A Quantile Regression Approach to the Heterogeneity in Price Elasticity of Domestic Water Demand

Mónica Maldonado-Devis[1] · Vicent Almenar-Llongo[2]

Abstract

This paper examines the problem of unobserved heterogeneity in urban water demand. It uses a panel quantile regression (QR) approach to focus on segments of consumers with different levels of water consumption. This estimation strategy is applied to a rich set of panel microdata capturing the consumption of water for 4,023 households in Valencia (Spain) between the years 2009 and 2011. To capture heterogeneity in a city's residential household water consumption, a QR approach is applied to the specified water demand model, enabling analysis for different quantiles (levels) of consumption. The QR shows the behaviour of the parameters for different consumption levels. It enables differentiation of consumer reactions to different independent variables at each quantile of the distribution of the dependent variable. The results provide strong evidence of unobserved heterogeneity at different levels. This approach is useful in that it can lead to better-informed tariff design by providing an understanding of heterogeneity in price elasticities.

1 Introduction

This paper adds to the body of research on domestic water demand, for which an updated literature review is provided by García-Valiñas and Suárez-Fernández (2022). This paper adds to this research by examining the case of the city of Valencia (Spain), using quantile regression (QR) analysis of a panel of household-level microdata to study the problem of unobserved heterogeneity.

Vicent Almenar-Llongo contributed equally to this work.

✉ Mónica Maldonado-Devis
  mmaldonado@edem.es

  Vicent Almenar-Llongo
  vicent.almenar@ucv.es

1 Department of Economic Analysis, EDEM Business School, Plaça de l'Aigua, 1, València 46024, Spain

2 Department of Economics and Business, Catholic University of Valencia, Corona, 34, València 46003, Spain

Although studies of domestic water demand in Spain have examined the cases of Zaragoza (Arbués et al. 2004; Arbués and Villanúa 2006; Arbués et al. 2010), Andalusia (Martínez-Espileira 2007; García-Valiñas et al. 2010; Pérez-Urdiales and García-Valiñas 2016; Pérez-Urdiales et al. 2016), and Barcelona (Domene and Saurí 2006; March and Saurí 2010; March et al. 2012), the complex case of Valencia has been the subject of only two studies (Maldonado-Devis and Almenar-Llongo 2021a, b). Of these studies, only those by Pérez-Urdiales et al. (2016) and Maldonado and Almenar (2021b) have addressed the issue of unobserved individual heterogeneity.

The presence of unobserved individual heterogeneity is a problem that affects the estimation of water demand functions, which means that a common demand function is unlikely to represent the behaviour of all users (Pérez-Urdiales et al. 2016). Due to broad diversity in behaviour, household consumption may exhibit heterogeneity (Huang 2015). There may be considerable heterogeneity in water consumption, even amongst individuals with similar observable characteristics (Pérez-Urdiales et al. 2016). This heterogeneity, which may not always be observable, has to do with a number of factors. For example, heterogeneity may be related to the specific features of each region, its climate, and its households, household size, number of household members, heterogeneous agents in terms of preferences, technology, and information (Hancevic and Navajas 2015; Pérez-Urdiales et al. 2016; Frondel et al. 2019; Kostakis 2021; Ben Zaied et al. 2022), and so on. It can also be related to the temporal evolution of consumption (Hancevic and Navajas 2015), which may become more efficient over time. Considering heterogeneity is important, particularly when analysing the effect of changes in price structure, because differences in price elasticities may be due to underlying heterogeneity.

The literature contains papers whose main objective is to study the role of individual heterogeneity. Scholars have used a range of methodological approaches to try to control for the problem of unobserved heterogeneity in residential water demand. Some examples are the inclusion of fixed effects at the household level (Pint 1999), the estimation of models comparing fixed and random effects (Worthington et al. 2009), the random coefficients model (Miyawaki et al. 2011), and the estimation of demand by group (Krause et al. 2003; Mansur and Olmstead 2012). Other examples include applying the latent class model (LCM), which generates homogeneous groups of consumers classified according to their unobserved preferences without the need for a priori selection to estimate demand (Pérez-Urdiales et al. 2016), and instrumental variables regression (Siddiquee and Ahamed 2020). Altarabsheh et al. (2023) used three alternative modelling approaches, each accounting for a different type of unobserved heterogeneity in the observed data: a random parameter ordered probit model with heterogeneity in means, a random thresholds random parameters hierarchical ordered probit model, and a latent class ordered probit model with class probability functions. Chovar-Vera et al. (2024) used a generalised least squares random effects model and the discrete/continuous choice model to study unobserved heterogeneity in water consumption. Another approach used to deal with the problem of unobserved heterogeneity is QR.

QR for modelling water demand and water tariffs has been applied by Cardoso (2013), Kim (2018), Anil Kumar and Ramachandran (2019), Deyà-Tortella et al. (2016) and Deyà-Tortella et al. (2019), Yoo et al. (2014), Morales-Martínez and Gori-Maia (2021), Kostakis (2021), Papacharalampous and Langousis (2021), and Ben Zaied et al. (2022). Wafaa et al. (2024) employed D-vine copula quantile regression to study water expenditure. However, in these examples, the analyses did not focus on the problem of individual unobserved heterogeneity. To the authors' knowledge, no paper in the domestic water demand literature has used QR to address the problem of individual unobserved heterogeneity. In contrast, studies of other utility sectors such as electricity have used this methodology to estimate demand and deal

with unobserved heterogeneity (Schleich et al. 2013; Huang 2015; Hancevic and Navajas 2015; Silva et al. 2017; Chindarkar and Goyal 2019; Frondel et al. 2019; Uhr et al. 2019; Kostakis 2020; Tilov et al. 2020).

In this paper, a demand function is estimated using QR to analyse consumer behaviour in the city of Valencia, considering heterogeneity. The aim of using QR to estimate the impacts of explanatory variables is to show that such impacts differ depending on water consumption levels (Cardoso 2013). QR makes it possible to determine whether the same variation in water price or any other variable affects domestic water consumption differently depending not only on the mean, as in the case of OLS estimation, but also on whether households are high, medium, or low consumers of water. In the case of the present study, QR models are relevant in that they enable observation of how the effect of a variable or factor varies according to the level of household water consumption. Moreover, it is assumed that there is heterogeneity in the effect of a variable due to the presence of missing variables or other factors. Household-level data are well suited to analyses of economic decisions such as household consumption and allow for effective control of household heterogeneity based on sociodemographic characteristics and/or characteristics of the household (including the size of the residence), as well as reducing aggregation bias (Blundell et al. 1992; Ščasný and Smutná 2021).

