SP + \alpha_3 AAP) + \beta \frac{I^*}{P},$$

[25] For both the linear and nonlinear estimations, an error term is added to the regression. The error term is omitted when writing the following estimable equations. The error term is ε_{it} in the OLS regressions and $u_i + \varepsilon_{it}$ in the GLS specifications, where ε_{it} and u_i have the usual classical assumptions. A random utility assumption would cause the ε_{it} to be heteroskedastic (Brown and Walker 1989). However, there is no evidence of this causing a significant problem in the regressions.

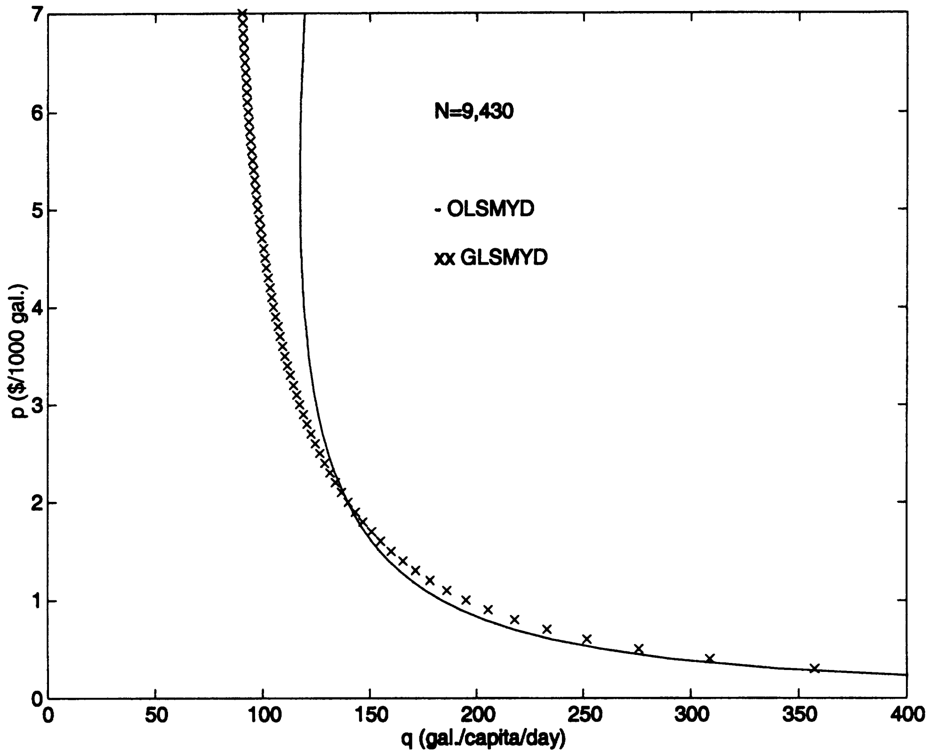

FIGURE 3
Plot of Estimated GCD Function with Month and Year Dummies

where I^* and P are as defined in Section 2 and $\alpha_0 + \alpha_1 C + \alpha_2 SP + \alpha_3 AAP = \gamma$. For the linear estimation, the estimable equation is

$$Q = \alpha_0' + \alpha_1' C + \alpha_2' SP + \alpha_3' AAP + \beta \frac{I^*}{P},$$

where $\alpha_i' = \alpha_i/(1 - \beta)$. Using the estimates of β and α_i', one can calculate, $\gamma = (1 - \beta)(\alpha_0' + \alpha_1' \overline{C} + \alpha_2' \overline{SP} + \alpha_3' \overline{AAP})$, where $\overline{X}$ denotes the mean of variable X.

SGE (γ, β) refers to the estimation where both γ and β are linear combination of the exogenous variables. The Stone-Geary equation with nonconstant γ and β is

$$Q = [1 - (\beta_0 + \beta_1 C + \beta_2 SP + \beta_3 AAP)](\alpha_0 + \alpha_1 C + \alpha_2 SP + \alpha_3 AAP) + (\beta_0 + \beta_1 C + \beta_2 SP + \beta_3 AAP) \frac{I^*}{P},$$

$$\gamma = \alpha_0 + \alpha_1 \overline{C} + \alpha_2 \overline{SP} + \alpha_3 \overline{AAP},$$

and

$$\beta = \beta_0 + \beta_1 \overline{C} + \beta_2 \overline{SP} + \beta_3 \overline{AAP}.$$

For the linear estimation, the estimable equation is

$$Q = \alpha_0' + \alpha_1' C + \alpha_2' SP + \alpha_3' AAP + \beta_0 \frac{I^*}{P} + \beta_1 C \frac{I^*}{P} + \beta_2 SP \frac{I^*}{P} + \beta_3 AAP \frac{I^*}{P},$$

where $\alpha_i' = \alpha_i/(1 - \beta)$.

