An Estimation of Residential Water Demand Using Co-Integration and Error Correction Techniques

Martinez-Espineira, Roberto

April 2005

An Estimation of Residential Water Demand Using Co-Integration and Error Correction Techniques

Abstract

In this paper short- and long-run price elasticities of residential water demand are estimated using co-integration and error-correction methods. Unit root tests reveal that water use series and series of other variables affecting use are non-stationary. However, a long-run co-integrating relationship is found in the water demand model, which makes it possible to obtain a partial correction term and to estimate an error correction model. The empirical application uses monthly time-series observations from Seville (Spain). The price-elasticity of demand is estimated as around -0.1 in the short run and -0.5 in the long run. These results are robust to the use of different specifications.

JEL Classification: C22, D12, Q25.

Keywords: seasonal unit roots, residential water demand, price elasticity, time-series, co-integration, Error Correction Model.

Revision: revised January 9

Introduction

While it is generally agreed that residential water users' short-run and long-run reactions to price changes might be substantially different, long-run water demand elasticities have been rarely estimated for European users. The main purpose of this paper is to estimate and compare short-run and long-run price elasticities of residential water demand using data from Seville (Spain). A secondary objective is to assess the usefulness of the techniques of co-integration (see Engle and Granger, 1987; Johansen, 1988, among others) and error correction (Hendry, Pagan, and Sargan, 1984) in the analysis of these price-elasticities of water demand. To the author's knowledge, no previous published work has applied this econometric methodology to the study of water demand, while it has proved very useful to estimate the demand for other types of transformed natural resources, such as gasoline and electricity. The analysis in this paper is similar to these previous studies in that it deals with a resource whose price could affect purchase patterns of capital stock (water-using appliances) and whose consumption might respond partly to habit.

Monthly time-series data on price and aggregate residential consumption over a ten-year period are matched with climatic data, data on non-price demand policies, and average income. The availability of monthly data allows not only for the use of much more accurate measures of consumption but also to test for seasonal effects in consumption and the peculiarities of dynamic effects that cannot be captured when using yearly data. The city of Seville was chosen as a case study because it has been already the subject of several analyses based on a variety of econometric specifications. This makes it possible to compare the results of the present study with alternative ones.

The econometric estimation proceeds in two steps. First, unit root tests are conducted to determine the degree of integration of the main variables. Then, a long-run equilibrium relationship between price and consumption is estimated. The stationarity of the different time-series involved is investigated using seasonal unit root tests and tests that consider structural breaks in the series . The long-run equilibrium relationship is then used as an error correction term in an error correction model (ECM henceforth). These techniques provide measures of the short- and long-run elasticities as well as the speed of adjustment towards long-run values. The elasticities estimated suggest, as it has been found in the literature, that household water demand is inelastic with respect to its own price but not perfectly so. The results show remarkable consistency between the different techniques used to analyze the dynamics of the relationships.

This paper is organized as follows. Section 1 lists some previous studies dealing with the estimation of residential water demand and applied works that use the techniques of co-integration and error correction. The characteristics of water demand in Seville are described in Section 2 and the data set is described in Section 3. The econometric methods and the results are presented in Sections 4 and 5 respectively. Section 6 concludes.

1 Background

Residential water demand has been extensively analyzed during the last decades. The main objective of this research is to estimate price elasticities of water demand from water demand functions where either individual or aggregate residential water use is made dependent on water price and other variables such as income, climatic conditions and type of residence. Water demand appears as inelastic but not perfectly inelastic. Most applied studies focus on areas of the USA (e.g. Schefter and David, 1985; Chicoine and Ramamurthy, 1986; Nieswiadomy and Molina, 1989; Renwick and Green, 2000). Some exceptions that use European data are Hansen (1996), Höglund (1999), Nauges and Thomas (2000), and Martínez-Espiñeira (2002). Due to differences in the way water is used and the way in which it is priced, there are sharp geographic variations in the size of price elasticities of water demand, especially between Europe and North America (Arbués et al., 2003; Dalhuisen et al., 2003). Therefore, it is important that European policy makers be provided with the results from analyses based on European data that consider long-run versus short-run usage responses to price changes.

A number of previous studies have found short-run elasticities smaller than their long-run counterparts. This suggests that consumers might need time to adjust their water-using capital stock and to learn about the effects of their use on their bills. These studies use some type of flow-adjustment model, where lagged consumption is included as an explanatory variable. The latter assumes that the actual adjustment to consumption is a fixed ratio of the total *desired* or equilibrium adjustment. The short-run elasticity is then given by a choice of utilization rate of the water-using capital stock, while the long-run is defined as the choice of both the size of this capital stock and the intensity of its use. Past consumption is introduced in the model with lags of different length and shape. Agthe et al. (1986), Moncur (1987), Lyman (1992), Dandy et al. (1997) are examples of this type of approach, while somewhat more sophisticated econometric techniques have recently been applied, including the use of dynamic panel data methods (Nauges and Thomas, 2001).

Lack of data on water-using capital stock usually prevents the use of stock-adjustment models, although in some cases (Agthe et al., 1986) a time variable proxies the evolution of the capital stock. Renwick and Archibald (1998) introduce information available on water related technology in a model that explicitly analyzes endogenous technical change. These studies find that, in agreement with economic theory, short-run responses to price changes are weaker than long-run ones. However, Agthe and Billings (1980) find, using a linear flow adjustment model, the short-run elasticity value (-2.226) much higher than the long-run value (-0.672), suggesting that, with monthly data, there could be a short-run overreaction to price changes and that alternative techniques of time-series analysis might help solve these inconsistencies.

None of these studies has used co-integration and/or error correction techniques to estimate short-run and long-run price effects. These methods have been extensively used since Engle and Granger's 1987 seminal paper. Electricity demand forecasting is among the earliest applications of co-integration (Engle et al., 1989). More recently, co-integration and error correction have been applied to the estimation of energy and gasoline demand. For example, Bentzen (1994), Eltony and Al-Mutairi (1995), and Ramanathan (1999) study the behavior of gasoline consumption. Fouquet (1995) investigates the impact of VAT introduction on residential fuel (coal, petrol, gas, and electricity) demand in the United Kingdom, while Beenstock et al. (1999) address the issue of seasonality in electricity consumption. Using co-integration analysis to estimate demand functions avoids problems of spurious relationships that bias the results and provides a convenient and rigorous way to discern between short-run and long-run effects of pricing policies.

2 Water demand in Seville

Residential water use represents about 74% of the demand for drinking water in the Seville and its metropolitan area. This proportion remained fairly constant during the nineties, except in 1992-93, when the Universal Exposition increased the share of institutional use (*EMASESA*, 2000, pp. 2-3). The total number of families living in the city of Seville in 1998 was 226,692 and the water supplier, *EMASESA*, had a total of 190,759 domestic customers at the end of 1998. The number of customers has increased significantly since 1997. This is because the water supplier implemented a campaign (*Plan Cinco*) of replacement of collective meters by individual meters, causing an increase in the average yearly growth of the number of domestic customers from 7% to %10-11 (*EMASESA*, 2000, p. 4).

According to company's estimates, Sevillan households use 53% of the water in the toilet, in the kitchen, and for washing clothes. These components could be significantly affected by the efficiency of water-using equipment and the frequency of its renewal. An extra 39% is used in showers, which could be determined by both habits and the characteristics of water-use equipment. Outdoor use is minimal (*EMASESA*, 2000, p. 7).

Seville suffered a serious draught between 1992 and 1995, during which important savings were achieved through measures such as media campaigns, municipal edicts and the ban of certain uses, water restrictions, and consumption control inspections. At the height of the drought, savings of around 25% with respect to previous years were achieved. In mid-1992, imbalances between supply and demand started to arise. Media campaigns were launched to ask for voluntary water conservation. Then this was made compulsory, since from September water supply was reduced to 20 hours daily, inducing savings of 15%. Daily water supply was reduced to 16 hours and at the end of 1992 consumption began to reflect a 25% reduction. At the beginning of 1993 the company had to resort to the emergency intakes as the only source of supply. During the first half of 1995, a 28% reduction with respect to the consumption previous to the drought was achieved. Restrictions increased to 10 hours a day. Eventually, the rain came at the end of 1995 and the drought was overcome thanks to the savings achieved in that period. The awareness campaign continued (in spite of the reservoirs having enough water) to maintain the population's saving habits (*EMASESA*, 2000, pp. 6-7). A more detailed description of the measures implemented to reduce demand can be found in the Appendix. See also García-Valiñas (2002).

Table 1: Evolution of pricing-block sizes.

	1991-1995	1996-1999
Block 1	0-7 m^3	0-7 m^3
Block 2	0-20 m^3	0-17 m^3
Block 3	$>$20 m^3	$>$ 17 m^3

3 Dataset description

EMASESA, the private company in charge of supplying water and sewage collection services in Seville provided the main data used for the estimations. They include information for the period 1991-1999 on tariffs, number of domestic accounts, and total domestic use.

