Urban Water Demand with Periodic Error Correction

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ABSTRACT. *Monthly demand for publicly supplied water to U.S. residences and businesses is estimated from a 10-year panel of 167 cities. A periodic error correction model integrates monthly, annual, and long-run time scales. Statistical consistency is validated by unit root tests adapted to the monthly frequency. Water and wastewater price elasticity of demand is estimated by sector, calendar month, and time horizon.* (JEL Q25)

I. INTRODUCTION

Local media have applied the phrase "water crisis" so often in describing the condition of some city that it has become cliché (Russ 2009; Cregan 2009; Evans 2009; Bond 2009). Despite the sensationalizing rhetoric, excess demand for publicly supplied urban water persists in many places and is arising in others. The resulting management issues underscore the troubled and oft-politicized nature of water planning. Urban water supply is naturally monopolistic due to its high capital requirements. Therefore, an assumption of the invisible hand theorem is unmet, and socially efficient allocation is not automatic. Most decision making is conducted by public water authorities, which do not have a strong track record of efficient adaptation (Grafton and Ward 2008; Lach, Ingram, and Rayner 2005; Hewitt 2000). Yet, experimentation, along with progress, is slowly occurring. Among the policy mechanisms being tried are alternative rate structures and higher rates. Perhaps rates that include water's opportunity costs will eventually be explored, as recommended by economists. If these approaches are to be successful, planners and regulators require consumer demand information to simultaneously establish rates and anticipate the level of water deliveries.

Traditionally, water utility systems have focused narrowly on adjusting water supply to meet level-price water demand (Dziegielewski 1999). Still, efficient supply enhancement requires knowledge of future aggregate demand, and carelessness over either revenue-seeking or efficiency-seeking changes to water and wastewater prices may lead to error in demand projections. Even under perfect information, the costs of supply enhancement continue to rise as the most accessible sources of water are tapped to capacity or depleted, necessitating rate changes that subsequently affect quantity demanded. These increasing costs further advance the value of traditionally underemployed demand management strategies, including efficient pricing.

Pricing, or rate-setting, is complicated by the balancing of multiple objectives. Unlike the textbook monopolist, the typical water utility system does not pursue the objective of profit maximization. In addition to economic efficiency, water utilities seek goals such as revenue sufficiency and fairness (Griffin 2006, 251), and they rank these more highly than efficiency. While public authorities commonly infer that their rate-setting efforts pursue multiple goals simultaneously, the Tinbergen principle warns that each goal requires a separate instrument (Young and McColl 2005). Moreover, achieving multiple goals involves the solution of a complex set of system objectives, which requires detailed knowledge of demand behavior. For example, when efficiency and revenue sufficiency are conjunctively sought, an efficient marginal rate may be derived from supply information alone, but the calculation of other rate components requires an estimate of future billed volumes (Griffin 2001; Edwards 2006). For demand management policies to improve, analytical

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techniques for estimating demand must evolve to support them.

Econometric estimates of residential demand for water abound (Dalhuisen et al. 2003), but existing demand estimates lack the detail to support many rate design applications. A time-path of adjustment to consumer equilibrium is seldom explicitly estimated in prior econometric work; seasonal patterns of demand tend to be underrepresented; and the important commercial and industrial sectors of demand are often set aside or assumed to be proportionally linked to residential use. Water management policies that fail to consider the time-path of adjustment risk outpacing consumers' ability to develop new habits or optimize their stocks of water-associated capital, such as landscaping, plumbing fixtures, and appliances. Policies without seasonal considerations risk incurring excess demand during cyclical demand peaks. Policies that fail to differentiate between household demand and commercial demand risk decreased efficiency relative to sector-tailored policies. The empirical results of this research indicate that slow adjustment, seasonality, and sectoral sensitivity are all characteristic of the sample. Simpler models that are unable to accommodate these characteristics are therefore misspecified to some extent.

The present research incorporates a demand function into a dynamic consumption model using the error correction (EC) technique, thereby merging both short- and long-run demand drivers and possibly improving forecast accuracy (Engle, Granger, and Hallman 1989). Seasonal demand behavior is modeled by identifying and accounting for periodic integration in the associated series (Boswijk and Franses 1995a). Commercial and industrial contributions to aggregate demand are modeled by including sectoral intensity factors in the estimating equation. Unlike dynamic water demand studies considering only a single locale, the present research includes original data from a panel of 167 geographically dispersed cities within the United States, observed monthly from January 1995 through December 2005. The breadth of the sample allows a model to be fitted over a wider range of conditions than previously possible. The multitude of community cross sections allow a uniquely statistical look at the problem of nonstationarity in quantity demanded.

II. DEVELOPING THE THEORETICAL MODEL

Structural and Dynamic Demand

The object of most econometric water demand research is a demand function for water, which is a mapping of consumption quantities over the range of possible prices and other variables. For convenience, the relationship between price and quantity demanded is often characterized by a price elasticity scalar. Such demand functions rely on mathematical structure implied by microeconomic theory, so they are called structural models as opposed to statistical models, which are theoretically unrestricted. The early structural models were well suited to examining the belief held by noneconomists that rates do not affect use (Howe and Linaweaver 1967). The persistent testing and rejection of this hypothesis by economists is a contribution of our literature (Espey, Espey, and Shaw 1997), albeit only haltingly applied to policy. The same models are pivotal to the determination of consumer valuation that is necessary for thorough policy and project appraisals, because it is the demand function that identifies the marginal benefit of price and quantity changes.

It is unlikely, though, that water consumers instantaneously adapt to demand perturbations such as price and weather shocks (Griffin and Mjelde 2000; Carver and Boland 1980). During periods of adjustment to new conditions, consumers are constrained by their learned behaviors (habits) and by their inventories of water-associated durable goods, for example, appliances and landscaping. While adjusting, customers can experience nonzero excess demand in the sense that the quantities they demand would not be optimal in a longer view during which habits and durable possessions can be refined. A demand correspondence is not a demand function if multiple consumption quantities can be mapped to the same argument values, so the structure supporting the typical static demand model can lead to conflicting results in a dynamic context. Conversely, the dynamic demand correspondence offers little insight into consumer welfare or willingness to pay.