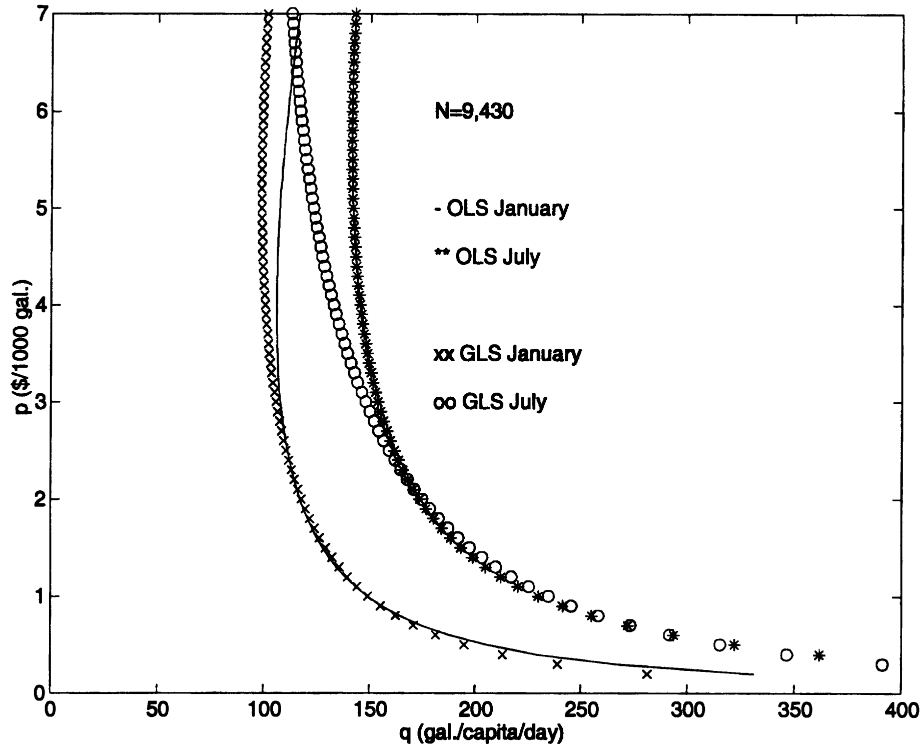

FIGURE 4
PLOT OF ESTIMATED GCD FUNCTION: SEASONALITY

Stone-Geary Results and Comparison to GCD

The algorithm used for the nonlinear GLS estimation is presented in the Appendix. Raw results from all different specifications and estimation procedures are provided in Table 6 (linear estimation results) and Table 7 (nonlinear estimation results). To better assess the robustness of our results, plots of the estimated functions are given for all the different specifications using the nonlinear estimates evaluated at the sample means (Figure 6). The graph shows very little variation between the specifications to the extent that it is difficult to distinguish between them.

Hausman-Wu tests for GLS random-effect regressions are quite poor when month and year dummies are not included. These test results suggest that there is some correlation between the regressors and the effects and cast doubt on consistency of the parameter estimates.[26] Since the Hausman-Wu tests for the GLS regressions with month and year dummies give significantly better results, emphasis is placed on these regression results. The hypothesis of correlation is rejected at the 0.01 level for SGE(γ). Hausman-Wu tests results are not as good when β is variable, and we cannot reject the hypothesis of correlation at the 0.1 level. However, this does not necessarily imply correlation. When β is not fixed, the regression relies more heavily on variables that are combined with time-invariant exogenous variables. The Hausman-Wu test drops the purely time-invariant variables that enter in the estimation of γ, but it does leave all the time-invariant

[26] Because nonlinear and linear results are very similar Hausman-Wu tests are not calculated for nonlinear regressions. Hausman-Wu tests on linear regressions are reported in Table 6.