This research is important because it addresses two gaps in the literature. First, it contributes to the understanding of unobserved heterogeneity in household price elasticity by introducing the spatial scale with a suburban multilevel model, which is a novel approach in studies of household water demand in cities. Moreover, it does so using QR, a methodology that few studies in the domestic water demand literature have used. Identifying different consumer behaviours and different elasticities within a city can help provide a better understanding of the possible effect of domestic water pricing policies. Second, at the local level, this paper helps identify the domestic water demand characteristics in the conurbation of Valencia, a water-stressed and water-scarce area. Thus, this research may be helpful for improving the design of tariff policies to ensure better allocation of water resources.

This article has four sections. Following this Introduction, Section 2 describes the study context. Section 3 describes the database used in the estimates of domestic water demand, the methodological approach, and the estimated model. Section 4 presents the estimation and results. Section 5 offers a discussion and presents the general conclusions derived from the results. It also highlights possible future lines of research.

2 Description of the Study Context

This study examines the city of Valencia, Spain. The city of Valencia is part of a conurbation located in a water-stressed area. Therefore, urban water demand plays a more important role than a simple analysis of water consumption would suggest. Valencia is a sizeable urban area that places a large strain on a hydrological zone where agriculture uses considerable water resources. The urban area of Valencia has substantial population growth and high seasonality in its service activities. It competes for water use with a large agricultural industry and with one of the most important wetlands in Spain, the Albufera natural park, which also belongs to the urban area.

The city of Valencia has 18 administrative districts and 87 neighbourhoods. There are considerable differences in land use and degree of urbanisation across districts and neighbourhoods. Some districts have up to three times the population density of the city average. In

contrast, some peripheral districts have a lower degree of urbanisation and a below-average population density. Whereas some areas are highly urbanised, others have a high proportion of undeveloped land. Differences in population density (as well as income) across districts and neighbourhoods may influence the behaviour of consumers of drinking water. Indeed, the data on domestic water consumption reveal significant differences between the city's neighbourhoods. These differences become more pronounced as the level of data disaggregation increases.

In Valencia, the consumer water bill includes all payments for services within the urban water cycle. Specifically, it includes tariffs for water supply, VAT, payments for sewerage services, the Tamer charge (a waste rate explained later), the city council's investment fees (as a fixed amount per month), and the fees of the basin authority (as a uniform variable price). These payments have different structures and legal implications. In Valencia, the tariff structure is an increasing rate tariff (IRT), which differs from the structure typically used for domestic consumption. The water supply tariffs have a two-part IRT structure consisting of a fixed part that depends on the meter size and a variable part in two blocks with a limit of 12 m^3 per two-month period for the first block. The upstream water supply tariff has a one-part structure that corresponds to a uniform volume-based payment. Next, there is a sewerage charge with a uniform variable price in addition to a sanitation charge. The sanitation charge also has a two-part structure. The variable part is uniform for all m^3 consumed. Both the variable and the fixed parts of the charge correspond to the amounts for locations with more than 500 inhabitants. Lastly, the water bill includes a charge to finance metropolitan waste management, treatment, and disposal. In 2009, the metropolitan waste treatment authority (EMTRE) established the Tamer charge for metropolitan waste treatment and disposal. It consists of a fixed charge or a fixed-plus-variable charge depending on how much the user consumed in the previous year and whether the user's consumption exceeded 260 m^3. The Tamer charge increases the proportion of the fixed part of the bill.

These payments can be summarised as a simple structure. The final water price structure consists of a fixed part and a volume-based part (€/m^3), which differs depending on whether the user consumes more than 12 m^3 in the two-month period. The Tamer charge must be added to this price structure.

3 Methods

3.1 Data

The analysis was conducted using a large sample of microdata. Such a database is unusual in this field given the difficulty in obtaining household-level data. Household data are usually randomly selected over the study area, making it difficult to capture the influence of the neighbourhood on water consumption (House-Peters and Chang 2011). However, the weighted distribution of the sample enabled analysis of consumption differences between different neighbourhoods. Also, the panel nature of the data enabled analysis of possible temporal differences.

For this study, a sample of data on 4,023 household was gathered. This sample was the same as the one used by Maldonado-Devis and Almenar-Llongo (2021a, b). Households were selected using stratified random sampling with proportional allocation. The selected household number for each district and neighbourhood was proportional to its size in the overall population of the city.

Once the data on the households and their consumption were complete, the next step was to request data on the number of people and the composition of the families living in these households from the city council. The official statistics office only provided the number of people in each household from the 2011 city census. Finally, data on the surface area and age of the previously selected households were obtained from the online service of the cadastre. Aggregating the data from these three sources provided a raw data set containing all available data at the household level.

Subsequently, filters were applied to the data set, reducing the number of observations. This process eliminated households for which not all data were available or for which the available data did not correspond to the target of the study (i.e. households with zero consumption or with consumption of more than 1000 m^3). Of the 87 administrative neighbourhoods in the city of Valencia, 10 were eliminated from the sample for three reasons. First, the water consumption figures were abnormally low and were thus unrepresentative. Second, either no data existed or the data were anomalous. Third, some neighbourhoods were grouped because very few data were available considering the contribution to the total population.

The outcome of the sampling process was a panel consisting of domestic water consumption data on 4,023 households for 17 two-month periods (from 2009 to 2011). The 4,023 households proportionally distributed across 18 districts and 73 neighbourhoods enabled observation of socioeconomic differences at the intra-urban level in the city of Valencia.

According to the microdata sample, the average number of people per household was 2.55. On average, the households had a surface area of approximately 112 m^2 and were 40 years old. Generally, the neighbourhoods with the fewest people in each household were the inner-city neighbourhoods. In contrast, the peripheral neighbourhoods had larger household sizes.