The inclusion or omission of an adjustment process separates the time-independent water demand models from the dynamic models. The former class contributes insights primarily at longer time horizons, whereas the latter may more accurately model short-run behavior. A structural model can utilize slow-moving variables that either do not vary or are not measured monthly, just as a dynamic model can incorporate seasonal changes that are insignificant or average out in the long run (Engle, Granger, and Hallman 1989). In contrast to the literally hundreds of structural water demand studies stand only a handful of dynamic demand studies (Bell and Griffin 2008a; Fullerton and Elias 2004; Nauges and Thomas 2003), although some essentially structural studies have employed the flow-adjustment hypothesis to deduce an adjustment rate (Lyman 1992; Carver and Boland 1980).

Regardless of the comparative advantages of the two approaches, the possibility that forecasts from a structural model may contradict those from a dynamic model creates a tension between them (Engle, Granger, and Hallman 1989). A dynamic model may be the preferred tool for balancing the objectives of controlling water use and covering production costs year to year, but only a structural model can be interpreted as a demand function. Fortunately, advancements in statistical treatment of time series now allow the simultaneous enjoyment of both sets of advantages. The integrated model proposed below will be used in the next section to estimate the demand for water in U.S. cities and to predict 12 monthly consumption quantities beyond the estimation sample. The model will also facilitate testing for monthly seasonality and instantaneous adjustment.

EC and Periodic Cointegration

The empirical model developed here is an extension of a model in first differences previously used to project annual changes in quantity demanded (Bell and Griffin 2008a). A shortcoming of the earlier application is its omission of a force summoning consumer equilibrium. Even though excess demand is not expected to be identically zero in any particular time period, its tendency toward zero is as omnipresent as individual self-interest, in the sense that individuals are not content with states of nonzero excess demand. Inclusion of a lagged expression of excess demand turns the difference model into an EC model (Engel, Granger, and Hallman 1989).

Excess demand reflects an imbalance that can be improved upon, an error to be corrected. A condition of excess demand implies that a higher level of aggregate utility could have been achieved at the same expenditure level with a different stock of capital or information; thus excess demand is not stable. Although the mechanisms and information requirements for rational consumers to resolve their ideal consumption bundles are not explicitly identifiable, the assumption that a locally stable structural demand exists implies that all solution paths starting from small levels of excess demand converge to points on the structural demand curve (McKenzie 2002, 56). Because utility systems set rates in advance of realized demand, convergence implies adjustments in quantity demanded. In a linear EC model, the speed of convergence is represented by the coefficient of the EC variable. If the EC coefficient is positive, the system is explosive. If the coefficient is equal to -1, full correction takes place in one time period. If the coefficient is in the interval $(0, -1)$, correction takes longer than a single period.

It is necessary for the consistency of the model that the EC term is stationary—that its conditional means are distributed about its sample mean—since the dependent variable is presumed to be stationary. The lagged EC term, which is the lagged residual of a structural demand function, may not in fact be stationary if the dependent variable of the structural model is not stationary. If this is the case, the residual will be consistent only if the structural model is cointegrated (Juselius 2006, 86). If the left- and right-hand sides of a regression model are cointegrated, their respective lacks of stationarity have canceled each other, so they are "superconsistent" with respect to each other, and their residual will qualify as a valid EC regressor. Stationarity is relative, however—"a convenient statistical approximation" (Juselius 2006, 20)—so it is important not to assign too much weight to the various tests of cointegration, the unit root tests. Superconsistency is not necessary for consistency of EC parameter estimates, and mere consistency can be tested ex post.

Water consumption patterns may exhibit seasonality, an attribute of many macroeconomic series for which new modeling techniques have been proposed within the cointegration literature. The technique of seasonal cointegration dictates the inclusion of multiple EC terms corresponding to multiple seasonal lags (Kunst 1993). Seasonal cointegration is mathematically appealing when the frequency of the data is quarterly, but much less so when the frequency is monthly. As the mathematical and computational requirements increase, economic interpretation of the results becomes more elusive. An alternative is periodic cointegration (Boswijk and Franses 1995a). Periodically cointegrated series are bound by a vector of coefficients that vary from season to season. In the case of monthly data, periodic cointegration is represented by a vector of 12 separate variable combinations, one for each calendar month. It has been established that a pair of series cannot compose a valid cointegrating relation in one season without being cointegrated in every season (Castro and Osborn 2008). In addition to an annual cycle, water demand may exhibit cycles longer than one year, but we will leave the possibility to further research. Some communities may experience seasonality that is only approximately annual in frequency, and this characteristic would be better modeled by seasonal integration than by periodic integration.

Use of the EC model has a single, recent precedent in the water demand literature. Martinez-Espineira (2007) illustrates well the difficulties of seasonal cointegration. Nine years of monthly data on a single community are further collapsed into quarterly observations to circumvent the daunting procedure of simultaneously testing stationarity in 12 monthly frequencies. Results of the battery of diagnostic tests are generally consistent but not definitive due to both the small sample size and the low power of existing unit root tests. Martinez-Espineira's paper is nevertheless a milestone in terms of introducing EC to water demand modeling that is extended here in data scope, variable sophistication, and use of the periodic EC alternative.

The object of the present research is community demand for publicly supplied water. The water demanded in the sample is delivered by a sole or majority supplier. Community demand is not synonymous with residential demand inasmuch as businesses as well as residents demand water within the community. Even though it is recognized that water consumption is not entirely residential, an expedient practice when using aggregate data is to simplify analysis by representing the dependent variable as the ratio of quantity demanded to population (for a recent example, see Ruijs, Zimmermann, and van den Berg 2008). Such a practice raises questions about the role of commercial and industrial activity in aggregate demand. The assumption that the extent of commercial and industrial water demands is proportional to population is stronger and less appealing than the assumption that the extent of residential demand is proportional to population, especially with respect to a diverse cross section of cities.

Nevertheless, a demand-per-capita dependent variable facilitates the planning convention of multiplying per capita demand by projected population. More generally, it separates intensive from extensive community demand growth, allowing a population-free intensive demand comparable to the results of a household-level study. Potential and practiced applications of community water demand are many and varied, so a flexible representation has the advantage of interoperability. In this spirit, the community demand model estimated in this research includes sectoral intensity factors as independent variables. By considering the extent of commercial and industrial activity (in dollars) per capita, the model incorporates more sectoral information without sacrificing the advantages of an intensive dependent variable.