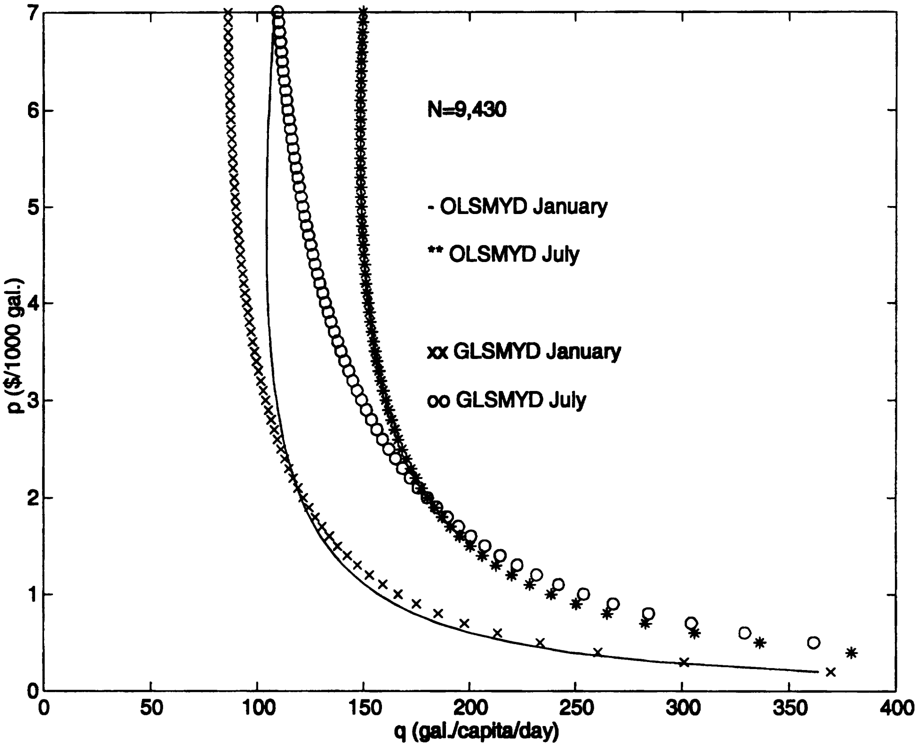

FIGURE 5
PLOT OF ESTIMATED GCD FUNCTION WITH MONTH AND YEAR DUMMIES: SEASONALITY

variables in β since they are all divided by P, which is time variant. Because the fixed effect coefficient on these variables must be zero, the difference between the fixed effect estimator and the random effect estimator is likely to increase. This argument questions the straightforward interpretation of the Hausman-Wu test when time-invariant variables are present and are combined with other variables in a nonadditive way. The addition of dummies might improve the test not so much by taking care of the correlation problem but by reducing the reliance on time-invariant variables. Because the test remains informative when it comes out positive, it is still preferable to rely on the regressions with the better Hausman-Wu test results.

Table 8 reports the estimated marginal budget shares (β), conditional water thresholds (γ), and price elasticities (ε) for the SGE(γ) and SGE(γ, β) regressions with dummies. The parameters and associated approximate standard errors are evaluated at the sample means, the January means, and the July means.[27] All parameters are highly significant.

Conditional water threshold. Results on the threshold parameter in gallons per capita per day (gcd) range from 114 to 128 on average. The January threshold is estimated between 86 and 118 gcd. The July threshold jumps to 155–176 gcd. Seasonal variations in γ are reduced when β is variable because the preference parameter picks up some of the variation.

One must be very careful when interpret-

[27] The threshold parameter involves an intercept which includes month and year dummies. For results evaluated at sample averages, the averages of coefficient estimates on month dummies and year dummies are used. For the January and July results, γ is calculated using the estimated coefficient on the appropriate month dummy.

TABLE 6
STONE GEARY: RESULTS OF LINEAR REGRESSIONS

$$Q = \alpha_0' + \alpha_1' C + \alpha_2' SP + \alpha_3' AAP + \beta \frac{I^*}{P}$$

$$\gamma = (\alpha_0' + \alpha_1' \overline{C} + \alpha_2' \overline{SP} + \alpha_3' \overline{AAP})(1 - \beta)$$

$$\beta = \beta \text{ or } \beta = \beta_0 + \beta_1 \overline{C} + \beta_2 \overline{SP} + \beta_3 \overline{AAP}$$

N = 9,430	OLS	GLS	OLSMYD[a]	GLSMYD[a]	OLS	GLS	OLSMYD[a]	GLSMYD[a]
α_0'[b]	39.72**	28.72**	59.66**	43.70**	109.25**	32.09**	117.02**	33.60*
	(3.36)	(11.88)	(4.78)	(12.24)	(7.39)	(16.08)	(8.05)	(15.98)
α_1'	0.075**	0.076**	0.070**	0.071**	0.034**	0.036**	0.035**	0.037**
	(0.0013)	(0.0010)	(0.0028)	(0.024)	(0.0029)	(0.0022)	(0.0038)	(0.0031)
α_2'	−0.59**	−0.55	−0.54**	−0.46	−1.82**	−1.57**	−1.84**	−1.54**
	(0.097)	(0.49)	(0.095)	(0.50)	(0.22)	(0.62)	(0.21)	(0.61)
α_3'	−1.46**	−1.36**	−1.43**	−1.29**	−1.01**	1.41**	−1.02**	1.44**
	(0.058)	(0.30)	(0.056)	(0.30)	(0.13)	(0.40)	(0.13)	(0.40)
β	0.0037**	0.0042**	0.0038**	0.0046**				
	(9E-5)	(0.0001)	(9E-5)	(0.0001)				
β_0					−0.0023**	0.0033**	−0.0013**	0.0049**
					(0.0005)	(0.0007)	(0.0005)	(0.0006)
β_1					3.5E-6**	3.4E-6**	3.0E-6**	2.7E-6**
					(2E-7)	(2E-7)	(2E-7)	(2E-7)
β_2					0.0001**	9.1E-5**	0.0001**	9.7E-5**
					(2E-5)	(2E-5)	(2E-5)	(2E-5)
β_3					−4E-5**	−0.0002**	-3E-5**	−0.0002**
					(9E-6)	(2E-5)	(9E-6)	(2E-5)
γ[c]	124	118	123	114	126	134	125	129
β	0.0037	0.0042	0.0038	0.0046	0.0035	0.0026	0.0036	0.0032
R^2[d]	0.41	0.46	0.45	0.53	0.43	0.50	0.46	0.56
F-Test	1643	—	402	—	1023	—	371	—
Hausman-Wu Test								
m	—	2.95	—	6.19	—	15.60	—	14.16
DF	—	2	—	17	—	5	—	20
Prob > m	—	0.23	—	0.99	—	0.008	—	0.82