The total amount billed per household per two-month period was calculated using the tariffs, fees, and charges for each year. The price variable in this study was the average price per m^3. It was calculated by dividing the total billed in each period by the cubic metres consumed. An increase in price was expected to lead to a decrease in water consumed. Simultaneously, it was expected that this decrease would lead to a higher price per unit. Higher consumption implies higher bills with lower average prices.

A bivariate analysis was also performed. A positive relationship was observed between the number people in a household and consumption. Also, the relationships of surface area with consumption and billing were positive. The relationship between household size and price paid per unit was negative. Despite a positive relationship between consumption and billing, not all neighbourhoods with the same consumption range were in the same billing range. These differences were caused by the inclusion of the Tamer charge bracket, which depended on consumption (in this case, in the year 2010).

3.2 Empirical Model

QR models the relationship between a set of independent variables and the dependent variable for different quantiles of the distribution of the dependent variable. Specifically, it shows whether the regressors' effects differ at different quantiles of the distribution. This method enables assessment of different effects of the independent variables on the entire distribution of the dependent variable. In this study, QR was used to answer the question of whether an explanatory variable has a varying impact across conditional quantiles of consumption (Tilov et al. 2020).

Just as ordinary least squares (OLS) fits a linear function to the dependent variable by minimising the expected squared error, QR fits a linear model using a generally asymmetric loss function or check function (Frondel et al. 2019). QR minimises absolute deviations weighted by asymmetric weights (not squared as in OLS). Compared to the classical OLS regression method, QR reportedly offers several advantages (Hancevic and Navajas 2015; Huang 2015; Frondel et al. 2019). QR is a semi-parametric method because, in its estimations, the zero mean and normally distributed homoscedastic error term assumptions on which OLS is based are not necessary. Therefore, in terms of econometric techniques, QR may be more efficient than OLS when the residual series is non-normal. Also, QR does not require any assumptions about random disturbance. Therefore, it can offer an effective approach in the presence of outliers, heteroscedasticity, or structural change because its estimators are not affected by the presence of extreme data or outliers. Although it could be argued that sample segmentation and subsequent estimation by OLS could lead to the same conclusion, this procedure could present a problem of selection bias (Heckman 1979). Therefore, QR can avoid the problem of sampling bias.

QR generally provides a richer characterisation of the data than OLS because quantile methods enable the study of the impact of a regressor on the full distribution of the dependent variable, not just the conditional mean. Moreover, QR has the advantage of being more robust to outliers than OLS. In fact, OLS can be inefficient when the dependent variable has a highly non-normal distribution.

QR also makes it possible to account for unobserved differences related to consumption intensity between households (Tilov et al. 2020) and to capture heterogeneity in the coefficients across quantiles of a consumption distribution and across households. QR gives more flexibility in the estimation of a factor effect on consumption level because it enables estimation of a range of conditional quantile functions.

All of these features are relevant because recent research on water demand has shown that the price elasticity of residential water demand may not be constant throughout the consumption distribution. If so, knowing the price elasticity for the average of the sample or population of consumers is insufficient to predict the possible impacts of a price change (Cardoso 2013).

With the high variability in the water consumption data set, classical OLS would lead to dubious conclusions. In particular, when the response is skewed, OLS may result in misleading regression coefficients (Huang 2015). An estimation using a subsample that considers, for example, only high-consumption households is a poor empirical strategy because it leads to the selection bias problem introduced by Heckman (1979) and mentioned earlier (Hancevic and Navajas 2015). This issue can be avoided with QR using the whole available sample to estimate the effects of the variables of interest on the distribution.

Much like Uhr et al. (2019) has noted for the case of electricity, QR analysis enables evaluation of the impact of price on specific locations of the consumption distribution. It thus provides a richer characterisation of elasticities than simply using the average coefficients. Therefore, the quantile estimations enable assessment of how different consumption groups of households, defined as consumption quantiles, react to an increase in the water price.

For all these reasons, QR is particularly well suited to the analysis of the responsiveness of water consumption across population groups with different levels of water consumption. Therefore, to address the possibility of heterogeneity in price elasticities, the QR method developed by Koenker and Bassett (1978) was applied.

QR is based on the concept of the quantile. For a sample of n observations ($y_i = 1, 2, ..., n$) with a distribution $F(y_i)$, the τ quantile, with value $0 < \tau < 1$, is some value b such that the proportion τ of observations lies below or at b and the proportion $1 - \tau$ lies above b.

Alternatively, the definition of quantile can be expressed as a minimisation problem of the following form:

$$Min_{b \in R} \left[\sum_{y_i \geq b} \tau |y_i - b| + \sum_{y_i \geq b} (1 - \tau)|y_i - 1| \right] \quad (1)$$

The QR model formulation for cross-sectional data, introduced by Koenker and Bassett (1978), is based on a standard model. Its extension to panel data with fixed effects can be expressed as follows:

$$y_i = X_i \beta_\tau + u_{\tau i} \quad (2)$$

where y_i is the dependent variable, X_i are the explanatory variables, β_τ is the parameter to estimate for quantile τ, and $u_{\tau i}$ is the random error that corresponds to quantile τ. Regarding the random error, the following assumption is made:

$$Quant_\tau (y_i | X_i) = X_i \beta_\tau \quad (3)$$
$$Quant_\tau (u_{\tau i} | X_i) = 0 \quad (4)$$

For k explanatory variables, the model takes the following form:

$$y_i = \beta_{\tau 0} + \beta_{\tau 1} x_{1i} + \; ... \; + \beta_{\tau k} x_{ki} + u_{\tau i} \quad (5)$$

and given a quantile τ, the parameter estimate by QR is obtained by solving the following minimisation problem:

$$min \sum_{i=1}^{n} \rho_\tau (y_i - \beta_0 - \beta_1 x_{1i} - \; ... \; - \beta_k x_{ki}) \quad (6)$$

$$\rho_\tau (u) = \tau - I(u \leq 0) \quad (7)$$

where u is the loss function of the QR, and $I()$ is the characteristic function, which is 1 if the condition is verified and 0 otherwise. The solution to the quantile estimation is given by iterative optimisation and/or linear programming methods. A vector $\beta = (\beta_1, \beta_2, ...\beta_k) \in \mathbb{R}_{kx1}$ is sought as a solution to the unconstrained optimisation problem. Because the function is not differentiable, it is possible either to use non-differentiable optimisation methods or to transform the problem in order to use conventional methods such as linear optimisation (Koenker and Hallock 2001).