The tariff consists of a fixed quota and an increasing three-block rate. Table 1 shows the evolution of the block sizes. The price for the first seven-unit block applies only to those users who use a total of less than seven cubic meters. If the consumer exceeds this level of use, the price of the second block applies also to these first seven cubic meters. This type of *step-rate* structure is in this case explicitly aimed at rewarding water conservation efforts. The rest of the tariff is based on conventional increasing blocks. The tariff includes a water supply fee, a sewage collection fee, and a treatment fee, and, from 1994, a wastewater infrastructure fee (*canon*) was collected on behalf of the Andalusian government. Finally, from 1993 to 1997, a temporary extra fee was charged for the company's finances to recover from the impact of the drought. The value of the fixed quota depends on the size of the meter, but the most common one for domestic users (13 mm) was adopted. The evolution of the prices in each block between 1991 and 1999, including all the elements of the water and sewage bill, is detailed in Table 2. All prices are expressed in constant pesetas (ESP) of 1992, translated into EURO equivalents (1 EURO = 166.386 ESP).

The original data were manipulated into the following variables (where the subscript

Table 2: Tariff evolution (1992 EURO equivalents, excluding VAT).

	Water						Sewage and Treatment			
Year	Fixed	PBL_1^*	PBL_2	PBL_3	Canon	TEC**	Fixed	Sewage	Treat.	Canon
1991	1.063	0.139	0.214	0.386	0.000	0.000	0.000	0.075	0.130	0.000
1992	1.010	0.138	0.212	0.384	0.000	0.000	0.000	0.082	0.123	0.000
1993	1.133	0.132	0.206	0.378	0.000	0.020	0.000	0.089	0.120	0.000
1994	1.187	0.126	0.204	0.398	0.016	0.019	0.270	0.088	0.118	0.016
1995	1.246	0.125	0.213	0.421	0.016	0.021	0.285	0.092	0.124	0.016
1996	1.443	0.126	0.252	0.505	0.015	0.093	0.505	0.111	0.131	0.015
1997	1.524	0.130	0.260	0.609	0.015	0.093	0.550	0.125	0.140	0.015
1998	1.540	0.131	0.263	0.616	0.050	0.000	0.555	0.126	0.141	0.040
1999	1.533	0.131	0.262	0.614	0.048	0.000	0.553	0.126	0.141	0.039

* PBL_i = water price in block i.
**TEC = Temporary Extra Charge

t refers to Month t):

- Q_t (m^3/capita month) is average per capita domestic water use. The raw data consist of 108 monthly values for total use. The company reads meters continuously at quarterly intervals for each individual meter and estimates monthly use in the following manner. For each individual, the average daily use during the reading period is calculated, then this average use is allocated to each month according to the number of days corresponding to that month in that particular reading period.[1] Although this procedure smooths off all intermonthly variation at the individual level, the estimated aggregate use mimics the actual pattern of intermonthly variation, since there is a large number of individual meters and they are read continuously. Annual data on the number of accounts were also collected. However, instead of using this variable to calculate average water use per account, values of total population in

[1] For example, if the reading period goes from 28-04-00 to 03-08-00 and the reading is 91 m^3, since the length of the period is 97 days, average daily use is 0.93 m^3. This average daily use would be multiplied by 2 to obtain April's consumption, by 31 for May, by 30 for June, by 31 for July and by 3 for August.

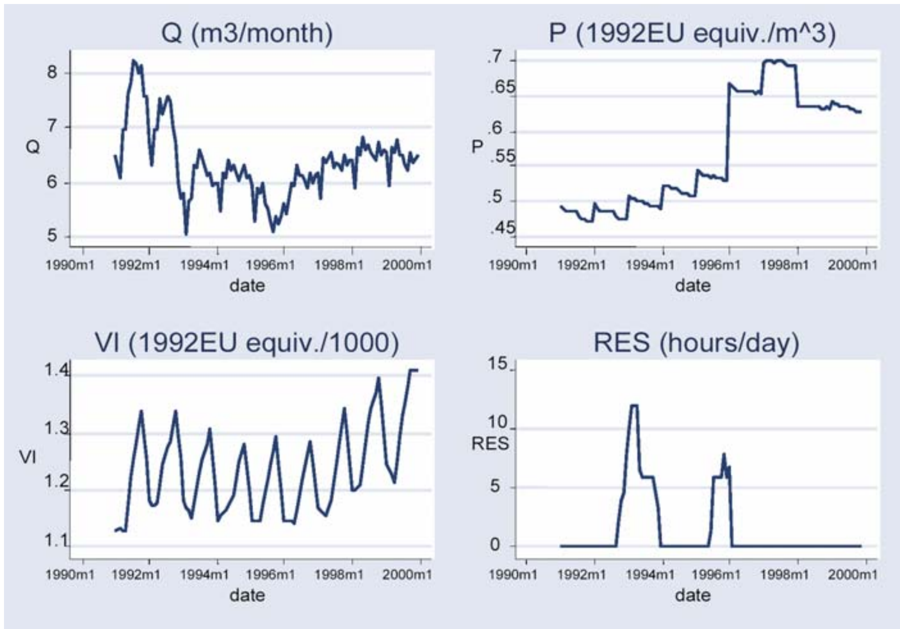

Figure 1: Evolution of the water use (Q), water marginal price (P), virtual income (VI) and water restrictions (RES) variables.

Seville were used to calculate monthly average use per capita. The reason is that during the study period the water company substantially increased the number of individual meters. The evolution of the values of both consumption per account and inhabitants per account strikingly show this effect of the introduction of individual meters described in Section 2. Figure 1 shows the evolution of the values of Q_t, including the effect of the drought during the first half of the decade. Conservation efforts persisted after the end of the drought, as described in Section 2, and water use levels did not fully return to pre-drought levels

- P_t (1992 EURO equivalents/m^3) is the marginal price of water. It corresponds to a variation on the Taylor-Nordin specification (Taylor, 1975; Nordin, 1976) for multipart tariff structures. Following Billings (1982), an instrumental marginal price and difference are derived from an artificial linearization of the tariff structure by regressing the constructed bill amounts associated with each integer value of potential (between 1 m^3 and 25 m^3) monthly water use per account on these water use values. This instrumental marginal price is the slope of that estimated regression. The estimated intercept provides an estimate for the Taylor-Nordin difference. This price formulation avoids problems of price endogeneity and reflects the fact that consumers have only an imperfect knowledge of the tariff structure and the block they are consuming in at each point in time. The strict application of the Nordin-Taylor's original specification has been the subject of debate (discussed in Arbués et al. , 2003). A perfectly informed consumer would react to the marginal price and the rate premium, but most consumers will not carefully study the tariff structure or changes in inframarginal rates because of information costs. Alternative approaches include the use of the average price, or both average and marginal price in the same or different models. The modified Nordin-Taylor specification was chosen for this study in light of the results obtained with different specifications by Martínez-Espiñeira (2002) in other Spanish regions and because it was successfully applied by Martínez-Espiñeira and Nauges (2004) in a previous study in Seville, which also makes it possible to compare results based on the same price specification but different econometric models. Additionally, the recent analysis by Taylor et al. (2004) casts doubts on the alleged empirical superiority of the average price specification. Monetary values were deflated using the official provincial-wise retail price index. No single available series of the price-index would be long enough to cover the whole price series, so the published series with base 1983 was adapted to merge with the series with base 1992. The evolution of this series is shown in Figure 1

- VI_t (1992 EURO equivalents) is *virtual income.* It is the difference between the average salaries (W_t) and D_t, the instrument for the *Nordin-difference* (Nordin, 1976) variable. It is the intercept of the estimated linear function used to derive P and it can be included as part of the virtual income definition, since it only exerts an income effect caused by the nonlinearity of the tariff structure (Billings, 1982), so, theoretically, its coefficient would have the same magnitude and opposite sign as the one of income.[2] The average salaries series (from the *Instituto Nacional de Estadística*) is used to proxy for household income. It had originally a quarterly frequency, so it was linearly interpolated to get monthly values. The values for P_t and D_t were calculated using the tariff schedules applied in each period. The evolution of this series is shown in Figure 1

- $RAIN_t$ is the current level of precipitation. Unit: mm/month.

- $TEMP_t$ is the average of the daily maximum temperatures in Month t. Unit: °C/10

- RES_t (hours/day) refers to the number of daily hours of supply restrictions applied as part of the emergency control measures during the worst drought periods. The number of hours of restriction a day is weighted by the number of days in the month to which that number applied. This variable has been calculated directly from the relevant city council drought-emergency decrees (*EMASESA*, 1997).The evolution of this series is shown in Figure 1

- BAN_t is a binary variable with value 1 when temporary outdoor-use bans were applied during the drought.

[2]By lumping D together with income the theoretical prediction is imposed as a restriction. In practice the effect of this variable on its own would not be significant, since the water bill amounts to such a small proportion of Sevillan households' disposable income.

Table 3: Summary Statistics.

Variable	N	Min	Max	Mean	Std. Dev.
ABONS	108	109,082	201,385	148,310	27,671
POP	108	683,028	719,588	702,529	9684
Q	108	5.054	8.201	6.352	0.648
P	108	0.472	0.700	0.571	0.080
W	108	1128	1410	1235	71,379
D	108	0.522	1.413	0.999	0.369
RES	108	0	12.00	1.40	2.99
BAN	108	0	1	0.273	0.445
SUM	108	0	1	0.333	0.474
$TEMP$	108	152	385	255.259	68.965
RAIN	108	0	3105	421.926	605.559
INF	108	0	1	0.319	0.466

- INF_t is a binary variable with value 1 if water conservation information campaigns were being applied during the drought

- SUM_t is a binary variable with value 1 in May, June, July, and August

The evolution of the BAN, SUM, $TEMP$ and $RAIN$ series is shown in Figure 2. Summary statistics for all variables are provided in Table 3. Evolution of the outdoor-use bans (BAN), summer dummy (SUM), average maximum daily temperatures ($TEMP$) and monthly precipitation ($RAIN$) variables.