[a] OLSMYD and GLSMYD correspond to OLS and GLS regressions with month and year dummies.
[b] The Month/Year dummy regression intercept corresponds to December 1985.
[c] Regression with dummies: all dummy coefficients are used to calculate γ.
[d] Adjusted R^2 are reported for OLS regressions. For GLS, a generalized version of the R-squared is used.
** Significant at the 1% level or better; * significant at the 5% level or better.

TABLE 7

STONE GEARY: RESULTS OF NONLINEAR REGRESSIONS

$$Q = (1 - \beta)(\alpha_0 + \alpha_1 C + \alpha_2 SP + \alpha_3 AAP) + \beta \frac{I^*}{P}$$

$$\gamma = \alpha_0 + \alpha_1 \overline{C} + \alpha_2 \overline{SP} + \alpha_3 \overline{AAP}$$

$$\beta = \beta \text{ or } \beta = \beta_0 + \beta_1 \overline{C} + \beta_2 \overline{SP} + \beta_3 \overline{AAP}$$

N = 9,430	OLS	GLS	OLSMYD[a]	GLSMYD[a]	OLS	GLS	OLSMYD[a]	GLSMYD[a]
α_0[b]	39.87**	28.90**	59.89**	43.80**	109.08**	35.00**	117.44**	34.68*
	(3.37)	(11.53)	(4.79)	(12.95)	(7.36)	(14.08)	(8.07)	(15.07)
α_1	0.076**	0.077**	0.070**	0.071**	0.034**	0.036**	0.035**	0.037**
	(0.0013)	(0.0010)	(0.0028)	(0.024)	(0.0029)	(0.0023)	(0.0038)	(0.0031)
α_2	−0.59**	−0.55	−0.54**	−0.46	−1.82**	−1.57**	−1.85**	−1.55**
	(0.098)	(0.48)	(0.095)	(0.53)	(0.22)	(0.52)	(0.21)	(0.56)
α_3	−1.46**	−1.36**	−1.44**	−1.29**	−1.01**	1.32**	−1.02**	1.40**
	(0.058)	(0.29)	(0.057)	(0.32)	(0.13)	(0.35)	(0.13)	(0.37)
β	0.0037**	0.0042**	0.0038**	0.0046**				
	(9E-5)	(0.0001)	(9E-5)	(0.0001)				
β_0					−0.0023**	0.0033**	−0.0013**	0.0049**
					(0.0005)	(0.0007)	(0.0005)	(0.0006)
β_1					3.5E-6**	3.4E-6**	3.0E-6**	2.7E-6**
					(2E-7)	(2E-7)	(2E-7)	(1E-7)
β_2					0.0001**	9.1E-5**	0.0001**	9.7E-5**
					(2E-5)	(2E-5)	(2E-5)	(2E-5)
β_3					−3E-5**	−0.0002**	−3E-5**	−0.0002**
					(9E-6)	(2E-5)	(9E-6)	(2E-5)
γ[c]	124**	118**	123**	114**	126**	134**	125**	128**
	(3.45)	(11.00)	(5.16)	(12.57)	(7.09)	(13.54)	(8.09)	(14.61)
β	0.0037**	0.0042	0.0038	0.0046	0.0035	0.0026	0.0036	0.0032
	(9E-5)	(0.0001)	(9E-5)	(0.0001)	(0.0005)	(0.0005)	(0.0005)	(0.0005)

[a] OLSMYD and GLSMYD correspond to OLS and GLS regressions with month and year dummies.
[b] The Month/Year dummy regression intercept corresponds to December 1985.
[c] Regression with dummies: all dummy coefficients are used to calculate γ and its standard error.
** Significant at the 1% level or better; * significant at the 5% level or better.