3.3 Estimated Model

For the explanatory variables discussed in this paper, the model took the following form:

$$C_i = \beta_{\tau 0} + \beta_{\tau 1} p_i + \beta_{\tau 2} S_{ki} + \beta_{\tau 3} I_i + u_{\tau i} \quad (8)$$

$$min \sum_{i=1}^{n} \rho_\tau (C_i - \beta_0 - \beta_1 P_i - \beta_2 S_i - \beta_3 I_i) \quad (9)$$

After performing the coefficient comparison and significance tests, it was concluded that the two-factor model offered the best fit.

The estimated final model was defined as follows:

$$log(C_{itk}) = \beta_0 + \beta_1 log(p_{itk}) + \beta_2 log(S_{ik}) + \beta_3 I_{ik} + \sum^{t} \gamma_t B_t + \sum^{k} \delta_k N_k + \epsilon_{itk} \quad (10)$$

where

- C_{itk}: two-month water consumption (in m³) of household i located in k in period t.
- P_{itk}: average price (in euros/m³) paid by household i located in k in the previous period ($lag P_i$). This term is the proposed solution adopted to resolve the problem of endogeneity.
- S_{ik}: area of household i located in k.
- I_{ik}: number of individuals residing in household i located in k.
- B_t: payment in the two-month period t.
- N_k: neighbourhood k.

The subscript t is reserved for time (from 2009 to 2011, with 17 observations for each household), the subscript i is reserved for the household (from 1 to 4,023), and the subscript k is reserved for the district or neighbourhood where household i is located (from 1 to 18 districts and from 1 to 73 neighbourhoods, coded using two digits, with the first digits indicating the district). Therefore, the QR model explains water consumption for household i located in neighbourhood k in the two-month period t as a function of the average water price paid by the household in the previous period (a price lagged by a single two-month period), the household's surface area, the number of residents in the household, the two-month payment, and the neighbourhood. All these factors are reported in the literature as influencing household water demand and consumption (Abu-Bakar et al. 2021).

4 Estimation and Results

Table 1 shows the estimation results for the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles. These quantiles represent low consumption, medium-low consumption, medium consumption, medium-high consumption, and high consumption households, respectively.

All four variables in the QR model were significant, irrespective of quantile. The estimates for all quantiles had similar goodness of fit (see Table 2).

Price elasticity increased with the quantile such that the higher the household consumption, the lower the price elasticity. Households that consumed the least had an elasticity greater than or equal to -1.13. Households with average consumption had an elasticity of -0.97. Households with the highest consumption had an elasticity of -0.67.

Table 1 Results of quantile model with two factors (neighbourhood and time)

	QR.10	QR.25		QR.50		QR.75		QR.90	
Intercept	2.04***	2.507	***	2.621	***	2.603	***	2.74	***
	−0.063	−0.052		−0.047		−0.048		−0.065	
log(lagPrice)	−1.13***	−1.098	***	−0.974	***	−0.822	***	−0.673	***
	−0.01	−0.008		−0.008		−0.009		−0.012	
log(Surface)	0.233***	0.205	***	0.212	***	0.243	***	0.24	***
	−0.012	−0.009		−0.008		−0.009		−0.012	
Individuals	0.067***	0.065	***	0.067	***	0.073	***	0.073	***
	−0.002	−0.002		−0.002		−0.002		−0.002	
Num. obs.	68.391	68.391		68.391		68.391		68.391	
Percentile	0.1	0.25		0.5		0.75		0.9	

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table 2 Significance of quantile estimation results

	QR.10	QR.25	QR.50	QR.75	QR.90
loglike	145,649.35	115,623.00	102,413.08	109,871.40	130,377.29
AIC	145,833.35	115,807.00	102,597.08	110,055.40	130,561.29
Pseudo-R2	0.322	0.332	0.343	0.343	0.328
n	68,391	68,391	68,391	68,391	68,391

It seems contradictory that the households that consumed the least had the highest elasticity. Intuition would suggest that households with low consumption should be less sensitive to price changes because, in many cases, they consume only what is essential (Pérez-Urdiales and García-Valiñas 2016). However, in the case of households with very low consumption, any change in average price would represent a small proportion because they pay a very high average price. In contrast, any small change in consumption would represent a very large proportion. Because the elasticity value measures the percentage change in quantity in relation to the percentage change in price, households that consumed little had high elasticity values (i.e. they were more elastic), even though in absolute terms they reduced their consumption only a small amount. The opposite was true for high-consuming households.

The effect of household surface area on water consumption was independent of household consumption. A similar result was observed for the number of people residing in the household.