4 Econometric methods

The techniques of co-integration (see Engle and Granger, 1987) and error correction (see Hendry et al., 1984, among others) are used to investigate the dynamics of household water consumption and to measure the short-run and long-run effects of the price of water on household demand.

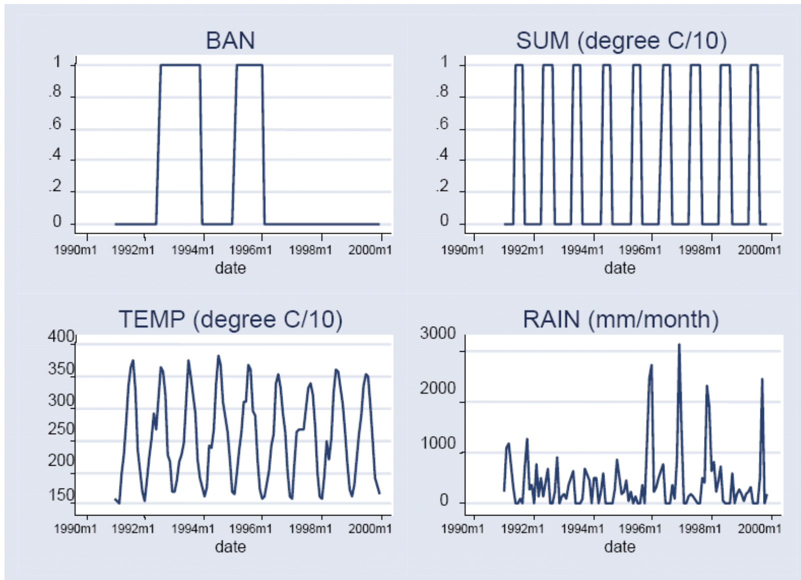

Figure 2: Evolution of the outdoor-use bans (BAN), summer dummy (SUM), average maximum daily temperatures ($TEMP$) and monthly precipitaion ($RAIN$) variables.

Let us consider the simple form of a dynamic model:

$$y_t = \mu + \gamma_1 y_{t-1} + \beta_0 x_t + \beta_1 x_{t-1} + \varepsilon_t, \quad t = 1, \ldots, T, \tag{1}$$

where y_t and x_t could represent respectively consumption and price at time t. The error term (ε_t) is assumed independently and identically distributed. We will assume in the following that x_t is a one-dimensional vector for ease of exposition. $\mu, \gamma_1, \beta_0, \beta_1$ are unknown parameters. In Model 1 the short-run and long-run effects of x on y are measured respectively by β_0 and $(\beta_0+\beta_1)/(1-\gamma_1)$. Re-arranging terms, we obtain the usual ECM:

$$\Delta y_t = \mu + \beta_0 \Delta x_t - (1-\gamma_1)(y_{t-1} - \theta x_{t-1}) + \varepsilon_t, \quad t = 1, \ldots, T, \tag{2}$$

where Δ represents the difference operator (e.g. $\Delta y_t = y_t - y_{t-1}$) and $\theta = (\beta_0+\beta_1)/(1-\gamma_1)$.

Thus, the estimation of the ECM gives directly a measure of the short-run and long-run effects of x on y through the estimates of β_0 and θ. The term $(y_{t-1} - \theta x_{t-1})$ in Model 2 can be seen as a *partial correction* for the extent to which y_{t-1} deviated from the equilibrium value corresponding to x_{t-1}. That is, this representation assumes that any short-run shock to y that pushes it off the long-run equilibrium growth rate will gradually be corrected, and an equilibrium rate will be restored. The expression $(y_{t-1} - \theta x_{t-1})$ is the *residual* of the long-run equilibrium relationship between x and y.[3] Therefore, this error correction term will be included in the model if there exists a long-run equilibrium relationship between x and y or, in other words, if both series are co-integrated in the sense of Granger (see Engle and Granger, 1987). If the series are co-integrated they will, in the long run, tend to grow at similar rates, because their data generating processes may be following the same stochastic trend, or may share an underlying common factor.

For any $0 < \gamma_1 < 1$, the absolute value of θ will exceed the absolute value of β_0 as long as β_0 and β_1 have the same sign. Under such likely conditions, the long-run adjustment to a change in the price of water will be weaker than the short-run adjustment. Although it would be a rare occurrence in practice, households might instead overreact in the short run to changes in prices. This effect has been observed in applications focusing on other commodities (Fouquet, 1995).

The econometric analysis will proceed in two steps. In the first step, we test if x and y are co-integrated series, by testing for the stationarity of the series. If the series are integrated of the same order, a co-integrating vector might be then found such that a linear combination of the non-stationary variables obtained with that vector is itself stationary. If this proves to be the case, the estimation of the Granger co-integration

[3] For this reason, it is commonly said that $(1-\gamma_1)$ provides a measure of the *speed of adjustment* towards the long run values.

relationship will give a measure of the long-run effect of x on y. In a second step, the co-integration residuals are used as an error correction term in the ECM above and the short-run effect and the speed of adjustment can be estimated.

4.1 Tests for order of integration

A time series is $I(i)$ (integrated of order i) if it becomes stationary after differencing it i-times. A non-stationary series can be represented by an autoregressive process of order p, so unit-root tests for a variable y_t usually rely on transformed equations of the form:

$$\Delta y_t = \mu + \lambda t + (\gamma - 1)y_{t-1} + \sum_{i=1}^{p-1} \gamma_j \Delta y_{t-i} + \varepsilon_t \tag{3}$$

This test, known as the Augmented Dickey Fuller, ADF, (Dickey and Fuller, 1981) allows for an $AR(p)$ process that may include a nonzero overall mean for the series and a trend variable (t). The inclusion of the term $\sum_{i=1}^{p-1} \gamma_j \Delta y_{t-i}$ simply allows for the consideration of a $p > 1$ in $AR(p)$. The special case where $p = 1$ corresponds to the Dickey-Fuller (DF) test. Its test statistics would be invalidated if the residuals of the reduced form equation

$$\Delta y_t = \mu + \lambda t + (\gamma - 1)y_{t-1} + \varepsilon_t$$

were autocorrelated.

To test the null hypothesis of nonstationarity, the t-statistic of the estimate of $(\gamma - 1)$ is compared with the corresponding critical values, calculated by Dickey and Fuller (1979 and 1981). A key consideration is how many lags of variable y to include in Equation 3 and whether to include a constant and a trend variable. The choice can be based on the $\overline{R}^2$, the Akaike Information Criterion (AIC), the Schwartz (1978) Bayesian Information Criterion, or the Schwert (1989) criterion. These criteria might lead to conflicting recommendations, so, for consistency, the sequential-t test proposed by Ng and Perron (1995) was used.

If the null of a unit root cannot be rejected, a second test is conducted to check whether the series are integrated of order one or more than one. The ADF test serves this purpose. It consists of testing for the null hypothesis of a unit root in the residual series of a regression in which the series has been differenced once. If the null of unit root is now rejected, the series is deemed $I(1)$ or integrated of order one.

4.1.1 Further unit root tests

In small samples, the most common Dickey-Fuller tests above can suffer from lack of power to reject the null hypothesis of non-stationarity (Baum, 2001; Eguía and Echevarría, 2004). Several complementary tests can be used that alleviate this problem. For example, the Dickey–Fuller Generalised Least Squares ($DFGLS$) approach proposed by Elliott, Rothenberg, and Stock (1996) is likely to be more robust than the first–generation tests (Baum, 2001).

An alternative to the DF-type of tests above is the $KPSS$ test (Kwiatkowski, Phillips, Schmidt and Shin, 1992),[4] which uses the perhaps more natural null hypothesis of stationarity rather than the DF style null hypothesis of I(1) or nonstationarity in levels. A $KPSS$ may be applied together with a DF-style test, hoping that their verdicts will be consistent.

Finally, DF-style tests potentially lead to confusing structural breaks with evidence of nonstationarity, while recent unit root tests allow for structural instability in an otherwise deterministic model (Perron, 1989, 1990; Banerjee et al., 1992; Perron and Vogelsang, 1992; Andrews and Zivot, 1992). It is therefore wise to conduct the latter when the

[4] Implemented as *kpss* for STATA by Baum (2000).

former do not reject the null of nonstationarity. For example, Andrews and Zivot (1992) propose a method that allows for a single structural break in the intercept and/or the trend of the series, as determined by a grid search over possible breakpoints. Contrary to the case of Perron (1990)'s test, *a priori* knowledge of the location of the break is not needed. Subsequently, the procedure conducts a DF style unit root test conditional on the series inclusive of the estimated optimal breaks. Clemente et al. (1998)'s tests allow for two events within the observed history of a time series. Following the taxonomy of structural breaks in Perron and Vogelsang (1992), either additive outliers (the AO model, which captures a sudden change in a series) or innovational outliers (the IO model, which allows for a gradual shift in the mean of the series) can be considered.