Price Specification

Because of the complexity of typical water rates and the absence of a true market for processed water, the rates of exchange for water cannot be called market prices. For a given utility system and client there is, however, a cost of the marginal unit of water, dw, that influences residual income, m. If that marginal cost is designated p then it is equal to the ratio of the change in income, dm, to dw:

$$p = \frac{dm}{dw}. \quad [1]$$

If p were known, it would enter an individual demand function, ω, with income and other prices, $\mathbf{P}$:

$$w = \omega(p, \mathbf{P}, m), \quad [2]$$

under the usual assumption of utility-maximizing water consumers operating in an environment of costless transactions. This is the perfect information rationale for using marginal price as an argument of an empirical demand function.

On the other hand, marginal price is generally unknown to the consumer (Foster and Beattie 1981a). By one estimate, fewer than 10% of utility customers are aware of the marginal price of service they face (Carter and Milon 2005). Most water customers receive total consumption and total expenditure information in their periodic bill, but marginal price information is difficult (costly) for consumers to access. Consumers have been found to respond less to marginal prices that are not included in the bill (Gaudin 2006). Modern water rate schedules can be complex, and they may be available only online or not at all, as opposed to being transparently identified within bills. It is plausible, then, that at least some consumers may attempt to decide consumption based on average price, which is essentially marginal price measured with error due either to fixed charges, a variable marginal rate (as with block rates), or both. Proponents of the average price specification are willing to accept a more complex model of consumer behavior to gain explanatory power.

Choosing a price metric is not a casual decision, because marginal price and average price are not generally simultaneously consistent within the boundaries of ordinary least squares. For example, if ω is a utility-maximizing demand function and the linear specification

$$w = \alpha + \beta p + \gamma m + \delta \mathbf{P} \quad [3]$$

is a consistent estimator of ω, then $w = \omega'(ap, \mathbf{P}, m)$ is also utility-maximizing as long as

$$w = \lambda + \phi ap + \varphi m + \theta \mathbf{P} \quad [4]$$

is consistent. Even in the case that average price, ap, is computed from a relatively simple rate schedule with a fixed charge, k, such that

$$ap = \frac{pw + k}{w}, \quad [5]$$

[3] and [4] cannot coexist, since [4] implies

$$w = \lambda + \phi p + \phi\left(\frac{k}{w}\right) + \varphi m + \theta \mathbf{P}. \quad [6]$$

With k and w both variable, either $\phi = 0$, which implies the spurious result that $\beta = 0$, or $\phi \neq 0$, which implies that [3] is inconsistent (as well as heteroskedastic). Admittedly, a maximum-likelihood pair of quadratic conjugate solutions to [6] could be found; but their error structure would be indeterminate, and estimation would be arduous. Reconciling the two price metrics becomes even more complicated as less linear functional forms and more involved pricing policies are considered. Because of this inconsistency, advocates of marginal price specification do not always accept average price as a legitimate alternative specification (Griffin, Martin, and Wade 1981).

It is tempting to pose the question of price perception as a dichotomy between marginal price and average price. Arguably, only marginal price leads to efficient decision making, yet how can consumers respond to a marginal cost that is unknown? The juxtaposition need not be a dichotomy, though. One alternative is to explicitly model efficient decision making as a balance between how much water to consume and how much effort to expend in understanding rates. Empirically, this approach is likely to require additional data pertaining to effort expenditures and approaches to information discovery by consumers.

Another alternative is to take marginal price as the theoretical limit of price perception applicable to equilibrium consumption, and average price as the month-to-month price metric of least cost. An implication of this "dim perception" model of marginal price is that price knowledge becomes a learning process. Adaptation to a new marginal rate may take months or years (Bushnell and Mansur 2005). In the meantime, customers may rely on the more accessible average price estimate. This research takes the second alternative, essentially specifying a marginal-price demand function within an average-price dynamic consumption equation. Among other benefits, this tack allows the demand function to be interpreted in a standard way by welfare applications without making strenuous assumptions about perfect information. Our choice of price specifications is thus made on theoretical and practical grounds, rather than on the strictly empirical basis suggested by some (Foster and Beattie 1981b).

Aggregation

Aggregation of the community demand function means treating thousands of individual choices as a single decision. When rates are multitiered (block rates), these choices include both quantity and price components. One way to match up quantities and prices is to study microdata on individual households and businesses. Observing household budgeting decisions has theoretical appeal, but it is not as informative for policy or project evaluation as direct observation of the community aggregate, and it magnifies statistical endogeneity (Shin 1985). The latter weakness is a consequence of predominately increasing block rate structures, leading to consumption neighborhoods wherein a small positive change in quantity will accompany a large positive change in price, spuriously diluting negative price effects.

An alternative to surveying every household and business within a community is to treat the mean of consumption as a point-mass serving as the representative consumer. In this research, the representative consumer is actually a distribution of consumption levels mapped onto the price schedule. The procedure originated with Schefter and David (1985) and has been employed with some success recently (Diakité, Semenov, and Thomas 2009; Bell and Griffin 2008a; Martinez-Espineira 2003). The introduced distributional information smooths abrupt endogenous price changes while including more of the complex price schedule in a scalar price metric and acknowledging differential effects of rate changes on people operating in different blocks. Distributed consumption seems considerably more realistic than point-mass consumption, even though additional and potentially ad hoc distributional assumptions are usually required.

III. BUILDING THE EMPIRICAL MODEL

The Sample

The data consist of originally compiled monthly consumption, price, demographic, and weather observations on 167 U.S. cities, each with population exceeding 25,000. The sample spans nine states (Alaska, California, Florida, Indiana, Kansas, Minnesota, Ohio, Texas, and Wisconsin) and the time horizon 1995 through 2005, for 132 possible monthly observations per city. Although expansive, the scope of the sample is constrained by the availability of historical water deliveries data, which is determined by state reporting protocols. Compared with a balanced panel of 22,044 observations, the data are 76% complete, with 16,804 observations. Summary statistics are given in Table 1. A detailed account of data collection and data characteristics has been provided by Bell and Griffin (2008b), but a few highlights follow.