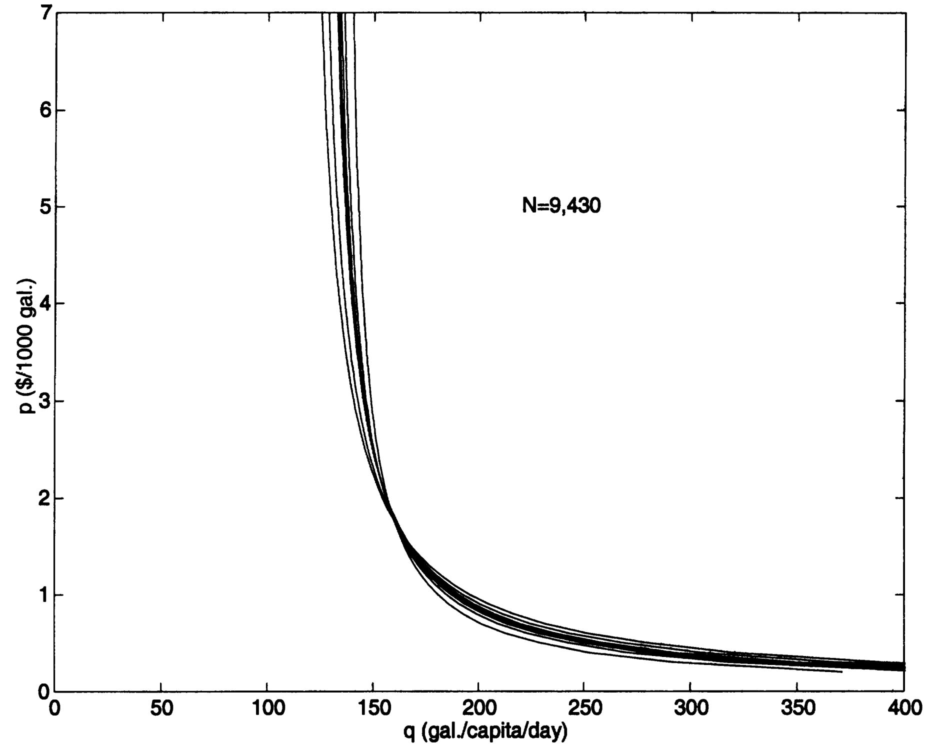

FIGURE 6
PLOT OF NONLINEAR ESTIMATIONS OF STONE-GEARY DEMAND EVALUATED AT SAMPLE MEANS

ing γ for several reasons. First of all, water production is used instead of water consumption. This implies that all losses to the system are included in the threshold. Water utilities (or city planners) need to interpret this parameter as a per capita production threshold, which can be lowered proportionately to a reduction in losses. To obtain the consumer's water use threshold, the γ estimate must be corrected by the average losses of the community.

The second caveat is all other goods are assumed to be gross complements to water consumption. In particular, the tradeoff between a more expensive water-efficient durable good versus one that is less expensive but uses more water is not considered. Threshold parameters are likely to be reduced if technology changes allow water to be economized. The availability of water-efficient durable goods, such as water-efficient toilets and washing machines, will have an impact on water demand and the water use threshold. However, this will only be observed if our time period allows for large price reduction in these goods. Also, residential customers are likely to reassess their decision to maintain lawns if the price of water increases beyond the levels of our sample, a fact that cannot be captured in our estimates.

Finally, it is important to note that the estimated threshold is conditional on the price structure in place. A price structure that incorporates fixed charges does not allow marginal prices to be clearly defined. Consequently, individuals use average price in their decision to consume water, as is the case in the Texas sample we use (see Section 2). A large threshold indicates that conservation practices which are not price-based (or only affect prices of substitutes) may potentially have more impact on the reduction of water

TABLE 8
NONLINEAR ESTIMATION OF STONE-GEARY CONDITIONAL WATER THRESHOLDS (γ), MARGINAL BUDGET SHARES (β), AND PRICE ELASTICITIES (ε)

		SGE(γ)		SGE(β, γ)	
		OLSMYD[a]	GLSMYD[a]	OLSMYD[a]	GLSMYD[a]
Yearly average	γ	123**	114**	125**	128**
		(5.16)	(12.6)	(8.10)	(14.61)
	β	0.0038**	0.0046**	0.0036**	0.0032**
		(9E-5)	(0.0001)	(0.0005)	(0.0005)
	ε	−0.23**	−0.28**	−0.22**	−0.19**
		(0.0057)	(0.0082)	(0.029)	(0.028)
January	γ	95**	86**	115**	118**
		(5.08)	(12.5)	(7.77)	(14.52)
	β	0.0038**	0.0046**	0.0021**	0.0017**
		(9E-5)	(0.0001)	(0.0005)	(0.0005)
	ε	−0.27	−0.33	−0.15	−0.12
		(0.0057)	(0.0082)	(0.029)	(0.029)
July	γ	176**	166**	155**	162**
		(6.76)	(13.1)	(9.54)	(15.17)
	β	0.0038**	0.0046**	0.0053**	0.0047**
		(9E-5)	(0.0001)	(0.0005)	(0.0005)
	ε	−0.19**	−0.24**	−0.27**	−0.24**
		(0.0057)	(0.0082)	(0.034)	(0.029)