4.1.2 Seasonal unit root tests

The tests described above for the stationarity of the series are not sufficient when the data exhibit a seasonal character, since seasonal unit roots must be investigated. A number of seasonal unit root tests have been proposed for the case of monthly data (Franses, 1991; Beaulieu and Miron, 1993) as an extension to the one suggested by Hylleberg et al. (1990).

Seasonal unit root tests often exhibit poor power performance in small samples[5] and that the power deteriorates as the number of unit roots under examination increases. For example, in a simple test regression with no deterministic variables, the $HEGY$ (Hylleberg et al., 1990) test procedure in the quarterly context requires the estimation of four parameters, whereas in a monthly context this number increases to twelve. In addition, the algebra underlying monthly seasonal unit root tests is more involved than in the quarterly case and the associated computational burden non-negligible. To circumvent these problems, the analysis of seasonal unit roots draws on the results found by Rodrigues and

[5] Rodrigues and Osborn (1999) provide Monte Carlo evidence on the monthly seasonal unit root tests.

Franses (2003). These authors find out which unit roots affecting monthly data can also be detected by applying tests on quarterly data and, in particular, they show that 'with regard to the zero frequency unit root, there is a direct relationship between the monthly and quarterly root'. This means that the problem of non-stationarity of the series can be highly simplified by collapsing the monthly data into quarterly data (obtaining $N/3$ quarterly observations on all relevant variables by summing the monthly values or averaging them, depending on the nature of the variable) and then using the original $HEGY$ test. If all the null hypotheses of any type of seasonal roots can be rejected based on the quarterly test, the monthly series can be also deemed free of seasonal unit roots.

To test for a seasonal unit root in the $\{y_t, t = 1, \ldots, T\}$ series, HEGY propose to apply OLS on the following model:

$$y_t - y_{t-4} = \pi_0 + \pi_1 z_{1,t-1} + \pi_2 z_{2,t-1} + \pi_3 z_{3,t-2} + \pi_4 z_{3,t-1} + \varepsilon_t, \tag{4}$$

$$\begin{aligned} \text{where} \quad z_{1t} &= (1 + L + L^2 + L^3) y_t, \\ z_{2t} &= -(1 - L + L^2 - L^3) y_t, \\ z_{3t} &= -(1 - L^2) y_t, \end{aligned}$$

with L, the lag operator. To find that y_t has no unit root at all and is therefore stationary, we must establish that each of the $\pi_i (i = 1, \ldots 4)$ is different from zero. Moreover, we will reject the hypothesis of a seasonal unit root if π_2 and either π_3 or π_4 are different from zero, which therefore requires the rejection of both a test for π_2 and a joint test for π_3 and π_4. HEGY derive critical values for the tests corresponding to each of the following null hypothesis: $H_{01} : \pi_1 = 0$, $H_{02} : \pi_2 = 0$, $H_{03} : \pi_3 = 0$, $H_{04} : \pi_4 = 0$, $H_{03+04} : \pi_3 = 0$

and $\pi_4 = 0$. The tests statistics are based on *Student*-statistics (t-stat) for the first four tests and on a *Fisher*-statistic (F-stat) for the last one.

4.2 Co-integration

If these unit root tests suggest that the series are integrated of the same order, their long-run relationship is then investigated applying OLS on the simple model:

$$y_t = \theta x_t + \mu_t \tag{5}$$

Series x and y are said to be co-integrated if there exists a linear combination of those non-stationary series that is itself stationary. This means that their linear combination yields a stationary deviation (the residuals series ($\widehat{\varepsilon}_t$) is stationary). Following Engle and Granger (1987)'s approach, a unit root test[6] is applied whereby the resulting t-statistic is compared with the critical values provided by Engle and Yoo (1987).[7] The null hypothesis in this case is that of non-cointegration, so rejecting a unit root in the residuals in a DF type of test will constitute evidence of a co-integrating relationship among the variables.

If the series are proved to be co-integrated, $\hat{\theta}$ in Equation 5 provides a measure of the long-run effect of x on y. Therefore, the long-run estimates of the price-elasticities are calculated using the estimated coefficients of the price variables in this equation. Additionally $\hat{u}_t$ can be used as an error correction term in the ECM:

$$\triangle y_t = \mu + \beta_0 \triangle x_t - (1 - \gamma_1)\hat{u}_{t-1} + \varepsilon_t, \quad t = 1, \ldots, T, \tag{6}$$

[6]The ADF test applied in this instance does not contain neither a trend nor a constant term, since the OLS residuals will be mean zero with a constant included in the co-integration regression.

[7]The critical values calculated by Dickey and Fuller are not appropriate, since the t-statistic's distribution is affected by the number of variables in the co-integration regression (Engle and Yoo, 1987).

from which $\widehat{\beta}_0$ and $(1 - \hat{\gamma}_1)$ would represent estimates of the short-run effect and the speed of adjustment towards the long-run values respectively. Short-run price elasticities are then derived from the estimates of price variables in this model.

5 Results

5.1 Unit root tests

First, the order of integration of all relevant series was investigated, using a test of seasonal integration (see Section 4.1.2) and the ADF test 4.1. Table 4 summarizes the seasonal tests applied on the series collapsed into quarterly data. The non-rejection of H_{01}, together with the rejection of both H_{02} and the joint hypothesis H_{03+04}, suggests the presence of a unit root at the zero frequency and no seasonal unit roots. Since there is a correspondence between the quarterly and the monthly root at the zero frequency, not detecting seasonal unit roots at the quarterly level is enough to consider that the series is affected only by unit roots at the zero level and no testing at the monthly level is necessary. The table shows that the null of seasonal unit roots can be rejected for all series,[8] with the not very surprising exception of $TEMP$.

After detecting with the seasonal approach the presence of only unit roots at the zero frequency, the order of integration of the series was further tested using Dickey-Fuller-type tests. Two auxiliary DF regressions with and without a trend were used, and the optimal lag was chosen by an automatic sequential t-test. The results, shown in Table 5, reveal that the trend component is not relevant in most cases. Table 5 shows that most variables proved to be $I(1)$. The hypothesis tests permit the rejection of the null of non-stationarity of the differenced series at the 99% level of confidence. Once again, there are some doubts

[8] The test also permitted to reject the null hypothesis of seasonal unit roots in the INF series, although the estimates are not shown, since this variable is not used in most of the main final water demand models.

Table 4: Quarterly seasonal unit root test.

Variable	Test	HEGY model specification[(a)]							
		SEAS		TREND		STREND		CONST	
		t-stat[(b)]	Lags[(c)]	t-stat	Lags	t-stat	Lags	t-stat	Lags
Q	H_{01}	-1.947	8	-2.379	0	-1.199	8	-2.929*	0
	H_{02}	-3.998**		-3.684**		-3.867**		-3.848**	
	H_{03+04}	17.857**		6.176**		16.407**		6.485**	
P	H_{01}	-0.033	1,4,5	-1.136	0	-1.528	0	-1.108	0
	H_{02}	-4.116**		-2.708**		-2.795*		-2.708**	
	H_{03+04}	12.143**		11.666		13.407**		11.701**	
P^2	H_{01}	0.044	1,4,5	-1.237	0	-4.016**	4	-1.124	0
	H_{02}	-4.455**		-2.750**		-3.475**		-2.743**	
	H_{03+04}	14.219**		12.233**		20.187**		12.194**	
VI	H_{01}	1.181	0	-0.787	1	0.311	0	-0.791	1,5
	H_{02}	-3.172**		-0.418		-3.051		-0.829	
	H_{03+04}	6.711**		0.332		6.604		0.744	
RES	H_{01}	-2.970*	6	-2.643	3,5,7	-3.549*	0	-2.732*	5,6
	H_{02}	-3.177**		-4.419**		-4.299**		-3.291**	
	H_{03+04}	15.982**		2.785*		7.027**		13.050**	
$TEMP$	H_{01}	-2.419	0	-3.401*	2,3,8	-2.399	0	-3.800**	2,3,6,7,8
	H_{02}	-2.133		-1.281		-2.111		-1.057	
	H_{03+04}	8.117**		0.040		7.850**		0.280	
$RAIN$	H_{01}	-2.062	4	-1.888	0	-2.775	2,4,8	-1.779	0
	H_{02}	-1.674*		-1.674*		-3.193**		-1.677*	
	H_{03+04}	2.437*		2.437*		7.753**		2.400*	

(a) Test specifications: SEAS (Seasonal dummies + constant) TREND (Constant + trend) STREND (Seasonal dummies + constant + trend) CONST (constant only)

(b) HEGY estimates, ** and * denote a t-ratio significant at the 5% and 10%

(c) lag length and lags of the fourth difference of the time-series to be included in the auxiliary regression

Table 5: Augmented Dickey-Fuller unit root tests.