Price observations were gathered through electronic and personal contact with over 1,000 municipal and state agencies nationwide. Water prices for 37,159 observation-months in 319 communities were obtained, with sewer prices for 23,060 observation-months in 210 communities. Missing sewer price observations in the sample panel are estimated from a univariate regression on water prices. Price and cost variables in the analysis

TABLE 1
Summary Statistics

Variable	Units	Obs.	Mean	Std. Dev.	Min.	Max.
Daily Use	mGal	16,804	27.4	68.1	0.034	1,340
Population	thousands	16,804	141.7	355.6	27.6	3,828.5
Commerce	$million	16,804	2,447.6	6,640.2	142.7	81,900.0
ResPrice	$/kGal	16,804	2.65	1.57	0.00	10.09
CommPrice	$/kGal	16,804	3.14	1.58	0.00	12.24
ResFixed	$/month	16,804	17.39	18.53	0.00	302.00
CommFixed	$/month	15,728	70.38	99.38	0.00	1,132.38
CPI	rel. 1982	16,804	1.746	0.128	1.503	1.992
PPI (BMNR)	rel. 1982	16,804	1.395	0.111	1.25	1.736
Income	$000/year	16,804	22.85	6.81	9.46	53.23
MinTemp	degrees F	16,734	53.13	53.62	− 3.74	81.84
MaxTemp	degrees F	16,734	73.72	16.40	11.39	111.58
DryPart	proportion	16,733	0.797	0.014	0.00	1.000

are sums of water and sewer prices and costs. Residential prices are those charged to 0.75 inch connections, and commercial prices correspond to 2 inch connections. As illustrated in Table 1, the biggest difference between the two schedules tends to be the magnitude of fixed charges.

Within the price sample, an average of 1,200 gallons per month is allowed per residential customer and an average of 2,700 gallons per business at no marginal charge. Approximately 85% of utility systems bill monthly, with the rest billing bimonthly or quarterly. Fixed charges are lowest on average in New England, although the region is not as well represented as South, West, and Midwest regions in the price dataset. Marginal prices are lowest in the West, perhaps paradoxical for a region associated with increased water scarcity, but reconcilable given the conventional focus of rate design on cost recovery rather than efficiency. Decreasing block rate structures are most common in the Midwest. Nominal marginal rates grew over the sample horizon faster than inflation, but fixed fees increased more slowly; so the relative proportion of water charges attributed to the volume of consumption increased from 1995 to 2005.

Aggregate delivery volumes (Daily Use) were obtained from state records for 216 utility systems over 25,833 observation-months. The existence of historical volume data is rare in the absence of a state-level reporting program, so a bias is incurred against data in the New England region, where perhaps water availability is less of a concern and data collection efforts appear weaker (based on our contacts with data sources). No observations from New England are included in the regressions due to the missing volume data. Monthly volume supplied per capita averages 6.0 thousand gallons (kGal), with Alaska averaging only 4.0 kGal and Texas averaging 7.2 kGal. Winter average supply (December and January) averages 5.0 kGal, whereas summer average supply (July and August) averages 7.8 kGal. Between 0.177 gallons (Alaska) and 0.54 gallons (Texas) is supplied per dollar earned, with a mean of 0.43 gallons per dollar. The winter average is 0.354 gallons per dollar earned, and the summer average is 0.549.

Population data are taken from the U.S. Census, personal income (Income) and nonfarm income (Commerce) from the Bureau of Economic Analysis, and inflation measures (Consumer Price Index and Producer Price Index) from the Bureau of Labor Statistics. The climate measures, monthly highest and lowest recorded temperatures (MinTemp and MaxTemp) and the proportion of days when less than 0.1 inches of precipitation was recorded (DryPart) are taken from the National Climatic Data Center.

The Dependent Variable

The applicability of an EC regressor derived from a distinct structural model depends on the stationarity, or integration level, of the

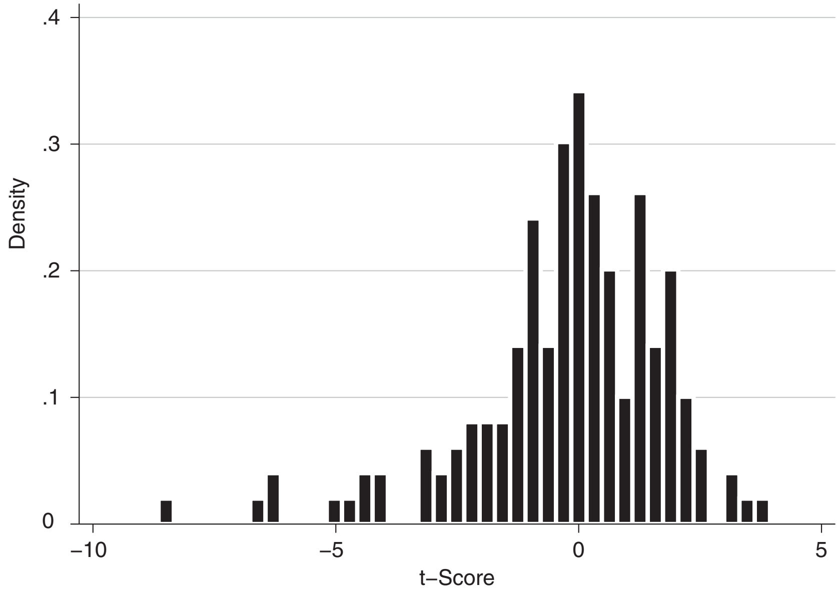

FIGURE 1
Testing for a Periodic Unit Root in Quantity Delivered

regressor itself and not, per se, on the cointegration status of its components. The EC technique applied to stationary series will be equally consistent and confer many of the same advantages as if applied to nonstationary but cointegrated series. Similarly, periodic EC applied to aperiodic series will produce consistent, if redundant, estimates. Nevertheless, the academic interest in cointegration is sufficient to merit a preliminary examination of the dependent variable, total daily quantity of water demanded per capita.

