Determinants of the price response to residential water tariffs: meta-analysis and beyond

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Abstract

Meta-analyses synthesise available data on a phenomenon to get a broader understanding of its determinants. This work proposes a two-step methodology. 1) Based on a broad dataset of residential water demand studies, it builds a meta-regression model to estimate mean and standard deviation of price elasticity of residential water demand. 2) The resulting meta-model serves as a basis for implementing an approach that directly simulates the range of price elasticities resulting from policy-relevant combinations of its determinants. This simulation approach is validated using the available dataset. Despite evidence of low average price elasticity, the scenarios simulated using our meta-regression estimates show that increasing block rate tariffs are associated with higher price elasticity, and stresses the importance of using state-of-the-art methodologies when evaluating the price response. This completes other methodological insights obtained from the meta-analysis itself. Policy implications on the use of pricing to bring about water savings are discussed.

Keywords: price-elasticity, residential water demand, discontinuous prices, meta-analysis

Key points

1) Meta-analysis of residential water price elasticity from largest database yet.
2) Resulting statistical model used to formulate a simulation approach
3) Approach validated using available dataset.
4) Approach can give a primary estimate of the efficiency of new pricing policies
5) Approach shows the impact of tariff structure and estimation methodology

Data availability

We are committed to make available along with the paper the dataset we developed and we used to carry out the analyses here reported.

Dataset name: Meta-dataset on water demand

Short description:

"Meta-dataset on water demand" is a dataset that contains hand collected data about primary studies published from 1963 to 2013 which have tried to estimate the residential water demand and water price elasticity in particular. Observations are at single estimate level. They are 615, coming from 124 primary studies. The research paper describes the variables included in the dataset with the relative sources. The dataset is useful for replication purposes. Moreover, making it available would facilitate accumulation and processing of future empirical evidence.

Developers:

The dataset was assembled by building on data made available by Dalhuisen et al. (2003), which comprise 51 primary studies published before 2001. Some additional 73 primary studies were added to obtain the final dataset.

The final dataset was assembled by Riccardo Marzano (riccardo.marzano@polimi.it) with contributions from Silvia Padula and Charles Rougé.

Form of repository: Spreadsheet

Size of archive: 188 KB

Software required: MS Office

Access form: (here the link to the repository where the dataset will be available)

1. Introduction

Pricing is an appealing instrument to bring about water savings. The increasing emphasis of water policies on "putting the right price tag on water" (EC, 2012) and the shift to discontinuous pricing structures such as increasing block rates (IBRs) are two instances of current attitudes toward water pricing, which is aimed at promoting water conservation while maintaining equity and affordability (Rogers et al., 2002). This paper offers a synthesis on the existing evidence on the response of households to water prices by means of a meta-analysis. Contrary to previous studies on this topic, it also goes beyond by validating an exploratory simulation approach based on meta-analysis results. It then uses this approach to produce supplementary insights regarding some of the determinants of price response such as tariff structure. There are three main motivations for this effort.

First, severe droughts have recently hit a few US states and Latin American countries, and episodes of water shortage have occurred in Asia and also in Europe (Kummu et al., 2010; MacDonald, 2010). The debate on water use efficiency and the implementation of conservation policies has grown in scope and urgency as a result, as it has been extended to more geographical locations, including countries traditionally unaffected by large-scale water shortage events.

Second, and despite the ongoing debate involving policymakers, scientists and citizens on water conservation, policy remedies are unclear. On the one hand, demand management has emerged as a cost-effective complement or even as an alternative to supply-side solutions – the expansion of infrastructure capacity. On the other hand, command-and-control policies such as use restrictions or mandatory retrofit programs seem to be less cost-effective than price measures in the short and long run (Olmstead & Stavins, 2009; Escriva-Bou et al., 2015).

Finally, despite an extensive literature focusing on estimating the price elasticity of water demand, it remains unclear whether, to what extent and under which circumstances, consumers respond to changes in the price of water. This is particularly true when pricing structures move from traditional two-part tariffs with a uniform, steady and generally low uniform rate to more complex pricing structures, such as increasing or decreasing block rates, drought prices, or time-of-use prices.