[a] OLSMYD and GLSMYD correspond to OLS and GLS regressions with month and year dummies.
** Significant at the 1 percent level or better.

use per capita than price increases on water. This does not mean that a fundamental change in the price structure, making marginal prices more transparent, would not be a better policy tool.

These considerations make our results problematic for long-run predictions when increased water scarcity would bring about modifications of the pricing system and change the value of γ. In addition, the water threshold is only a function of our climate variable, average rainfall, and percent of population of Spanish origin. Only *SP* is likely to increase and have some impact on the level of γ.[28] Ideally, if a longer time series with data on the price and availability of water conserving goods were available, one could make γ a function of these new variables as well, allowing γ to vary over time.

Nonetheless, even when production data is used, results on this conditional threshold parameter are still informative in the short run. They show that, given the range and structure of water prices, given the availability and prices of other goods that could partially "substitute" for water, and with losses of 20–25%, more than half of water use may not be responsive to price.

Elasticities. The elasticities obtained from the Stone-Geary specification and evaluated at the appropriate means are lower than the GCD results. The range of price elasticities using Stone-Geary is 0.19 to 0.28, compared to 0.35 to 0.47 using GCD. The results also indicate that the Stone-Geary specification allows significant seasonal variation in elasticities. When β is fixed, summer elasticities are lower than winter elasticities. This is not surprising because the Stone-Geary elasticity is inversely proportional to the expenditure; with β fixed, the increase in Q, due mostly to factors other than a price decrease, domi-

[28] SP impacts the threshold negatively and the elasticity positively, indicating that the Hispanic population is more flexible in their use of water. γ is significantly reduced in all the estimations when the maximum value of *SP* (35.3 percent) is used. When elasticities are allowed to vary with *SP*, we obtain values of γ ranging from 70 to 88 gcd (compared to 124–134 gcd at the mean value of *SP*).

TABLE 9
STONE-GEARY PRICE ELASTICITIES AT HIGHEST SAMPLE VALUES OF PRICE, INCOME, AND QUANTITY

$$\varepsilon = -\beta(\cdot)\frac{I^*}{PQ}$$

	SGE(γ)		SGE(β, γ)	
Variable at Maximum Value[a]	OLSMYD[b]	GLSMYD[b]	OLSMYD[b]	GLSMYD[b]
Price (P)	−0.065	−0.079	−0.062	−0.055
Price and Quantity (Q)	−0.015	−0.018	−0.014	−0.013
Income (I*)	−0.51	−0.63	−0.49	−0.43
Income and Quantity	−0.012	−0.14	−0.11	−0.10
Price, Income, and Quantity	−0.033	−0.041	−0.032	−0.028

[a] All other variables are at their mean value.
[b] OLSMYD and GLSMYD correspond to OLS and GLS regressions with month and year dummies.

nates. If one wants to measure seasonal elasticities, the marginal budget share parameter needs to vary with the seasonal variables (*C*, in our estimation). When β is allowed to vary, the result of higher price elasticities for summer demand is re-established. Both the OLS and GLS estimation of SGE(γ, β) give a seasonal variation of elasticity estimates larger than the GCD regression. Stone-Geary results give an increase in elasticity between winter and summer of 0.12 (from 0.15 to 0.27 for OLS and from 0.12 to 0.24 for GLS), whereas the GCD results showed an increase of 0.06.

The main objective is to determine whether the simple Stone-Geary specification could provide ranges of elasticities comparable to the more flexible GCD form yet allow for out-of-sample use in simulations when variables increase over time. Table 9 reports price elasticities at the sample maxima of price, income, and quantity. It shows that the Stone-Geary specification yields a large variation in price elasticity when the values of most variables increase. All elasticities calculated at maxima are lower than elasticities calculated at the sample averages. The only exception is when the elasticity is calculated at maximum income only. This seems reasonable since the price relative to income has decreased. Unlike the GCD estimation results, price elasticities remain strictly negative in all cases.