Regarding the neighbourhood fixed effect, in some districts, all neighbourhoods showed similar behaviour for all quantiles (an example is given by the differences in consumption by quantiles for District 19 in Fig. 1). However, in some districts, behaviour differed greatly across neighbourhoods (e.g. District 13). Additionally, in some districts, all neighbourhoods
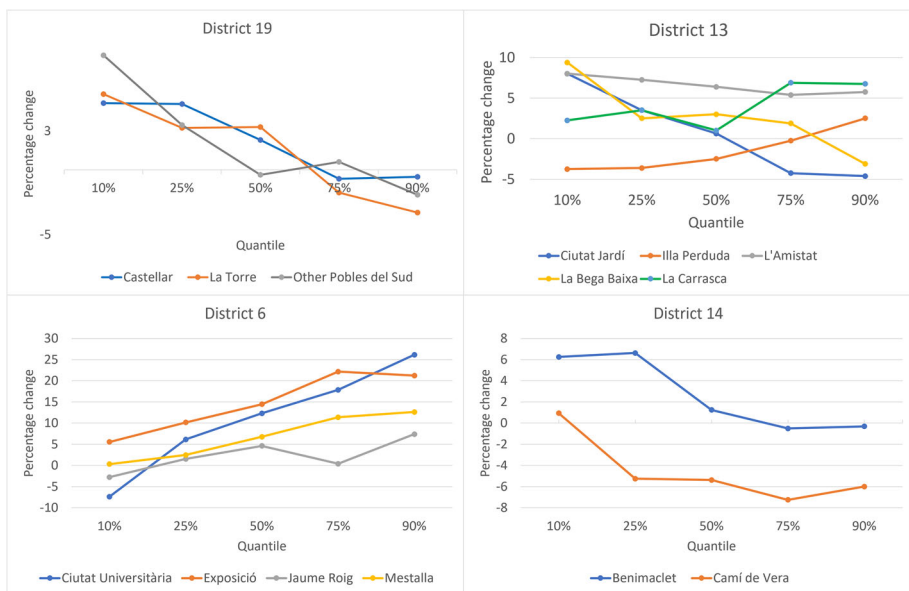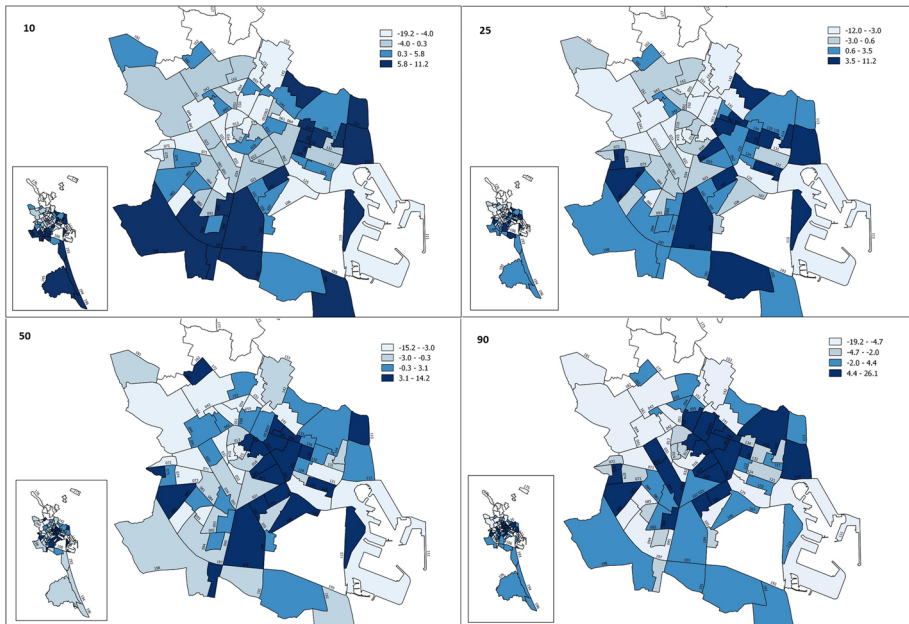

Fig. 1 Quantile model: Consumption differences by district

had a positive sign for the relationship between quantile and consumption difference (e.g. District 6). Conversely, in some districts, all neighbourhoods had a negative sign for the relationship between the quantiles and the percentage differences in consumption with respect to the mean. As the quantile increased, the difference in consumption with respect to the mean of that quantile decreased (e.g. District 14).

Likewise, the behaviour by neighbourhood was analysed because, within the same district, there were neighbourhoods in which households in any quantile had consumption that was below the city average for households in that quantile, whereas others had above-average consumption for all quantiles. To illustrate this point, Fig. 2. shows differences in consumption in neighbourhoods with respect to the city average for each quantile.

The maps show how households in different neighbourhoods behaved for different quantiles. The behaviour of the neighbourhoods with respect to the different consumer groups could be classified as follows: neighbourhoods with above-average consumption in each quantile and for all quantiles; and neighbourhoods with below-average consumption in each quantile and for all quantiles. However, there were neighbourhoods with different cases depending on how many quantiles had consumption above and below the city average: (1) there was below-average consumption for low consumers (quantile 10) and above-average consumption for all others; (2) consumers with low, medium-low, and medium consumption (quantiles 10, 25, and 50) consumed below the average, and consumers in quantiles 75 and 90 consumed above the average; (3) household consumption in the low quantiles (10, 25, and 75) was above average, and consumption in the medium-high and high quantiles was below average; or (4) all quantiles were above the average, except quantile 50, which was below the average.

Finally, a fixed effect was included in the model for each two-month period to analyse the effects of time on consumption. The results are shown graphically for each year in Fig. 3. The

Fig. 2 Quantile model: Differences in consumption by neighbourhood by quantile
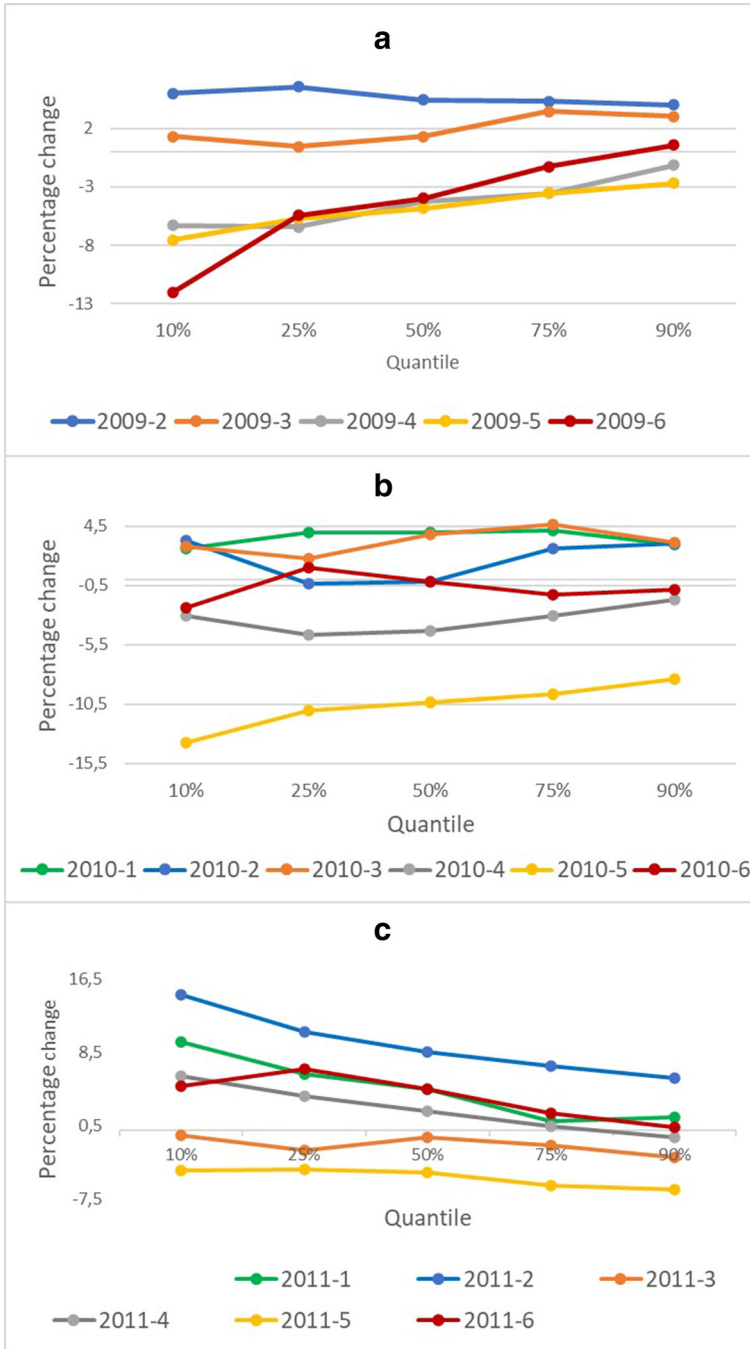
Fig. 3 Quantile model: Time fixed effects