A candidate test of periodic integration is that proposed by Boswijk and Franses (1995b). Periodic integration with a single common root process (a common stochastic trend) in periodic data is equivalent to aperiodic integration in the same data stacked as an annual vector. A univariate autoregressive equation on the stacked vector can be performed functionally as an autoregression on the pooled monthly data with monthly dummies. A Dickey-Fuller-style test is performed on the vector product of the estimated autoregressive parameters. Just as in the Dickey-Fuller test, the null hypothesis is that the estimated parameter (in this case the vector product of estimated parameters) equals unity, implying the existence of a unit root, thus that the series is nonstationary. The alternative is theoretically one-sided, although a few observations in practice produce an autoregressive parameter greater than unity.

Boswijk and Franses suggest a likelihood ratio test based on imposing the unity restriction, but only the asymptotic distribution of this test is known, and the time series samples here are small. Therefore, a *t*-statistic on the distance between the nonlinear combination of estimated parameters and unity is presented alongside an *F*-test on the imposed restriction, with the understanding that results may be more demonstrative than rigorous.

The quantity demanded panel is unbalanced by missing observations, so the periodic unit-root hypothesis is tested separately for each community rather than in a pooled test. The *t*-test median over all communities is 0.005, with 78% of observations greater than -1.30. The *F*-test median is 1.175, with 68% of observations less than 2.70. The distribution of *t*-scores is displayed graphically in Figure 1. Although critical values for both tests vary with the number of time observations in each panel, –1.30 is higher than the 95% critical value for any one-sided t-test, and 2.70 is lower than the 90% critical value for $F(1,120)$, which is the most restrictive case among the panels tested. Therefore, individual test statistics fail to reject the null in over 70% of cases. The hypothesis that all quantity data are periodically integrated of order one cannot be rejected either. These results sound the alarm that residuals generated from a linear regression on quantity demanded will generally not be stationary in the absence of a periodic cointegrating vector. Periodic cointegration is justified on this basis.

The Structural Model

The long-run structural model employed at this stage is a Cobb-Douglas model. The Cobb-Douglas functional form is still the most popular (Basani, Isham, and Reilly 2008; Olmstead, Hanemann, and Stavins 2007; Musolesi and Nosvelli 2007). Other common forms include the semilog (Kostas and Chrysostomos 2006) and linear (Ruijs, Zimmermann, and van den Berg 2008). The Stone-Geary form also has its adherents (Gaudin, Griffin, and Sickles 2001; Martinez-Espineira and Nauges 2004).

Interpretation of the model parameters is different in the context of an EC model than it would be as a stand-alone regression. In addition to the usual explanations for nonzero residuals, such as measurement error and random innovation, disequilibrium due to slow adjustment must also be included. In deference to the periodic integration results of the previous subsection, one structural model per calendar month will be estimated, not as a predictive model but to contribute long-run perspective to the dynamic model.

Covariates include weather and climate measures, residential and commercial marginal price indices, sectoral intensity ratios, and income. For each month, the weather measures are average within-month daily minimum temperature, average within-month daily maximum temperature, and the proportion of days in the month with less than 0.10 inches precipitation (MinTemp, MaxTemp, and DryPart). The climate measures consist of the 30-year averages of each weather measure, by month (AvMinTemp, AvMaxTemp, and AvDryPart). Personal income is taken directly from the Bureau of Economic Analysis. Income not only reflects the contemporaneous budget constraint, it proxies the level of capital expenditure, including water-using durables. Unfortunately, the geographic boundaries of the income aggregates do not consistently correspond to the areas of municipal water service coverage. Also, mean personal income may be an insufficient statistic when the distribution of income within communities matters. Finally, personal income data is annual rather than monthly.

Marginal prices (ResPrice and CommPrice) are adjusted for inflation and weighted across residential and commercial price schedules according to an assumed distribution (Bell and Griffin 2008a). Household consumption and business consumption within a given community are each assumed to be distributed lognormally over quantities demanded. Total, mean, and median consumption are sufficient statistics to describe a lognormal distribution. Medians of consumption for each observation are calculated so that the ratio of mean to median is identical to the ratio observed in the distribution of total consumption across observations (which is 2.48). The unique distributions so defined are mapped onto each residential and commercial rate schedule to produce a weighted marginal price index. The same weighting is applied to average prices in the formulation of the short-run average price indices, although these are summed discretely every 500 gallons from 500 to 100,000, whereas the marginal price indices are integrated continuously. None of the sample communities experiences a price that is strictly zero.

In order to represent community differences in commercial activity, commercial and industrial intensity ratios (CommIntensity and IndIntensity) are included as covariates by dividing the monetized nonfarm and industrial outputs, respectively, by population. Industry is the subsector of commerce primarily concerned with physically transformative processes, which can in many cases demand high levels of input water. Its inclusion is problematic because its distinction from other forms of commerce is arbitrary, water uses vary widely within the industrial sector, and an unknown portion of the industrial sector obtains water from wholesalers or is self-supplied. The error associated with this measure should therefore be considered underestimated by the regression. Nevertheless, as one of the more significant factors in the regression (Table 2), its inclusion is cautiously justified. An industrial price is not included because the combination of measurement error and collinearity with the other price measures would eclipse any reliable explanatory power.

Results of the structural regressions for each calendar month are presented in Table 2. The residuals of this regression, lagged one year, will constitute the EC term of the dynamic regression in differences. A hypothesis of this research is that seasonality at the monthly frequency is a consideration in water demand. If seasonality is evident, then the monthly coefficients should be significantly different from the coefficients of a pooled regression of all months. To settle this question, a Chow test is performed comparing each monthly regression to the pooled regression of the other 11 months. The appropriate statistic is $F(12, 14{,}762)$, but for simplicity, results were compared to the 1% critical value of $F(12, \infty)$, which is 2.185. The hypothesis that all monthly parameters are indistinguishable from all pooled parameters is rejected for every month except April (1.920) and October (0.820), which is expected since a pooled average, like a broken clock, should still be right twice per cycle. These results indicate the unlikelihood of a constant demand relationship, and they support the probability of 12-phase (monthly) seasonality, but they do not preclude the possibility of other intra-annual (such as 4-phase) or extra-annual (such as El Niño) cyclic frequencies.