In the absence of a definitive, consensus answer emerging on these issues, syntheses are helpful. Several reviews have been written on the estimation of the residential water demand, including Arbués et al. (2003), Grafton et al. (2011), House-Peters & Chang (2011), Nauges & Whittington (2009), Worthington & Hoffman (2008). Over the years, literature has enlarged the spectrum of adopted methodologies. This, in turn, has led to a better handling of the uncertainties and nonlinearities that exist between water consumption and its determinants, and more generally, a better understanding of the complex spatial and temporal patterns of water usage.

A quantitative alternative to reviews are meta-analysis methods, which have become widely used in the economics and management literature (Stanley & Jarrell, 1989; Moeltner et al., 2007; Geyskens et al., 2009; Nelson & Kennedy, 2009; Tunçel & Hammitt, 2014). Meta-analysis allows statistical evidence from different studies to be combined to obtain a quantitative and systematic overview on the effect size of interest, and to derive common summary statistics with corresponding confidence intervals. This technique generally results in increased statistical power, and can result in improved parameter significance and accuracy compared to primary studies alone. This allows the researcher to provide more reliable within-sample predicted values of the dependent variable under a particular set of conditions. Moreover, a meta-regression analysis (MRA) makes it possible to test hypotheses about the relationships between the effect size of interest and some primary study-specific factors in order to identify what causes study-to-study variations in empirical results. In doing so, it may offer suggestions on how to improve primary data, study design, and model specifications and techniques.

Three previous meta-analyses provided summary statistics of water price elasticity. Espey et al. (1997) used a sample of 124 price elasticity estimates from 24 journal articles produced between 1967 and 1993. They reported a mean water price elasticity of -0.51. Dalhuisen et al. (2003) extended the previous sample and ran their meta-regression on 296 estimates taken from 51 studies produced between 1963 and 2001. They obtained a sample mean of -0.41. Sebri (2014) focused on 100 studies produced between 2002 and 2012 and obtained a mean value of -0.365. The bulk of the literature indicates that water demand is price inelastic, and few studies have reported price elasticity estimates larger than -0.25, i.e. smaller in absolute value (see Renwick & Archibald, 1998; Martínez-Espiñera & Nauges, 2004).

Nevertheless, these systematic reviews highlighted the high heterogeneity that affects water demand studies. They rely on data at different disaggregation levels, both over time (annual, monthly and daily data) and over space (household versus municipality or country data). They focus on either average or marginal prices. They make use of very diverse demand specifications and estimation techniques.

This work goes beyond the meta-analysis on residential water price elasticity recently carried out by Sebri (2014) in two respects. First, this analysis is based on a sample of 124 primary studies produced from 1964 to 2013, whose size in terms of studies is considerably larger than that of the one used in previous available meta-analyses. In fact, it considers a publication time span that bridges both Dalhuisen et al. (2003) and Sebri (2014). We estimate a meta-regression model that is robust to heteroskedasticity stemming from the variation in precision of sampled price elasticity estimates. As in previous meta-analyses on the same topic, our specifications include a wide array of study- and location-specific factors (data characteristics, methodologies, socio-economic factors, tariff structures, and so on). Our specifications are also robust to the presence of outlier values.

Second, in this paper, we go beyond the meta-regression model by formulating, validating and demonstrating a simulation approach that extrapolates the meta-analysis model to evaluate the plausible range of price elasticity estimates for set values of some of the meta-model specifications, which we call scenarios. We simulate scenarios aimed at directly answering policy-relevant questions where a meta-analysis can only tell whether the question is worth asking. For instance, the meta-analysis shows that using DCC models (discrete-continuous choice; Hewitt & Hanemann, 1995; Olmstead et al., 2007; Olmstead, 2009) to analyze the price response with increasing block rates (IBR) leads to values of price elasticity that are greater in a statistical sense. Yet, this is not a direct quantification of how price elasticities are affected by 1) tariff structure and 2) methodological choices. The simulation approach we propose provides this quantification. Besides, it makes it possible to explore the impact of combined impacts of several variables, whereas a meta-regression model can only yield insights on the influence of individual variables.