Variable	No trend			With trend			
	t-stat$^{(a)}$	Lags$^{(b)}$	B-stat$^{(c)}$	t-stat	Lags	B-stat	Trend t-ratio
Q	-2.527	4	0.64	-2.922	4	0.64	-2.00***, 2.01$^{***(d)}$
ΔQ	-6.276***	5	0.73	-6.966***	8	1.00	2.48**
P	-1.165	0	0.26	-1.888**	0	0.26	1.50
ΔP	-3.801***	7	0.22	-10.550***	0	0.25	-0.26
P^2	-1.202	0	0.23	-1.847	0	0.27	1.42
ΔP^2	-10.569***	0	0.23	-10.525***	0	0.23	-0.28
VI	0.333	8	1.47**	-3.970**	8	1.46**	-4.15***, 4.18$^{***(d)}$
ΔVI	-12.709***	8	1.29*	-13.800***	8	1.07	3.35***
RES	-2.547	1	0.99	-3.369*	2	0.47	-1.23
ΔRES	-5.472***	1	0.48	-5.454***	1	0.48	-0.28
$TEMP$	-8.921***	8	1.45**	-9.016***	8	1.44**	1.17
$\Delta TEMP$	-12.192 ***	8	1.43**	-12.041***	8	1.43**	-0.22
$RAIN$	-6.849***	0	0.89	-5.100 ***	4	0.37	0.43
$\Delta RAIN$	-5.946***	0	1.13	-12.273***	0	1.14	0.09

(a) t-ratio of estimates *** ,** and * denote a t-ratio significant at the 1%, 5% and 10%

(b) The number of lags (with a maximum of 8) to be included was selected using the Ng-Perron sequential-t test

(c) Bartlett's (B) statistic of a cumulative periodogram white-noise test (H0: error is white noise)

(d) This series exhibited a quadratic trend rather than a linear trend.

about the climate variables. $TEMP$ appears to be stationary, but the seasonal unit root tests did not reject the hypothesis of seasonal roots, so this variable should be considered with caution, since it might be $I(0,1)$. In the case of $RAIN$, we also see that the series might actually be stationary in levels also at all frequencies, $I(0)$. Since a definite claim cannot be made that the climatic variables are nonstationary, their introduction in the co-integration relationship and error-correction model cannot be understood in the same way as the remaining variables. For this reason, an alternative model that accounts for seasonality using only the binary variable SUM is also reported.[9]

The augmentation of the basic DF regression with extra lags (in Section 4.1) was

[9] A model (not reported but available upon request) based on a co-integration equation that did not include neither SUM nor the climatic variables ($TEMP$ and $RAIN$) resulted in very similar price elasticities (see Section 5.5) but slightly worse fit than the models that include seasonal variables. This, of course, confirms the intuition that the seasonal variables do not substantially affect the long-run dynamics of the water demand.

motivated by the need to generate iid errors. The number of lags was selected using an Ng-Perron (1995) sequential-t test. A maximum of 8 lags was considered, given the small sample size. A cumulative periodogram white-noise test was used to check that the error was white noise in the unit root test regressions.[10] An alternative solution is the Phillips and Perron (1988) test (PP), which uses the same models as DF but, instead of lagged variables, employs a non-parametric correction (Newey and West, 1987) for serial correlation. The critical values for both the Dickey Fuller and Phillips Perron tests have the same distributions (critical levels are reproduced in Hamilton, 1994). In principle, the PP tests should be more powerful than the ADF ones, so the unit root tests were conducted using both. The results of the PP test are not reported, but available upon request.

5.2 Further unit root tests

As described in Section 4.1.1, the conclusions of the Dickey-Fuller type tests can be suspect in small samples and when the possibility of structural breaks has to be considered. A $DFGLS$ (ERS) test was used to confirm the nonstationarity of the main series in the model. Since it is more powerful than the basic Dickey Fuller tests, this test will more easily reject the null of nonstationarity. A $KPSS$ test was also conducted to test the alternative hypothesis of stationarity of the series. The results of both types of tests, in Table 6, show no relevant differences with respect to those described in Section 5.1.

Similarly, structural breaks in the model's series could affect the conclusions of the unit root tests, above all because of the effects of the drought and the conservation measures adopted by the water utility. For this reason the Clemente et al. (1998)'s tests, which

[10] In the case of $TEMP$ and VI there were some doubts about whether the error had been whitened. However, we do not suspect that this results in a bias of the unit root tests coefficients substantial enough to affect their conclusions.

Table 6: DFGLS and KPSS unit root tests.

	DFGLS (no trend)		DFGLS (trend)		KPSS (no trend)		KPSS (trend)	
	t-stat	Lags	t-stat	Lags	t-stat	Lags	t-stat	Lags
Q	-2.511**	6	-2.565	6	0.620**	3	0.427***	3
ΔQ	-2.082**	4	-5.287***	3	0.045	3	0.038	3
P	-0.559	1	-1.737	1	2.320***	3	0.274***	3
ΔP	-7.234***	1	-7.297***	1	0.106	3	0.099	3
P^2	-0.619	1	-1.715	1	2.250***	3	0.270***	3
ΔP^2	-7.210***	1	-7.260***	1	0.107	3	0.099	3
VI	1.151	8	-1.612	8	0.630**	3	0.209**	3
ΔVI	-12.183***	8	-12.269***	8	0.035	3	0.028	3
RES	-2.932***	6	-3.134***	6	0.387*	3	0.129*	3
ΔRES	-4.303***	7	-4.317***	7	0.049	3	0.038	3
TEMP	-0.938	8	-2.594	7	0.019	3	0.014	3
ΔTEMP	-7.190***	8	-8.960***	8	0.339	3	0.016	3
RAIN	-6.253***	1	-6.548***	1	0.111	3	0.059	3
ΔRAIN	-0.963	6	-2.554	5	0.020	3	0.018	3

allow for either one ($CLEMAO1$ and $CLEMIO1$) or two ($CLEMAO2$ and $CLEMIO2$) structural breaks in the time series,[11] were used to obtain further confirmation of the nonstationarity of the main series considered. The results (Tables 7 and 8) confirm that most series exhibit evidence of structural breaks. However, even when these are considered, there is not enough evidence to reject the null of nonstationarity.[12]

Since the additional unit root testing supports the notion that, with the exception of the climatic variables, the series used in the demand model are nonstationary, the next step is to analyze the co-integrating relationships among those variables.

5.3 Co-integration regression analysis

All the series in first-differences are stationary, so the next step is to check that there is a long-run equilibrium relationship between the variables. This requires an extension of the

[11] These were implemented in Stata using *clemao*2 and *clemio*2, respectively (Baum, 2005).

[12] Although the case of nonstationarity for the Q series is less clear now that what the tests in Section 5.1 suggested.

Table 7: CLEMAO1 and CLEMIO1 unit root tests.

	CLEMAO1			CLEMIO1		
Variable	t-stat$_{d_1}$	t-stat$_{\rho-1}$	Lags	t-stat$_{d_1}$	t-stat$_{\rho-1}$	Lags
Q	-8.345***	-1.407	8	-4.274	-5.579**	3
ΔQ	-1.008	-6.447**	3	1.790*	-6.767	8
P	26.786***	-2.121	2	5.236***	-5.376**	0
ΔP	0.411	-12.216**	1	-0.763	-17.668**	0
P2	25.907***	-1.993	2	5.215***	-5.364**	0
ΔP^2	0.420	-12.094**	1	-0.738	-17.508**	0
VI	5.789***	-3.499	6	2.567**	-2.028	8
ΔVI	-0.839	-10.819**	8	-0.577	-12.731**	8
RES	-2.979	-3.137	6	-2.074**	-3.852	2
ΔRES	-0.970	-3.469	7	-0.326	-9.861**	0
TEMP	0.786	-7.373**	8	1.193	-7.874**	8
ΔTEMP	-0.838	-9.729**	8	0.628	-11.562**	8
RAIN	2.061**	-7.822**	1	-0.006	-7.836**	0
ΔRAIN	0.034	-9.308**	2	-0.421	-6.650**	8

Table 8: CLEMAO2 and CLEMIO2 unit root tests.

	CLEMAO2				CLEMIO2			
Variable	t-stat$_{d_1}$	t-stat$_{d_2}$	t-stat$_{\rho-1}$	Lags	t-stat$_{d_1}$	t-stat$_{d_2}$	t-stat$_{\rho-1}$	Lags
Q	-10.349***	4.274***	-5.726**	9	-4.296***	4.333***	-5.412	9
ΔQ	-2.155**	2.192**	-5.425	10	-3.052***	4.750***	-7.620**	10
P	26.019***	-4.053***	-2.571	2	8.298 ***	-5.808***	-8.080**	8
ΔP	1.557	-2.037**	-14.196**	1	0.375	-0.805	-21.296**	8
P^2	26.141***	-4.707***	-2.576	2	9.130***	-6.744***	-8.900**	0
ΔP^2	1.617	-2.124**	-14.744	1	0.530	-0.924	-22.293**	0
VI	-1.193	5.886	-5.121	7	-1.651	3.344***	-2.231	8
ΔVI	-1.248	0.135	-12.335**	8	-2.349**	2.782***	-13.851**	8
RES	10.478***	-11.215***	-2.933	5	5.257***	-5.872***	-5.150	0
ΔRES	-2.072**	0.212	-3.355	8	-1.528	-0.067	-11.981	0
TEMP	0.621	0.184	-7.019**	8	0.791	0.880	-8.104**	8
ΔTEMP	-0.969	0.621	-9.698**	8	0.567	-0.201	-11.324**	8
RAIN	1.909*	-0.863	-8.616	8	-0.438	0.581	-8.846**	0
ΔRAIN	0.169	-0.189	-9.684	2	-1.650	1.236	-8.637**	4

linear relationship between water consumption and a series of variables that the economic theory suggests appropriate. The model given by Equation (5) was extended into two alternative models (time subscripts have been dropped to simplify the exposition):

$$Q = \alpha + P + P^2 + RES + VI + BAN + SUM + \mu \tag{7}$$

including the binary variable SUM instead of the climatic variables (see Section 3) and:

$$Q = \alpha' + P + P^2 + RES + VI + BAN + TEMP + RAIN + \mu' \tag{8}$$

Table 9 shows the OLS estimated coefficients of each of the variables and their t-statistics in these estimations. The ADF test shows that the hypothesis that the residuals in Model 7 are non-stationary can be rejected. The relevant t-ratio is -5.625[13] in the usual test of a unit root and must be compared with the critical values provided by Engle and Yoo (1987), which depend on the dimension of the time-series and on the number of variables included in the model. The DW statistic is also higher than the R^2, which suggests the existence of the co-integration relationship.[14] The long run price-elasticity calculated at the means of price and quantity according to Model 7 is -0.491. All the variables present the expected signs and are highly significant.