estimates for the time fixed effects show that consumption behaviour was similar in 2009 and 2010 but different in 2011. In 2011, consumption increased for all quantiles in all two-month periods. In other words, the increase in consumption observed in the average data for 2011 occurred equally for low- and high-consumption households. Moreover, consumption in the corresponding two-month periods in summer was lower in all years. This finding confirms the claim that consumers in Valencia reduce their consumption in the summer, regardless of their level of consumption.

5 Discussion and Conclusions

The main insight from the analysis is that there is considerable heterogeneity in price elasticity. The findings suggest that, due to this heterogeneity, households from different categpries (with similar characteristics) respond differently to a uniform tariff or even a uniform increase (or decrease) in their existing tariff. Analysis using a QR model reveals five responses to changes in average prices. The values of price elasticity lie in the range (-1.13, -0.67). These results show that users with low consumption have the highest elasticities, while users with high consumption react the least to changes in average prices. The results of the quantile estimation are consistent with those from other studies showing that users with high consumption have lower elasticities (Wichman et al. 2016; Klaiber et al. 2014; Baerenklau et al. 2014).

The estimates can be compared with those of two studies based on the same database. These studies provided a unique price elasticity estimate of -0.88 with a basic panel model (Maldonado-Devis and Almenar-Llongo 2021a) and -0.87 with a multilevel analysis (hierarchical or mixed model; Maldonado-Devis and Almenar-Llongo 2021b). The estimates can also be compared with those of similar studies of the problem of unobserved individual heterogeneity in the estimation of residential water demand. In the results of these studies, elasticity ranged from -1.23 to 0.9, according to Pérez-Urdiales et al. (2016), and -1.43 to -1.14, according to Wichman et al. (2016). Notably, water price elasticities depend on the data aggregation level and sample size (Flores-Arévalo et al. 2021) and partly reflect differences in pricing structures (Bruno and Jessoe 2021). Alternatively, they may be an artifice of model specification (Puri and Maas 2020) or may differ notably when accounting for different climatic conditions within a region. Notably, the demand for water in Spain has been found to be inelastic (Hoyos and Artabe 2017).

Crucially, the techniques used to analyse domestic water demand in the city of Valencia provide strong evidence of heterogeneity in consumption at the neighbourhood and individual levels. Moreover, they reveal behaviour with respect to the average price of water that differs from that observed in other studies of Spanish cities.

The effect of household surface area on water consumption is independent of household consumption. A similar result is observed for the number of people in the household. Again, the values are similar to those observed in the two models mentioned earlier. Thus, regarding the existence of differences in consumer behaviour depending on level of consumption, the results indicate that the effect of the variables *surface area* and *people per household* is the same at all levels of consumption and that there are differences in price elasticity between quantiles.

The analysis of the time effect reveals that only a small part of the variability in consumption in the city of Valencia should be associated with the season. Two further interesting results are that consumption decreased in the summer months for all neighbourhoods and

for all consumption levels and that behaviour differed in all two-month periods of 2011, increasing for all quantiles in all two-month periods.

This paper deals with urban water demand in a water-scarce environment. Although urban and domestic consumption decreased in the period 2008 to 2011, there is still a need to manage this water use more effectively in a large city located in a water-stressed area. Such management is especially important, given the increase in per capita consumption (litres per person per day) in the city of Valencia.

Climate change threatens to add further stress to urban water supply systems (Miller and Yates 2006). Hence, the pressure exerted by the drinking water supply in large urban water-deficient or water-stressed areas requires management of demand. This management should allow for more efficient consumption and should help resolve what can often be extreme situations. The study of population heterogeneity is thus a key first step towards assessing the efficiency and equity of policy interventions.

The results of studies of price elasticity of household water demand, such as this one, may be useful for water utilities interested in stabilising and anticipating future revenue while meeting conservation goals (Puri and Maas 2020). They also have policy implications because water pricing is considered an efficient means of long-term sustainable planning of water resources management (Hoyos and Artabe 2017). They may be of interest to those responsible for local water management. In particular, water managers could use analysis of the variability of domestic water consumption in a city at different levels to improve the supply service to help increase citizen well-being. Identifying different consumer behaviours and different elasticities at different consumption levels can help provide a better understanding of the possible effect of certain pricing policies. Similarly, it can be useful to target non-price policies such as promoting water-saving habits and installing household water-saving devices for consumers who are less responsive to price. Thus, the fact that the findings suggest that there is heterogeneity between water consumers could be used to draw policy conclusions.

Finally, as possible future additions to quantile analysis, it would be of interest to introduce the weight of consumers at each quantile for each neighbourhood and the estimation of the parameters of this model from a Bayesian perspective to explain the effects of model choices on elasticity.

Data availability/Materials availability The data were obtained under a confidentiality agreement with the company Aguas de Valencia-EMIVASA because users could be identified with the microdata.