A cursory examination of Table 2 reveals that residential price and industrial intensity are the most consistently significant covariates. The price signal is generally stronger in the warmer summer months. Residential demand seems to be more sensitive to seasonality than commercial demand. Although the residential and commercial mean price elasticities of -0.147 and -0.124 are low (in absolute value), their combined mean of -0.272 is consistent with previous research (Dalhuisen et al. 2003). Evidence supporting the hypothesis that water-consuming sectors should be treated separately can be drawn from the sectoral intensity variables and by comparing the effects of the two price indices. Although industrial intensity appears to figure significantly in all months, commercial intensity is significantly positive only in July and August. The residential and commercial price variables (whose pairwise correlation is 0.831) exhibit effects that appear to be generally similar and that are in fact statistically indistinguishable in every period. The null hypothesis that residential and commercial consumption can be adequately described in a single-sector model cannot be rejected, although the evidence supports identification of a separate industrial sector.

Personal income enters negatively, which is an unexpected result. The negative income effect could be essentially spurious, resulting from the disappointingly high level of income aggregation, or it could reveal a higher stock of political capital in more affluent communities. It is possible that such communities could exert a monopsonistic influence on price and quantity supplied; however, the lack of corroborating evidence from prior literature casts doubt on this explanation. Average maximum temperature and average minimum temperature coefficients frequently carry opposite signs, indicating that temperature spread is an important determinant of water demand.

The distribution of t-statistics testing the null hypothesis of periodic integration in the residuals is illustrated by Figure 2. The median t-score is -26.53, with 85% of test statistics lying outside the 95% (one-sided) probability interval of the null, allowing a handy rejection of the hypothesis that the residuals are systematically periodically integrated. The median F-test statistic is 468.0; 83.4% of statistics lie outside the 90% interval. With some caution, it may be said that the left- and right-hand sides of each structural relation are periodically cointegrated. Although the regressions summarized in Table 2 are consistent periodic cointegration vectors, they should not be taken as indicative of observed water demand behavior because they

TABLE 2
Results of Cobb-Douglas Regression by Month

Variable	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
MinTemp	−0.222	−0.032	−0.223	0.129	−0.554	−0.14	−0.881	0.145	−0.638	−0.478	−0.208	0.009
	(0.093)	(0.105)	(0.214)	(0.281)	(0.389)	(0.593)	(0.597)	(0.6)	(0.499)	(0.294)	(0.212)	(0.074)
MaxTemp	0.324	−0.136	−0.01	0.691	2.156*	1.553	1.866*	1.522	1.983*	0.578	0.268	−0.306
	(0.236)	(0.232)	(0.327)	(0.445)	(0.44)	(0.598)	(0.615)	(0.62)	(0.622)	(0.419)	(0.266)	(0.239)
DryPart	0.054	−0.001	0.135	0.038	0.045	0.137	0.474*	0.298*	0.187	0.07	−0.024	0.339*
	(0.05)	(0.02)	(0.121)	(0.059)	(0.042)	(0.069)	(0.09)	(0.086)	(0.077)	(0.086)	(0.064)	(0.111)
AvMinTemp	0.312*	−0.042	−0.43	−1.061*	−0.539	−0.621	0.484	−0.574	−0.095	−0.537	−0.446	−0.556*
	(0.092)	(0.149)	(0.272)	(0.321)	(0.413)	(0.639)	(0.651)	(0.646)	(0.586)	(0.35)	(0.266)	(0.173)
AvMaxTemp	−0.45	0.347	1.121*	1.197	0.383	1.432	1.339	1.567	0.649	1.518*	0.87	1.254*
	(0.253)	(0.278)	(0.399)	(0.503)	(0.516)	(0.666)	(0.652)	(0.681)	(0.738)	(0.515)	(0.353)	(0.327)
AvDryPart	−0.143*	−0.13	−0.07	0.003	−0.049*	−0.091*	−0.068*	−0.081*	−0.099*	−0.059	0.006	0.224*
	(0.053)	(0.057)	(0.051)	(0.037)	(0.018)	(0.018)	(0.016)	(0.018)	(0.027)	(0.031)	(0.043)	(0.059)
ResPrice	−0.123*	−0.112*	−0.121*	−0.151*	−0.164*	−0.155*	−0.175*	−0.178*	−0.191*	−0.196*	−0.142*	−0.061
	(0.042)	(0.042)	(0.041)	(0.042)	(0.042)	(0.052)	(0.049)	(0.05)	(0.057)	(0.044)	(0.039)	(0.04)
CommPrice	−0.084	−0.089	−0.105	−0.114	−0.138*	−0.139	−0.141	−0.136	−0.14	−0.112	−0.123*	−0.171*
	(0.052)	(0.051)	(0.048)	(0.047)	(0.047)	(0.085)	(0.056)	(0.056)	(0.063)	(0.05)	(0.045)	(0.05)
CommIntensity	0.065	0.006	−0.03	0.059	0.172	0.152	0.236*	0.277*	0.185	0.157	0.118	0.137
	(0.068)	(0.068)	(0.069)	(0.07)	(0.07)	(0.087)	(0.085)	(0.085)	(0.095)	(0.078)	(0.067)	(0.068)
IndIntensity	0.11*	0.106*	0.118*	0.103*	0.118*	0.115*	0.118*	0.116*	0.099*	0.104*	0.099*	0.103*
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.017)	(0.017)	(0.017)	(0.019)	(0.015)	(0.013)	(0.014)
Income	−0.31*	−0.254*	−0.153	−0.142	−0.222	−0.116	−0.141	−0.159	−0.089	−0.145	−0.276*	−0.33*
	(0.094)	(0.094)	(0.096)	(0.097)	(0.095)	(0.12)	(0.118)	(0.118)	(0.13)	(0.107)	(0.093)	(0.093)
Constant	7.867*	6.704*	4.374*	2.02*	0.29	−4.173	−6.58*	−5.899*	−3.012	1.158	5.33*	6.645*
	(0.879)	(0.939)	(0.972)	(1.076)	(1.174)	(1.609)	(1.619)	(1.548)	(1.585)	(1.142)	(0.888)	(0.904)
Obs.	1,207	1,213	1,215	1,226	1,229	1,224	1,223	1,236	1,245	1,256	1,261	1,251

Note: Standard errors in parentheses.
* $p < 0.01$.