The ADF test shows that the hypothesis that the residuals in Model 8 are non-stationary can be rejected too. The relevant t-ratio is -5.364[15]. The DW statistic is again

[13] This value permits the rejection of the null of no co-integration at a 99% confidence level, but it is achieved when the auxiliary regression includes no lags. Five lags are selected by Ng Perron's sequential t-ratio and the Akaike Information Criterion test, yielding a t-statistic of -3.053 and one lag is selected by the Hannan-Quinn (1979) criterion, yielding a t-statistic of -3.804.

[14] An alternative co-integrating regression test (Sargan and Bhargava, 1983) uses the DW statistic from the co-integrating regression. If the residuals are non-stationary, the DW statistic will approach zero as the sample size increases, so large values of the DW statistic suggest that a cointegrating relationship exists.

[15] This value permits the rejection of the null of no co-integration at a 99% confidence level, but it is achieved when the auxiliary regression includes no lags. If the auxiliary regression is run with the optimal

Table 9: Cointegration Models 7 and 8 and Error Correction equations ECM7 and ECM8.

Variable	Model 7	ECM7	Model 8	ECM8
P	-78.629***		-76.950***	
P^2	64.070***		62.569***	
RES	-0.066**		-0.067**	
VI	0.003***		0.002***	
BAN	-0.451**		-0.473**	
SUM	0.317***			
$RAIN$			0.000	
$TEMP$			0.002***	
ΔP_t		-37.437		-32.609
$\widehat{\varepsilon}_{t-1}$		-0.218*		-0.249**
ΔP_t^2		31.264		27.572
ΔRES_t		-0.076**		-0.098***
ΔSUM_t		0.317***		
ΔP_{t-1}		-71.006***		-79.555***
ΔP_{t-1}^2		54.729**		61.881***
ΔQ_{t-1}		-0.273**		-0.276**
$\Delta TEMP_t$				0.004***
$\Delta RAIN_t$				0.000
$cons$	26.489***	0.019	26.197***	0.019
ll	-47.07	-7.233	-50.1	-3.197
N	108	106	108	106
$\overline{R}^2$	0.644	0.386	0.619	0.425
Durbin-Watson	0.919		0.856	
Jarque-Bera ($\kappa(2) =$)		2.044		2.059
ARCH-LM, order(1) ($\kappa^2(1)$)		2.913*		0.001
Breusch-Godfrey LM ($\kappa^2(1)$)		16.917***		1.876
White's general test ($\kappa^2(1)(44)$)		44.025		75.721**
Cook-Weisberg ($\kappa^2(1)$)		3.26*		0.78

higher than the R^2. The corresponding long run price-elasticity according to Model 8 is -0.494, basically the same as the one obtained with Model 7. Once again, all variables have the expected signs and are highly significant. The exception is $RAIN$, which presents a positive sign, while we would normally expect more precipitation to reduce water use. However, it cannot be rejected that its coefficient is null. According to the ADF tests, the null of no co-integration can only be rejected if the lag length of the auxiliary regression is not optimally chosen. However, the value of the DW test and economic intuition suggest that a long-run relationship would govern the variables concerned.

Since there are more than two nonstationary series involved in the model, there could exist more than one co-integrating relationship. For this reason and in order to obtain more definite evidence on the existence of a co-integrating regression, the Johansen and Juselius maximum likelihood method for co-integration (see Johansen, 1988; Johansen and Juselius, 1990; and Osterwald-Lenum, 1992, for details) was used to determine the number of co-integrating relationships. The summarized results are shown in Tables 10 and 11. The eigenvalues and the maximal eigenvalue and trace statistics for the VAR matrix are shown as well as the relevant critical values. The null hypothesis of more than one co-integrating relationship was rejected at the 1% level of significance in all cases, except in the case of the trace test for Model 7, which rejects the null of no-cointegration only at about the 15%. Likelihood-ratio and Wald test statistics for the exclusion of variables from that co-integrating relationship were also conducted, and all variables included in the co-integration tests were found relevant. Therefore, the Johansen tests support the assumption of co-integration for both models.

number of lags (three) the t-ratio is -4.192.

Table 10: Model 7 Johansen-Juselius co-integration rank test.

		H1:	
Eigenvalues (lambda)	H0: rank<=(r) r	Max-lambda statistics (rank<=(r+1))	Trace statistics (rank<=(p=7))
.40067781	0	54.779285	115.46473
.2222569	1	26.895414	60.685446
.16540982	2	19.347149	33.790032
Osterwald-Lenum Critical values (99% interval):			
Table/Case: 1* (assumption: intercept in co-integrating Equation)			
	H0:	Max-lambda	Trace
	0	51.91	143.09
	1	46.82	111.01
	2	39.79	84.45
Table/Case: 1 (assumption: intercept in VAR)			
	H0:	Max-lambda	Trace
	0	51.57	133.57
	1	45.10	103.18
	2	38.77	76.07
Sample: 1 to 108	N= 107		

5.4 Error correction models

Since most of the evidence points towards the stationarity of the residuals of the co-integrating regressions, their residuals can be introduced as error correction terms in two error correction models. The x_t variables in Equation 6 are substituted by first differences and lagged differences[16] of the co-integrating variables. The first error correction specification, $ECM7$ includes a *summer* variable, whereas the second model, $ECM8$ includes $TEMP$ and $RAIN$ (although $TEMP$ might suffer problems of seasonal unit roots and it is dubious that $TEMP$ and $RAIN$ are nonstationary, so this second model should be considered with caution). Table 9 reports the results of these OLS estimations. These include lagged values of the differences of some variables. VI was left out of the ECM

[16] The significance of lagged values was also tested.

Table 11: Model 8 Johansen-Juselius co-integration rank test.

Eigenvalues (lambda)	H0: rank<=(r) r	H1: Max-lambda statistics (rank<=(r+1))	Trace statistics (rank<=(p=8))
.58686628	0	94.586283	185.98108
.2725507	1	34.048574	91.394798
.23272295	2	28.345084	57.346224
Osterwald-Lenum Critical values (99% interval):			
Table/Case: 1* (assumption: intercept in co-integrating Equation)			
	H0:	Max-lambda	Trace
	0	57.95	177.20
	1	51.91	143.09
	2	46.82	111.01
Table/Case: 1 (assumption: intercept in VAR)			
	H0:	Max-lambda	Trace
	0	57.69	168.36
	1	51.57	133.57
	2	45.10	103.18
Sample: 1 to 108	N= 107		

models, since it showed problems of multicollinearity with the price variables and its introduction made them non-significant. It is reasonable to assume that changes in income tend to affect water use only in the long run, most likely through impacts on the composition of the capital stock. BAN was found non-significant too and it was removed from the ECM regressions. The speed of adjustment towards equilibrium ($\widehat{\varepsilon}_{t-1}$ in Table 9, corresponding to $(y_{t-1} - \theta x_{t-1})$ in the notation used in Equation 2) is given by -0.218 in $ECM7$ and -0.249 in $ECM8$. It can be seen that these error correction terms have the expected negative sign and are both significant, which further supports the acceptance of the co-integration hypothesis.

The Ramsey RESET-test (using powers of the fitted values of ΔQ_t) shows that the null hypothesis that Models $ECM7$ and $ECM8$ have no omitted variables cannot be rejected. Table 9 includes a battery of diagnostic tests used to check that the residuals are normally distributed and are neither autocorrelated nor heteroskedastic in the error correction equations. These include a Jarque-Bera (1980) test for normality of the residuals; White's (1980) general test statistic and Cook-Weisberg (1983) test,[17] which uses fitted values of ΔQ_t, for heteroskedasticity; a Lagrange multiplier test for autoregressive conditional heteroskedasticity (ARCH), based on Engle (1982); and a Breusch (1978)-Godfrey (1978) LM test. They all present acceptable values, with the exception of the Breusch-Godfrey LM test, which leads to the rejection of the null of non-autocorrelation in $ECM7$. An alternative model with extra lagged values of the price variables solves this problem and yields a short-run elasticity of -0.073, as reported below. The results of this additional augmented regression do not differ significantly from the ones reported and are available upon request.