Declarations

Ethics approval and consent to participate Not applicable

Consent for publication Not applicable

Conflict of interest The authors declare no conflict of interest.

References

Abu-Bakar H, Williams L, Hallett SH (2021) A review of household water demand management and consumption measurement. J Cleaner Prod J 292:125872. https://doi.org/10.1016/j.jclepro.2021.125872

Altarabsheh A, Abraham D, Altarabsheh I (2023) Unobserved heterogeneity and temporal instability in an analysis of household water consumption under block rate pricing. Aqua Water Infrastruct Ecosyst Soc 72(8):1512–1538. https://doi.org/10.2166/aqua.2023.063

Anil Kumar A, Ramachandran P (2019) Cross-sectional study of factors influencing the residential water demand in Bangalore. Urban Water J 16(3):171–182. https://doi.org/10.1080/1573062X.2019.1637905

Arbués F, Villanúa I (2006) Potential for pricing policies in water resource management: estimation of urban residential water demand in Zaragoza. Spain. Urban Stud 43(13):2421–2442. https://doi.org/10.1080/00420980601038255

Arbues F, Barberán R, Villanúa I (2004) Price impact on urban residential water demand: a dynamic panel data approach. Water Resour Res 40(11):1–9. https://doi.org/10.1029/2004WR003092

Arbués F, Villanúa I, Barberán R (2010) Household size and residential water demand: an empirical approach. Aust J Agric Resour Econ 54(1):61–80. https://doi.org/10.1111/j.1467-8489.2009.00479.x

Baerenklau KA, Schwabe KA, Dinar A (2014) The residential water demand effect of increasing block rate water budgets. Land Econ 90(4):683–699. https://doi.org/10.3368/le.90.4.683

Ben Zaied Y, Taleb L, Ben Lahouel B, Managi S (2022) Sustainable water demand management and incentive tariff: evidence from a quantile-on-quantile approach. Environ Model Assess, 27:967–980. https://link.springer.com/article/10.1007/s10666-021-09814-1

Blundell R, Bond S, Devereux M, Schiantarelli F (1992) Investment and Tobin's Q: evidence from company panel data. J Econom 51(1–2):233–257. https://doi.org/10.1016/0304-4076(92)90037-R

Bruno EM, Jessoe K (2022) Using price elasticities of water demand to inform policy. Annu Rev Resour Econ 13:427–441. https://doi.org/10.1146/annurev-resource-110220-104549

Cárdenas-Ovalle RA (2020) Demanda de electricidad residencial: Una perspectiva de regresión cuantílica. Ensayos Revista de economía 39(1):87–114. https://doi.org/10.29105/ensayos39.1-4

Cardoso ML (2013) Modeling portuguese water demand with quantile regression. Ph.D. Thesis, University Institute of Lisbon, Lisbon, Portugal, 2013

Chindarkar N, Goyal N (2019) One price doesn't fit all: an examination of heterogeneity in price elasticity of residential electricity in India. Energy Econ 81:765–778. https://doi.org/10.1016/j.eneco.2019.05.021

Chovar-Vera AM, Vásquez-Lavín FA, Ponce-Oliva R (2024) Estimating residential water demand under systematic shifts between uniform price (UP) and increasing block tariffs (IBT). Water Resour Res 60(4):e2022WR033508. https://doi.org/10.1029/2022WR033508

Deyà-Tortella B, García C, Nilsson W, Tirado D (2016) The effect of the water tariff structures on the water consumption in Mallorcan hotels. Water Resour Res 52(8):6386–6403. https://doi.org/10.1002/2016WR018621

Deyà-Tortella B, García C, Nilsson W, Tirado D (2019) Hotel water demand: the impact of changing from linear to increasing block rates. Water 11(8):1604. https://doi.org/10.3390/w11081604

Domene E, Saurí D (2006) Urbanisation and water consumption: influencing factors in the metropolitan region of Barcelona. Urban Stud 43(9):1605–1623. https://doi.org/10.1080/00420980600749969

Flores-Arévalo Y, Ponce-Oliva RD, Fernández FJ, Vásquez-Lavin F (2021) Sensitivity of water price elasticity estimates to different data aggregation level. Water Resour Manage 35:32039–2052. https://doi.org/10.1007/s11269-021-02833-3

Frondel M, Sommer S, Vance C (2019) Heterogeneity in German residential electricity consumption: a quantile regression approach. Energy Policy 131:370–379. https://doi.org/10.1016/j.enpol.2019.03.045

García-Valiñas MÁ, Suárez-Fernández S (2022) Are economic tools useful to manage residential water demand? A review of old issues and emerging topics. Water 14(16):2536. https://doi.org/10.3390/w14162536

García-Valiñas MA, Martínez-Espiñeira R, González-Gómez F (2010) Affordability of residential water tariffs: alternative measurement and explanatory factors in southern Spain. J Environ Manage 91(12):2696–2706. https://doi.org/10.1016/j.jenvman.2010.07.029

Hancevic P, Navajas F (2015) Consumo residencial de electricidad y eficiencia energética. Un enfoque de regresión cuantílica. Trimest Econ 82(328):897–927

Heckman JJ (1979) Sample selection bias as a specification error. Econometrica 47(1):153–161. https://doi.org/10.2307/1912352

House-Peters LA, Chang H (2011) Urban water demand modeling: review of concepts, methods, and organizing principles. Water Resour Res 47(5). https://doi.org/10.1029/2010WR009624

Hoyos D, Artabe A (2017) Regional differences in the price elasticity of residential water demand in Spain. Water Resour Manage 31:847–865. https://doi.org/10.1007/s11269-016-1542-0

Huang WH (2015) The determinants of household electricity consumption in Taiwan: evidence from quantile regression. Energy 87:120–133. https://doi.org/10.1016/j.energy.2015.04.101

Kim HG (2018) Estimating price elasticity of residential water demand in Korea using panel quatile model. Environ Resour Econ 27(1):195–214. https://doi.org/10.15266/KEREA.2018.27.1.195

Klaiber HA, Smith VK, Kaminsky M, Strong A (2014) Measuring price elasticities for residential water demand with limited information. Land Econ 90(1):100–113. https://doi.org/10.3368/le.90.1.100