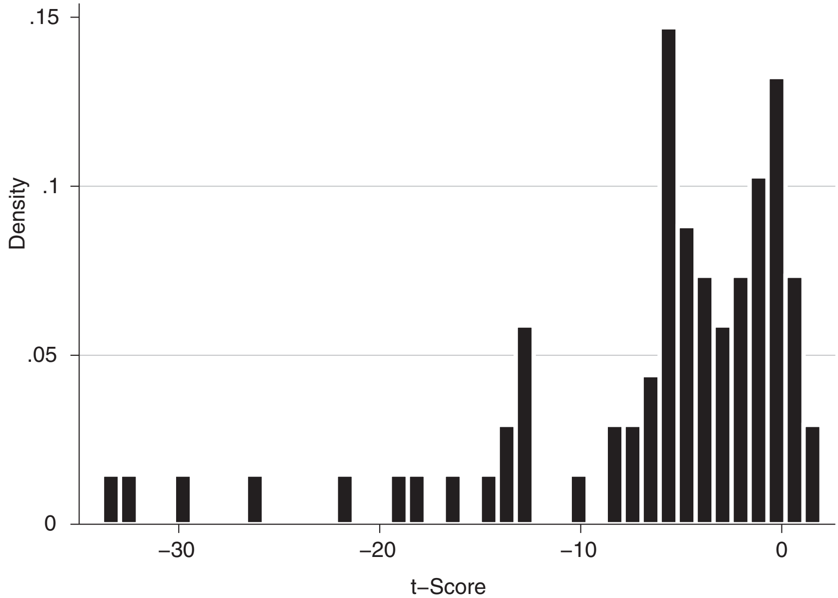

FIGURE 2
Testing for a Periodically Integrated Residual

omit important short-run components to be addressed in the dynamic model.

The Dynamic Model

The short-run model is a logarithmic model in annual first differences, augmented with pairwise products of covariates. The dependent variable, $\Delta \ln w$, is the annual log difference in daily consumption per capita:

$$\Delta \ln w = \beta_p \Delta \ln \mathbf{p} + \sum_{i=2}^{I} \beta_i \Delta \ln x_i + \sum_{i=2}^{I} \gamma_{pi} \Delta(\ln \mathbf{p} \ln x_i) + \sum_{i=2}^{I} \sum_{j=2}^{I} \frac{\gamma_{ij}}{2} \Delta(\ln x_i \ln x_j) + \delta EC + \nu. \quad [7]$$

Prices, **p**, are annotated separately from the other covariates, **x**, for clarity only. Except for the error correction term, *EC*, the model is taken from Bell and Griffin (2008a). In contrast to the earlier application, both residential and commercial prices are included in the present model. A product of the two prices is not included because its inclusion would obscure the price elasticity calculations. Also, the price metric here is average quasi-difference price rather than marginal quasi-difference price. The quasi-difference price is the difference between two price schedules, weighted by the distribution of lagged consumption. By weighting contemporaneous and lagged price schedules identically, the spurious endogeneity of a quantity-dependent price index is avoided. Only residential and commercial prices, weather realizations, and the EC term are included in this short-run regression since climate, income, and sectoral intensity are assumed to change too slowly to drive an annual model.

Estimation results are presented in Table 3. The last year of data is withheld from the estimation to test prediction accuracy. The EC term is highly significant, the most significant coefficient in fact, indicating that the pull to equilibrium is a motive force affecting quantity demanded at the annual level. Not only is the coefficient (-0.187) different from zero, it is different from -1, implying a multiyear adjustment path. It is noteworthy that the EC coefficient could reflect behavior other than consumption, such as mitigation of system losses by utilities.

TABLE 3
Results of Logarithmic Dynamic Regression

Variable	Coefficient	Std. Error	*t*-Score
ResPrice	−0.00194	0.0304	−0.06
CommPrice	0.00471	0.0140	0.34
MinTemp	−0.579*	0.0789	−7.34
MaxTemp	−0.110	0.144	−0.76
DryPart	−0.350	0.240	−1.46
ResPrice × MinTemp	−0.0500*	0.00682	−7.28
ResPrice × MaxTemp	0.0480*	0.00637	7.54
ResPrice × DryPart	0.000375	0.00203	0.18
CommPrice × MinTemp	0.00703*	0.00137	5.13
CommPrice × MaxTemp	−0.00733*	0.00137	−5.35
CommPrice × DryPart	0.0000355	0.000594	0.06
MinTemp × MaxTemp	0.174*	0.0281	6.20
MinTemp × DryPart	0.0753	0.0736	1.02
MaxTemp × DryPart	0.0184	0.110	0.17
EC	−0.187*	0.00519	−35.99

Note: $n = 12{,}547$. EC, error correction.
* $p < 0.01$.

Price covariates are significant only when paired with weather covariates (such as ResPrice*MinTemp), indicating the effect of the weather on price response. The frequency of absent precipitation (DryPart) does not appear to be as important in the short run as temperature. Mean high and low temperatures appear to be the motive force behind demand in the short run, not only in themselves but also in governing the effect of price.

Short-run elasticity is composed of two elements for each sector, the immediate response to a price shock and the momentum of adjustment to previous shocks. The shock response is computed with respect to the estimated parameters corresponding to that sector's price index according to the formula

$$\varepsilon = \beta_p + \sum_{i=2}^{I} \gamma_{pi} \ln x_i. \quad [8]$$

The adjustment elasticity, embedded in the EC component, can be understood as the proportion of long-run elasticity distributed to each period. Adjustment elasticities are products of the long-run price coefficients reported in Table 2 and the EC coefficient reported in Table 3.

Table 4 shows estimated short-run price elasticities derived by the dynamic model, grouped by month. The theoretical annual elasticity of demand due to a simultaneous price change in both residential and commercial schedules (Annual) is decomposed into sectors, with each sectoral elasticity further separated into contemporaneous (Beta) and lagged (EC) components. The contemporaneous components are slightly positive and generally smaller than the lagged components, contributing little or no price effect. From the EC coefficient reported in Table 3, each of the annual disequilibrium elasticity estimates is approximately 18.7% of the total estimated structural elasticity. None of the short-run elasticity means is statistically negative, owing primarily to variation in the data. It appears that communities take a minimum of one year to notice a price change and begin to react only in the second year.