5.5 Price elasticities

The computation of short-run price elasticities (e_{SR}) using the average price and water consumption, yields the following results. Using $ECM7$ and the co-integration regression in Model 7, $e_{SR} = -0.159$ (while the augmented model used to correct for autocorrelation would yield $e_{SR} = -0.073$) and the $e_{LR} = -0.494$. Similarly, $ECM7$ and Model 7 yield $e_{SR} = -0.101$ and $e_{LR} = -0.491$.[18]

These estimates of price-elasticities confirm that residential water demand is inelastic to its price, but not perfectly so. Almost all the papers published on residential water demand agree on this result. Additionally these results confirm the intuition that long-run elasticities are higher (in absolute values) than short-run ones (Dandy, et al., 1997; Nauges and Thomas, 2003; Martínez-Espiñeira and Nauges, 2004) and also than most of

[17] Also known as Breusch-Pagan (1979) test for heteroskedasticity.

[18] A model based on a co-integration equation that did not include neither SUM nor the climatic variables ($TEMP$ and $RAIN$) yielded $e_{SR} = -0.136$ and $e_{LR} = -0.491$.

the measures that have been obtained in other European countries.[19] The use of the co-integration approach to model the demand for water yields rather sensible results and helps to distinguish between the short-run effects and the long-run effects of pricing policies.

5.6 Wickens-Breusch one-step approach

The Engle-Granger procedure described above enjoys important attractive asymptotic properties but it also suffers weaknesses. In finite samples, the parameter estimates are biased. The extent of this bias can be severe, and will depend on omitted dynamics and failure of the assumption of weak exogeneity among other things. The reasonable size of the sample and the fact that the estimates agree with economic theory and previous empirical research based on alternative econometric techniques suggest in principle that this might be a minor problem in this case. Another problem, however, is that there is no possibility to test the long run parameters.[20] For these reasons, an additional regression was run using the one-step Wickens-Breusch (1988) approach. The results are reported in Table 12. The associated price-elasticities, calculated at the means of price and quantity are $e_{SR} = -0.08$ and $e_{LR} = -0.405$ in the model that uses SUM and $e_{SR} = -0.113$ and $e_{LR} = -0.514$ in the model that uses $TEMP$ and $RAIN$. The estimates are very close to the ones calculated with the Engle-Granger approach, which suggests that they can be accepted with more confidence. They also fall reasonably close to the values previously obtained using alternative econometric techniques on data from the same city. García-Valiñas (2002) estimated a price-elasticity of -0.25 for the first block of consumption and -0.77 for the second block, while García-Valiñas (2005) estimated the price-elasticity as

[19] See Arbués et al. (2003) for a review of water demand studies with a special focus on European cases.

[20] The limiting distributions of the β parameters are non-normal and non-standard. Standard hypothesis testing is invalid as t and F statistics do not have t or F distributions in the context of the co-integrating regression.

-0.49. Martínez-Espiñeira and Nauges (2004) found also that the short-run elasticity fell around the value of -0.10, using a Stone-Geary demand specification.

Note that these values of price-elasticities compare well to those obtained in other European areas, but are smaller than most values obtained in North America (see Arbués et al., 2003 or Dalhuisen et al, 2003). In particular, studies based on discrete-continuous choice models of water demand (Hewitt and Hanemann, 1995; Pint, 1999) obtain much larger price elasticity estimates.[21] This likely has to do with the fact that in Seville the largest component of residential water use is associated with indoor water use, while, contrary to many areas in the US, outdoor use is minimal. This confirms the notion that price elasticities may be very different depending on the area of study, so policies should be informed by studies based on at least similar areas.

6 Conclusions and suggestions for further research

This study is innovative in two aspects. This is the first time that co-integration and error correction techniques are employed in the field of water consumption. Moreover, the estimation of residential water demand using time-series monthly data is still rather uncommon in Europe. The application of these techniques to monthly data to the case of Seville leads to satisfactory results. The fit of the Granger co-integration relationship between water use and the variables that should be expected to influence it in the long run and of the error correction models is quite good. The dynamic properties of the series were analyzed using different approaches and two alternative specifications for the water demand functions were used. However, the results in terms of price elasticities, most of all in the short run, are remarkably close. This robustness to specification and testing

[21] However, note that Cavanagh et al. (2002) found smaller elasticities using a similar methodology for different geographical areas.

Table 12: Wickens-Breusch one-step cointegration regressions, Models 7 and 8 (dependent variable: ΔQ_{t-1}).

	Model 7	Model 8
P_{t-1}	-14.826	-12.811
Q_{t-1}	-0.197**	-0.219***
P_{t-1}^2	12.205	10.122
ΔQ_{t-2}	0.226**	
BAN_{t-1}	-0.186*	-0.286***
ΔP_{t-1}	-4.904**	-6.274**
ΔSUM_t	0.236**	
ΔSUM_{t-1}	-0.228**	
ΔRES_t	-0.054*	-0.071**
ΔP_{t-2}	68.637***	
ΔP_{t-2}^2	-53.915**	
SUM_{t-1}	0.121	
ΔQ_{t-2}		-0.417***
$\Delta TEMP_{t-2}$		0.004***
$RAIN_{t-1}$		0.000**
ΔINF_{t-1}		-0.558*
$\Delta RAIN_t$		0
ΔBAN_t		0.363
$CONS$	5.664*	5.354
$\overline{R}^2$	0.4553	0.4207
N	105	106
F	8.25***	7.35***
RESET	0.55	1.75
Jarque-Bera normality test ($\kappa(2)$)	21.49***	5.669*
ARCH-LM test statistic ($\kappa^2(1)$)	3.154	0.0265371
Breusch-Godfrey LM-statistic ($\kappa^2(1)$)	8856157	1.717
White's general test statistic ($\kappa^2(1)(44)$)	101.277*	89.592*
Cook-Weisberg test ($\kappa^2(1)$)	0.75	1.95

procedures leads to confidently accept the main results.

The estimates of the price effects obtained are less than one in absolute value, which confirms the inelasticity of household demand with respect to the price of water. As predicted by the theory, the long-run price elasticities are greater, in absolute value, than their short-run counterparts.

The measure of the impact of pricing policies on the behavior of households depending on the changes that these policies introduce in the tariff structure is still an open research area. The long-run effects of water pricing on water use should be investigated using other datasets, involving different regions, and, if possible, longer time-series or panel data. Ideally, studies should be conducted at the individual level, with observations linked to the ownership and frequency of renewal of capital stock.

References

Agthe, D. E. and R. B. Billings (1980). Dynamic models of residential water demand. *Water Resources Research 16*(3), 476–480.

Agthe, D. E., R. B. Billings, J. L. Dobra, and K. Rafiee (1986). A simultaneous equation demand model for block rates. *Water Resources Research 22*(1), 1–4.

Andrews, D. and E. Zivot (1992). Further evidence on the Great Crash, the Oil Price shock, and the unit-root hypothesis. *Journal of Business and Economic Statistics 10*, 251–270.

Arbués, F., M. A. García-Valiñas, and R. Martínez-Espiñeira (2003). Estimation of residential water demand: A state of the art review. *Journal of Socio-Economics 32*(1), 81–102.

Banerjee, A., R. Lumsdaine, and J. H. Stock (1992). Recursive and sequential tests of the unit-root and trend-break hypotheses: Theory and international evidence. *Journal of Business and Economic Statistics 10*(3), 271–287.

Baum, C. (2000). Tests for stationarity of a time series. *Stata Technical Bulletin 57*, sts15.

Baum, C. F. (2001). The language of choice for time series analysis? *The Stata Journal 1*(1), 1–16.

Baum, C. F. (2005). CLEMAO_IO: Stata module to perform unit root tests with one or two structural breaks. Statistical Software Components S444302, Boston College Department of Economics, revised 17 Jun 2005.

Beaulieu, J. J. and J. A. Miron (1993). Seasonal unit roots in aggregate U.S. data. *Journal of Econometrics 55*(1), 305–328.

Beenstock, M., E. Goldin, and D. Nabot (1999). The demand for electricity in Israel. *Energy Economics 21*(2), 168–183.

Bentzen, J. (1994). Empirical analysis of gasoline demand in Denmark using cointegration techniques. *Journal of Energy Economics 16*(2), 139–143.

Billings, R. B. (1982). Specification of block rate price variables in demand models. *Land Economics 58*(3), 386–393.

Breusch, T. S. (1978). Testing for autocorrelation in dynamic linear models. *Australian Economic Papers 17*, 334–355.

Breusch, T. V. and A. R. Pagan (1979). A simple test for heteroskedasticity and random coefficient variation. *Econometrica 47*(5), 1287–1294.

Cavanagh, S. M., W. M. Hanemann, and R. N. Stavins (2002). Muffled price signals:

Household water demand under increasing-block prices. FEEM Working Paper No. 40.2002.

Chicoine, D. L. and G. Ramamurthy (1986). Evidence on the specification of price in the study of domestic water demand. *Land Economics 62*(1), 26–32.

Clemente, J., A. Montañés, and M. Reyes (1998). Testing for a unit root in variables with a double change in the mean. *Economics Letters 59*, 175–182.

Cook, R. D. and S. Weisberg (1983). Diagnostics for heteroscedasticity in regression. *Biometrika 70*(1), 1–10.

Dalhuisen, J. M., R. Florax, H. L. F. de Groot, and P. Nijkamp (2003). Price and income elasticities of residential water demand: Why empirical estimates differ. *Land Economics 79*(2), 292–308.

Dandy, G., T. Nguyen, and C. Davies (1997). Estimating residential water demand in the presence of free allowances. *Land Economics 73*(1), 125–139.