Koenker R, Bassett G Jr (1978) Regression quantiles. Econometrica 46(1):33–50. https://doi.org/10.2307/1913643

Koenker R, Hallock KF (2001) Quantile regression. J Econ Perspect 15(4):143–156. https://doi.org/10.1257/jep.15.4.143

Kostakis I (2020) Socio-demographic determinants of household electricity consumption: evidence from Greece using quantile regression analysis. Curr Res Environ Sustainability 1:23–30. https://doi.org/10.1016/j.crsust.2020.04.001

Kostakis I (2021) The socioeconomic determinants of sustainable residential water consumption in Athens: empirical results from a micro-econometric analysis. Discover Sustainability 2(1):37. https://doi.org/10.1007/s43621-021-00047-6

Krause K, Chermak JM, Brookshire DS (2003) The demand for water: consumer response to scarcity. J Regul Econ 23:167–191. https://doi.org/10.1023/A:1022207030378

Maldonado-Devis M, Almenar-Llongo V (2021a) A panel data estimation of domestic water demand with IRT tariff structure: the case of the city of Valencia (Spain). Sustainability 13(3):1414. https://doi.org/10.3390/su13031414

Maldonado-Devis M, Almenar-Llongo V (2021b) Heterogeneity in domestic water demand: an application of multilevel analysis to the City of Valencia (Spain). Water 13(23):3400. https://doi.org/10.3390/w13233400

Mansur ET, Olmstead SM (2012) The value of scarce water: measuring the inefficiency of municipal regulations. J Urban Econ 71(3):332–346. https://doi.org/10.1016/j.jue.2011.11.003

March H, Saurí D (2010) The suburbanization of water scarcity in the Barcelona metropolitan region: sociodemographic and urban changes influencing domestic water consumption. Prof Geog 62(1):32–45. https://doi.org/10.1080/00330120903375860

March H, Perarnau J, Saurí D (2012) Exploring the links between immigration, ageing and domestic water consumption: the case of the Metropolitan Area of Barcelona. Prof Geog 46(2):229–244. https://doi.org/10.1080/00343404.2010.487859

Martínez-Espiñeira R (2007) An estimation of residential water demand using co-integration and error correction techniques. J Appl Econ 10(1):161–184. https://doi.org/10.1080/15140326.2007.12040486

Miller KA, Yates DN (2006) Climate change and water resources: a primer for municipal water providers. American Water Works Association: Washington, DC, USA

Miyawaki K, Omori Y, Hibiki A (2011) Is all domestic water consumption sensitive to price control? Jpn Econ Rev 62(3):365–386. https://doi.org/10.1111/j.1468-5876.2010.00532.x

Morales-Martínez D, Gori-Maia A (2021) The effect of social behavior on residential water consumption. Water 13(9):1184. https://doi.org/10.3390/w13091184

Papacharalampous G, Langousis A (2021) Probabilistic water demand forecasting using quantile regression algorithms. arXiv preprint arXiv:2104.07985. https://doi.org/10.48550/arXiv.2104.07985

Pérez-Urdiales M, García-Valiñas MÁ (2016) Efficient water-using technologies and habits: a disaggregated analysis in the water sector. Ecol Econ 128:117–129. https://doi.org/10.1016/j.ecolecon.2016.04.011

Pérez-Urdiales M, García-Valiñas MÁ, Martínez-Espiñeira R (2016) Responses to changes in domestic water tariff structures: a latent class analysis on household-level data from Granada, Spain. Environ Resour Econ 63:167–191. https://doi.org/10.1007/s10640-014-9846-0

Pint EM (1999) Household responses to increased water rates during the California drought. Land Econ 75(2):246–266. https://doi.org/10.2307/3147009

Puri R, Maas A (2020) Evaluating the sensitivity of residential water demand estimation to model specification and instrument choice. Water Resour Res 56(1):e2019WR026156. https://doi.org/10.1029/2019WR026156

Ščasný M, Smutná Š (2021) Estimation of price and income elasticity of residential water demand in the Czech Republic over three decades. J Consum Aff 55(2):580–608. https://doi.org/10.1111/joca.12358

Schleich J, Klobasa M, Gölz S, Brunner M (2013) Effects of feedback on residential electricity demand—Findings from a field trial in Austria. Energy Policy 61:1097–1106. https://doi.org/10.1016/j.enpol.2013.05.012

Siddiquee MSH, Ahamed R (2020) Exploring water consumption in Dhaka city using instrumental variables regression approaches. Environ Process 7:1255–1275. https://doi.org/10.1007/s40710-020-00462-3

Silva S, Soares I, Pinho C (2017) Electricity demand response to price changes: the Portuguese case taking into account income differences. Energy Econ 65:335–342. https://doi.org/10.1016/j.eneco.2017.05.018

Tilov I, Farsi M, Volland B (2020) From frugal Jane to wasteful John: a quantile regression analysis of Swiss households' electricity demand. Energy Policy 138:111246. https://doi.org/10.1016/j.enpol.2020.111246

Uhr DdAP, Chagas ALS, Uhr JGZ (2019) Estimation of elasticities for electricity demand in Brazilian households and policy implications. Energy Policy 129:69–79. https://doi.org/10.1016/j.enpol.2019.01.061

Wafaa EH, Abdelhak Z, ElHadj E, Salah-Eddine EA (2024) D-vine Copula quantile regression for a multidimensional water expenditures analysis: social and regional impacts. Water Resour Manage, 1–17. https://doi.org/10.1007/s11269-024-03813-z

Wichman CJ, Taylor LO, Von Haefen H (2016) Conservation policies: who responds to price and who responds to prescription? J Environ Econ Manag 79:114–134. https://doi.org/10.1016/j.jeem.2016.07.001

Worthington AC, Higgs H, Hoffmann M (2009) Residential water demand modeling in Queensland, Australia: a comparative panel data approach. Water Policy 11(4):427–441. https://doi.org/10.2166/wp.2009.063

Yoo J, Simon S, Kinzig AP, Perrings C (2014) Estimating the price elasticity of residential water demand: the case of Phoenix. Arizona. Appl Econ Perspect Policy 36(2):333–350. https://doi.org/10.1093/aepp/ppt054