Figure 7 shows the plot of the OLS and GLS estimated Stone-Geary function with month and year dummies and nonconstant marginal budget shares and compares it to the previous GCD results. For the comparison, the one-way random effect estimation of GCD with month and year dummies is used since it was shown to behave best at higher prices. The Stone-Geary estimated functions have a steeper slope and retain higher quantity levels than GCD at higher prices. This is a direct result of the Stone-Geary formulation, which constrains the function to be asymptotic to a minimum quantity determined by the threshold parameter. The function is still well behaved in that it is downward sloping everywhere. This result improves upon the OLS estimated GCD function (Figure 3).

V. CONCLUSION

The motivation for using Stone-Geary was simple: we wanted a function with few, easily interpretable, parameters that could be used in dynamic management problems that require more than just price elasticities on the demand side. Alternative functional forms that retain a simple parameter structure are the linear and log-linear forms. Linear demand forces the elasticity to increase as price increases, and the log-linear form maintains constant price elasticity. Constant price elasticity has been commonly used in water management models that include the computation

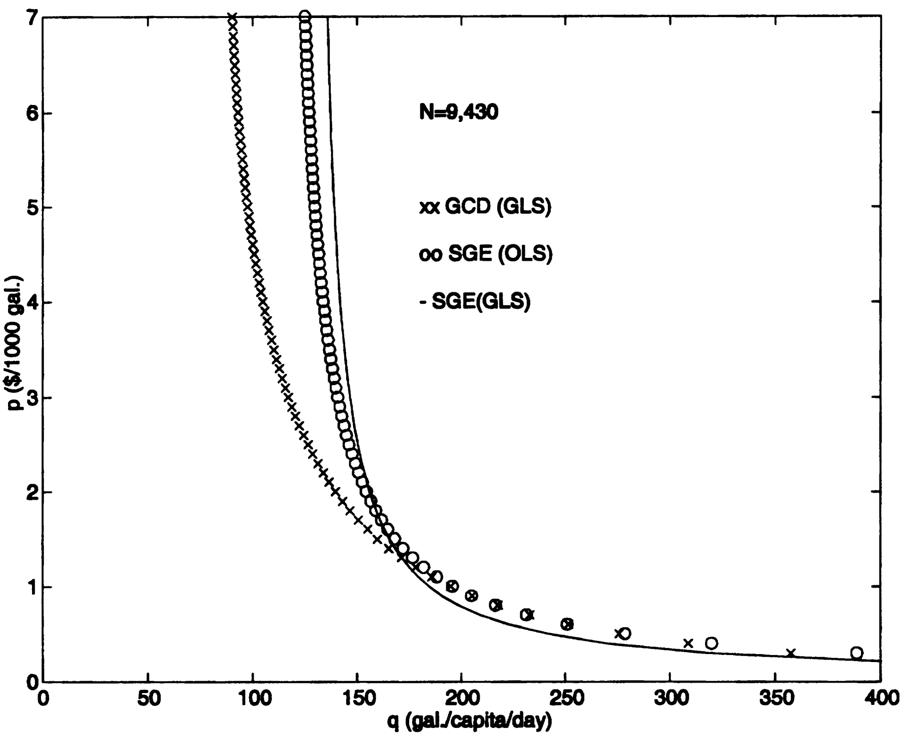

FIGURE 7
COMPARISON OF ESTIMATED GCD AND STONE-GEARY DEMANDS

of consumer surplus. However, research using more flexible functional forms provides strong evidence that water demand price elasticities vary seasonally and over time.

It is surprising that the Stone-Geary function has not been used in water demand estimation. The behavior it implies, that individuals will use a minimum amount of a good regardless of price fluctuations, and then decide on the rest according to a preference parameter, the price, and their income, seems well suited for water. Furthermore, the fact that water is a normal good and has inelastic demand makes it a good candidate for a Stone-Geary specification. The form is parsimonious enough to parameterize demand in structural dynamic models of water management and our analysis shows that the specification is also able to provide estimates of elasticities comparable to other more complicated forms.

A good benchmark was needed to evaluate the performance of the Stone-Geary specification. The General Cobb-Douglas (GCD) estimation of municipal water demand in Texas was refined using econometric techniques that allow the panel structure of our data to be fully exploited. The new random effect estimation (GLS) improves upon the OLS procedure. Price elasticities are similar but slightly higher. Elasticity estimates of 0.39 to 0.47 are obtained using GLS, compared to 0.37 using OLS. Summer elasticities were 0.06 points higher than winter elasticities for OLS and GLS results. GCD gives price elasticities that decrease both in price and income. When calculated at the maxima of our price and income data, elasticities were significantly lowered. Of all the estimations of GCD, only GLS with month and year dummies retained a negative price-quantity relationship at high prices.