The dynamic EC model is used to project each 2004 observation one annual step forward. The results reported in Table 5 include predicted mean daily consumption per capita, mean absolute percent error (MAPE), and mean squared error (MSE) of the preferred model (EC), compared to the observed 2005 data mean and two benchmarks. The benchmarks include predictions from the monthly structural models and from the dynamic model reestimated without an EC term. The EC model (as well as the non-EC dynamic model) clearly outperforms the structural models on all measures, illustrating the importance of temporal consideration in model-

TABLE 4
Annual Average Price Elasticity by Month and Sector

	Obs.	Residential Beta	Residential *EC*	Residential Total	Commercial Beta	Commercial *EC*	Commercial Total	Annual
Jan	1,227	0.016	− 0.023	− 0.007	0.000	− 0.016	− 0.016	− 0.023
Feb	1,226	0.013	− 0.021	− 0.007	0.000	− 0.017	− 0.016	− 0.024
Mar	1,228	0.011	− 0.023	− 0.012	0.001	− 0.020	− 0.019	− 0.031
Apr	1,239	0.009	− 0.028	− 0.020	0.001	− 0.021	− 0.020	− 0.040
May	1,242	0.006	− 0.031	− 0.025	0.001	− 0.026	− 0.025	− 0.050
Jun	1,238	0.004	− 0.029	− 0.025	0.001	− 0.026	− 0.025	− 0.050
Jul	1,237	0.004	− 0.033	− 0.029	0.001	− 0.026	− 0.025	− 0.054
Aug	1,250	0.004	− 0.033	− 0.029	0.001	− 0.025	− 0.024	− 0.053
Sep	1,259	0.005	− 0.036	− 0.030	0.001	− 0.026	− 0.025	− 0.055
Oct	1,271	0.007	− 0.037	− 0.029	0.001	− 0.021	− 0.020	− 0.049
Nov	1,275	0.009	− 0.027	− 0.017	0.001	− 0.023	− 0.022	− 0.040
Dec	1,265	0.014	− 0.011	0.003	0.000	− 0.032	− 0.032	− 0.029

TABLE 5
Comparison of Model Predictions

Model	Observed	EC	Structural	Dynamic
Mean (gal)	209.9	182.8	163.7	193.8
MAPE	—	21.6	41.0	21.7
MSE	—	14,436	26,158	21,998

Note: n = 1,612. EC, error correction; MAPE, mean absolute percent error; MSE, mean squared error.

ing water demand. The EC model only marginally outperforms the non-EC dynamic model. Inclusion of the EC term is arguably recommended on the grounds of avoiding theoretical misspecification rather than on predictive grounds.

IV. CONCLUSIONS

An atypically broad panel of monthly demand data for publicly supplied water in American urban centers is analyzed using a periodic EC model. Although the model can be applied to household data as well as community data, the independent variables used in the analysis mitigate the relative weakness of aggregate data. A microlevel approach can be pursued by more conventional means when such data are available.

The EC model allows examination of the time path of demand by integrating shorter and longer perspectives in a single estimation model. The estimated effect of the lagged residual implies that demand adjustments are not instantaneous or even as quick as a single year. The model significance and predictive power of the dynamic model in annual differences allows a rejection of the possibility that a purely structural model is well specified for time-dependent applications. Estimation of distinct structural relations for each calendar month allows a test of seasonality of demand. Rejection of the null hypothesis that structural parameters are equivalent across months suggests that ignoring seasonality can lead to misspecification, even when weather and climatic factors are taken into account. Inclusion of both residential and commercial price indices, as well as commercial and industrial intensity ratios, tests the adequacy of the more common single-sector model. Although some evidence suggests that businesses, especially industrial businesses, demand water differently than households, the single-sector model is not conclusively rejected.

Some new possibilities are suggested by the results. Ignoring the distinction between the sectors may be unwise. Social costs arising from temporary misalignment of supply and demand may be reduced by adjusting residential rates and commercial rates differentially to the same target price. Many rate setters change the entire rate schedule uniformly, either for convenience or out of an interest in intersectoral equity. Recognizing that tensions exist inherently among competing objectives is a necessary step to striking good balances. For example, the dictum of efficiency requires that all sectors face natural water's opportunity costs, and these should be locally equivalent across sectors. Thus, efficiency is best advanced by equal rates except where marginal processing costs differ sectorally.

Demand factors appear to be seasonal in a way that is not entirely captured by climatic conditions. This finding speaks to the use of seasonal management policies, especially if a risk of acutely exceeding peak capacity is present. Short-run demand response may be only marginally significant in summer months, but it is very close to zero in nonsummer months. Also, annual elasticity appears to be much lower than structural elasticity, indicating a very slow adjustment process. Managers cannot expect an immediate readjustment to changing conditions. Applying these findings may require a deeper consideration of the habits and durable possessions of water users, which are both seasonal and slow to evolve. Because of the dim perception consumers have of marginal water cost, information must also be counted as a valuable capital good.

The periodic EC model produces near-term forecasts with an appealingly low level of error (21.6% MAPE), even though it may not be the best model for projecting future conditions or for testing hypotheses regarding price elasticity. The model and the exercise of developing the model underscore the inadequacy of the term "price elasticity." Many elasticities have been generated in this research alone, varying with time horizon, season, sector, and model. Meaningful comparison and application of these estimates depends on an explicit characterization of which elasticity is to be derived.

Community water consumption series could contain a seasonal stochastic trend, as the series in this sample apparently do. If this is the case, ordinary least squares estimates of demand cannot be assumed consistent. Fortunately, the data of the present sample are seasonally cointegrated. Unit root tests are available to assist in the determination of trend stationarity, as are seasonal and periodic integration tests to determine cyclical patterns. When demand relations tend to equilibrate slowly, an integrated structural/dynamic model such as an EC model will provide improvements in both forecasting and insight over either a static or a dynamic model alone. Finally, as the accuracy of these findings is limited by the quality of the available data, it will be interesting to see if similar findings persist as data recording becomes more widespread, more uniform, and more precise.

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