Dickey, D. A. and W. A. Fuller (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association 74*(366), 427–431.

Dickey, D. A. and W. A. Fuller (1981). Likelihood ratio statistics for autoregressive processes. *Econometrica 49*(4), 1057–1072.

Eguía, B. and C. Echevarría (2004). Unemployment rates and population changes in Spain. *Journal of Applied Economics VII*(1), 47–76.

Elliott, G., T. J. Rothenberg, and J. H. Stock (1996). Efficient tests for an autoregressive unit root. *Econometrica 64*, 813–836.

Eltony, M. N. and N. H. Al-Mutairi (1995). Demand for gasoline in Kuwait. an empirical analysis using cointegration techniques. *Energy Economics 17*(3), 249–253.

EMASESA (1997). *Crónica de una Sequía*. Sevilla: EMASESA.

EMASESA (2000). Water demand management: The perspective of EMASESA. Technical report, EMASESA.

Engle, R. (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. *Econometrica 50*(4), 987–1007.

Engle, R. and C. W. J. Granger (1987). Cointegration and error correction: Representation, estimation and testing. *Econometrica 55*(2), 251–76.

Engle, R. F., C. W. J. Granger, and J. S. Hallman (1989). Merging short and long run forecasts: An application of seasonal cointegration to monthly electricity sales forecasting. *Journal of Econometrics 40*(1), 45–62.

Engle, R. F. and B. S. Yoo (1987). Forecasting and testing in co-integrated systems. *Journal of Econometrics 35*(1), 143–159.

Fouquet, R. (1995). The impact of VAT introduction on UK residential energy demand. An investigation using the cointegration approach. *Energy Economics 17*(3), 237–247.

Franses, P. (1991). Seasonality, nonstationarity and forecasting of monthly time series. *International Journal of Forecasting 7*, 199–208.

García-Valiñas, M. Á. (2002). Residential water demand: The impact of management procedures during shortage periods. *Water Intelligence Online 1*(May).

García-Valiñas, M. A. (2005). Efficiency and equity in natural resources pricing: A proposal for urban water distribution services. *Environmental and Resource Economics 32*(2), 183 – 204.

Godfrey, L. G. (1978). Testing against general autoregressive and moving average error models when the regressors include lagged dependent variables. *Econometrica 46*(6), 1293–1301.

Hamilton, J. D. (1994). *Time Series Analysis*. Princeton NJ: Princeton University Press.

Hannan, E. and B. G. Quinn (1979). The determination of the order of an autoregression. *Journal of the Royal Statistical Society Series B 41*(2), 190–95.

Hansen, L. G. (1996). Water and energy price impacts on residential water demand in Copenhagen. *Land Economics 72*(1), 66–79.

Hendry, D. F., A. R. Pagan, and J. D. Sargan (1984). Dynamic specification. In Z. Griliches and M. D. Intrilligator (Eds.), *Handbook of Econometrics*, Volume III. Amsterdam: North-Holland.

Hewitt, J. A. and W. M. Hanemann (1995). A discrete/continuous choice approach to residential water demand under block rate pricing. *Land Economics 71*(2), 173–192.

Höglund, L. (1999). Household demand for water in Sweden with implications of a potential tax on water use. *Water Resources Research 35*(12), 3853–3863.

Hylleberg, S., R. F. Engle, C. W. J. Granger, and B. S. Yoo (1990). Seasonal integration and cointegration. *Journal of Econometrics 44*(1), 215–238.

Jarque, C. M. and A. K. Bera (1980). Efficient tests for normality, homoskedasticity, and serial independence of regression residuals. *Economics Letters 6*, 255–259.

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control 12*, 231–254.

Johansen, S. and K. Juselius (1990). Maximum likelihood estimation and inference on cointegration - with applications to the demand for money. *Oxford Bulletin of*

Economics and Statistics 52, 169–210.

Lyman, R. A. (1992). Peak and off-peak residential water demand. *Water Resources Research 28*(9), 2159–67.

Martínez-Espiñeira, R. (2002). Residential water demand in the Northwest of Spain. *Environmental and Resource Economics 21*(2), 161–187.

Martínez-Espiñeira, R. and C. Nauges (2004). Is really all domestic water consumption sensitive to price control? *Applied Economics 36*(15), 1697–1703.

Moncur, J. (1987). Urban water pricing and drought management. *Water Resources Research 23*(3), 393–398.

Nauges, C. and A. Thomas (2000). Privately-operated water utilities, municipal price negotiation, and estimation of residential water demand: The case of France. *Land Economics 76*(1), 68–85.

Nauges, C. and A. Thomas (2001). Dynamique de la consommation d'Eau potable des ménages: Une étude sur un panel de communes françaises. *Economie et Prevision 143-144*, 175–184. Numéro spécial: 'Economie de l'Environnement et des Resources Naturelles'.

Nauges, C. and A. Thomas (2003). Long-run study of residential water consumption. *Environmental and Resource Economics 26*(1), 25–43.

Newey, W. K. and K. D. West (1987). A simple positive semi-definite heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica 55*(3), 1029–1054.

Ng, S. and P. Perron (1995). Unit root tests in ARMA models with data-dependent methods for the selection of the truncation lag. *Journal of the American Statistical Association 90*(268-81), 268–81.

Nieswiadomy, M. L. and D. J. Molina (1989). Comparing residential water estimates under decreasing and increasing block rates using household data. *Land Economics 65*(3), 280–289.

Nordin, J. A. (1976). A proposed modification on Taylor's demand-supply analysis: Comment. *The Bell Journal of Economics 7*(2), 719–721.

Osterwald-Lenum, M. (1992). A note with fractiles of the asymptotic distribution of the maximum likelihood cointegration rank test statistics: Four cases. *Oxford Bulletin of Economics and Statistics 54*(4), 361–78.

Perron, P. (1989). The Great Crash, the Oil Price shock and the unit root hypothesis. *Econometrica 58*, 1361–1401.

Perron, P. (1990). Testing for a unit root in a time series regression with a changing mean. *Journal of Business and Economic Statistics 8*, 153–162.

Perron, P. and T. J. Vogelsang (1992). Nonstationarity and level shifts with an application to purchasing power parity. *Journal of Business and Economic Statistics 10*, 301–320.

Phillips, P. C. B. and P. Perron (1988). Testing for a unit root in time series regression. *Biometrika 75*(2), 335–346.

Pint, E. (1999). Household responses to increased water rates during the California drought. *Land Economics 75*(2), 246–266.

Ramanathan, R. (1999). Short- and long-run elasticities of gasoline demand in India: An empirical analysis using cointegration techniques. *Energy Economics 21*(4), 321–330.

Renwick, M. E. and S. O. Archibald (1998). Demand side management policies for residential water use: Who bears the conservation burden? *Land Economics 74*(3), 343–359.

Renwick, M. E. and R. D.Green (2000). Do residential water demand side management policies measure up? An analysis of eight California water agencies. *Journal of Environmental Economics and Management 40*(1), 37–55.

Rodrigues, P. M. M. and P. H. Franses (2003). A sequential approach to testing seasonal unit roots in high frequency data. Econometric Institute Report 2003-14. Erasmus University Rotterdam.

Rodrigues, P. M. M. and D. R. Osborn (1999). Performance of seasonal unit root tests for monthly data. *Journal of Applied Statistics 26*(8), 985–1004.

Sargan, J. D. and A. Bhargava (1983). Testing residuals from least squares estimators for being generated by the Gaussian Random Walk. *Econometrica 51*(1), 153–174.

Schefter, J. E. and E. L. David (1985). Estimating residential water demand under multi-tariffs using aggregate data. *Land Economics 61*(3), 272–80.

Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics 6*(2), 461–464.

Schwert, G. W. (1989). Tests for unit roots: A Monte Carlo investigation. *Journal of Business and Economic Statistics 7*(2), 147–159.

Taylor, L. D. (1975). The demand for electricity: A survey. *The Bell Journal of Economics 6*(1), 74–110.

Taylor, R. G., J. R. McKean, and R. A. Young (2004). Alternate price specifications for estimating residential water demand with fixed fees. *Land Economics 80*(3), 463–475.

White, H. (1980). A heteroskedasticity-consistent covariance estimator and a direct test for heteroskedasticity. *Econometrica 48*(4), 817–838.

Wickens, M. R. and T. S. Breusch (1988). Dynamic specification, the long run and the estimation of the transformed regression models. *The Economic Journal 98*(390), 189–205.

Appendix: Summary of demand measures

Measures taken to reduce demand were of three types:

1. Changes in tariff structure to promote savings (see Tables 1 and 2).

2. Meter Replacement Campaign (*Plan Cinco*) to increase the reliability of consumption readings. In the year 2000, meters in Seville and its metropolitan area were on average less than four years old.

3. Promotion of the replacement of collective meters in blocks of dwellings by individual ones. A total of 18,822 supplies corresponding to 226,034 buildings, 87% of them located in the city of Seville, was to be included in the project. 50% of these buildings have between two and eight dwellings, 28.4% have between 9 and 16 dwellings, 10.8% are buildings with between 17 and 24 dwellings and the same percentage corresponds to buildings with more than 25 dwellings. The supply company has provided a series of measures to facilitate the replacement, taking into account the problems and disadvantages encountered (EMASESA 2000, pp. 9-10) .