The Stone-Geary results give elasticities ranging from 0.19 to 0.28. Although lower, and likely not providing as good a fit within the sample as GCD results, these estimates are not out of the range of price elasticity estimates in the literature. Summer elasticities were 0.12 points higher than winter elasticities, indicating that Stone-Geary can successfully generate large seasonal variation. It is important to note that the marginal budget share parameter β in Stone-Geary must be allowed to vary with the monthly climate variable to get this result. Stone-Geary gives estimates of price elasticities that increase with income but decrease with price and quantity. At the maximum price, income, and quantity, elasticities in the 0.03 to 0.04 range are obtained. These results are similar to the ones obtained with GCD. Such results cannot be obtained when using linear or log-linear forms. Moreover, the Stone-Geary estimation results on these elasticities are more robust to the type of estimation than the GCD results, and the negative price quantity relationship is preserved. This is encouraging if one wishes to use the estimation results over a larger range of prices.

Finally, the Stone-Geary results suggest that approximately three quarters of the total water usage is not responsive to price changes. This threshold needs to be lowered to reflect the 15–20% system losses in Texas communities that creates a gap between water production and water consumption. However, this still leaves more than half of water demand unresponsive to price increases. The reader is cautioned about the conditional nature of this parameter. Ideally one would want to include some long-term determinants of the threshold water use. Indeed, increased water prices are expected to eventually affect the decision to buy water-intensive durable goods, which in turn will reduce the water use threshold. Also, increased water scarcity is likely to bring about price reforms to give the right price signal to consumers. This is why a longer-term analysis would be necessary to look at the behavior of this threshold over time. The estimated water threshold, nonetheless, gives information conditional on the type of data used and the length of the time series. For time periods limited to five years and given a price range of about 0.2 to 6.2 dollars per thousand gallons provided by our data, water consumption cannot on average be reduced by more than 40 percent using a price instrument of the current type. In practice, the Stone-Geary threshold parameter could be estimated as a cross-section-specific parameter using dummies for the different areas. It could then be used to target different demand management policies to different areas with different characteristics, as suggested in Renwick and Archibald (1998).

The exclusion of all other prices and, in particular, prices of water-consuming durable goods, results in an important reservation about using the Stone-Geary results in long-run management problems. More data is needed to include these variables in the analysis. They could be included without changing the structure of the Stone-Geary system by simply adding more exogenous variables as determinants of the threshold level and possibly the preference parameter.

Further work could compare the results of the Stone-Geary to a nonparametric or semiparametric demand estimation such as in Hausman and Newey (1995). Such types of estimations have not yet been used in the water demand literature but could reduce the possibility of mispecification, provide an even less restrictive benchmark than the GCD, and allow closer inspection of the size and variation in elasticities.

APPENDIX

In order to estimate the nonlinear Stone-Geary form with nonlinear GLS, the exogenous variables need to be transformed.[29] The variance decompositon described here is adapted from Greene (1997, 625–35). The error variance is divided into two components: σ_ε^2, the variance specific to the regular error term, and σ_u^2, the variance specific to the cross-sectional effect. The panel is unbalanced: each cross section i has T_i observations and $\sum_i T_i = N$. There are K regressors ex-

[29] Available statistical packages handle linear GLS for estimating random effect specifications but do not handle nonlinear GLS.

cluding the intercept. The variance is decomposed using

$$m_{ee} = \frac{e'e}{\sum_i T_i}, \quad \text{for } i = 1 \text{ to } N,$$

and

$$m_{**} = \frac{e_{**}'e_{**}}{N - K}; \; e_{**i} = Q_i - \hat{\beta}'\overline{X}_i,$$

where m_{ee} is the mean squared error from the linear OLS regression, $\hat{\beta}$ is a vector of OLS parameter estimates, and $\overline{X}_i$ is a vector of the group means of exogenous variables. OLS estimates rather than within estimates from a Least Square Dummy Variable estimation are used for m_{ee} because of the presence of time-invariant variables.

The probability limits are

$$m_{ee} = \sigma_\varepsilon^2 + \sigma_u^2,$$

and

$$\sigma_u^2 = m_{**} - \sigma_\varepsilon^2 \times \hat{Q}_n, \text{ where } \hat{Q}_n = \frac{1}{N} \times \sum_{i=1}^{N} \frac{1}{T_i}.$$

One can solve for the estimated σ_ε^2 and σ_u^2 using

$$\hat{\sigma}_\varepsilon^2 = \frac{1}{1 - \hat{Q}_n} \times (m_{ee} - m_{**}),$$

and

$$\hat{\sigma}_u^2 = \frac{1}{1 - \hat{Q}_n} \times m_{**} - \frac{\hat{Q}_n}{1 - \hat{Q}_n} \times m_{ee}.$$

Given the above, all the variables in the model, including intercept and dummies, are transformed using

$$XT_i = X_i - \beta_i\overline{X},$$

where

$$\beta_i = 1 - \frac{\hat{\sigma}_\varepsilon}{\sqrt{T_i \times \sigma_u^2 + \sigma_\varepsilon^2}}$$

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