The rest of the paper is organised as follows. Section 2 reviews the studies conducted on water demand. Section 3 presents the data and describes the methodology for the meta-analysis. Section 3 reports the results of our meta-regression model. Then, Section 4 builds on these results to formulate, validate and exploit a scenario simulation approach. Section 5 concludes and discusses the implications of the findings.

2. Meta-analysis: data and methodology

The selection process for the primary studies pertaining to the meta-sample is presented first (Section 2.1). Then, the data (Section 2.2) and methods (Section 2.3) used in the meta-sample are presented and analyzed. This leads to the model used in this meta-analysis, which is then introduced (Section 2.4).

2.1. Building the meta-sample

The 51 studies included in the dataset from Dalhuisen et al. (2003) were completed by relying upon two previous review articles on the estimation of residential water demand (i.e. Arbues et al., 2003; Worthington & Hoffman, 2008) along with a complementary search protocol based on the following steps. First, we identified a list of keywords that were kept as simple as possible for the sake of inclusiveness. These keywords were: (1) *water*, (2) *demand* and (3) *price elasticity*. Second, we conducted a Boolean search and explored the following online databases: (1) Scopus, (2) ISI Web, (3) RePEc, (4) ScienceDirect, (5) Springer, (6) Wiley, (7) Social Science Research Network (SSRN), (8) the National Bureau of Economic Research (NBER), and (9) the Centre for Economic Policy Research (CEPR). Third, we read the abstracts of all articles we obtained from the queries in order to eliminate those not relevant to the topic. Upon completion of the first three steps we ended up with a list of 352 articles, which we further filtered based on two criteria. On one hand, we selected only those articles that made use of econometric techniques, a common approach since the seminal paper by Howe & Linaweaver (1967), to estimate the residential water demand. Studies using any other methodology to estimate water price elasticities were screened out. On the other hand, we included only price elasticities of residential water demand. When primary studies included residential and non-residential water demand estimates, we discriminated among various estimates reported in the same study in order to select only those using data pertaining to residential consumption.

The above described screening process yielded 73 articles which were added to the extant sample of 51 studies used by Dalhuisen et al. (2003), which also included 12 unpublished studies that were kept in our sample. Therefore, our final dataset includes 124 papers produced from 1963 to 2013 comprising 615 estimates of water price elasticities obtained using data from 31 countries (see Figure 1). A coding protocol was designed to operationalise the information gathered from the sampled studies. Two of the coauthors read all the papers to ensure a reliable coding of the effect size and all the meta-analysis explanatory variables. A list of the sampled studies and information coded in the meta-analysis is available upon request.

Fig. 1a - Distribution of the sampled water demand studies over publication year.

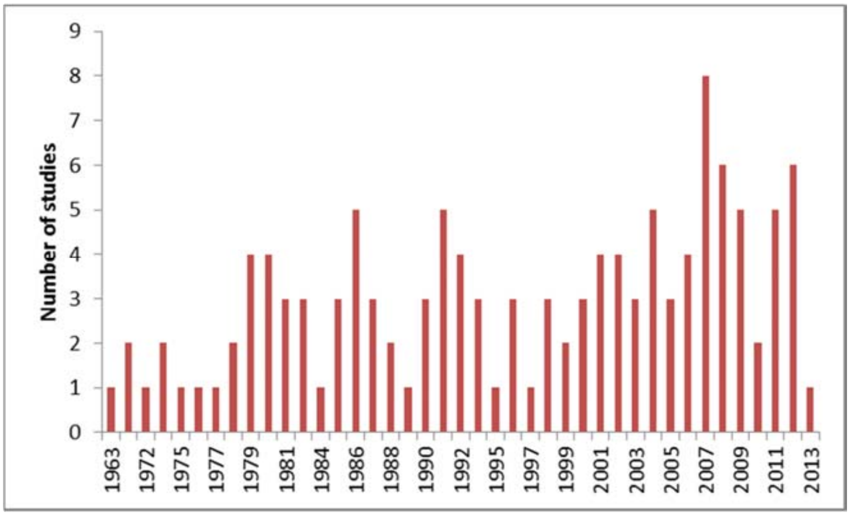
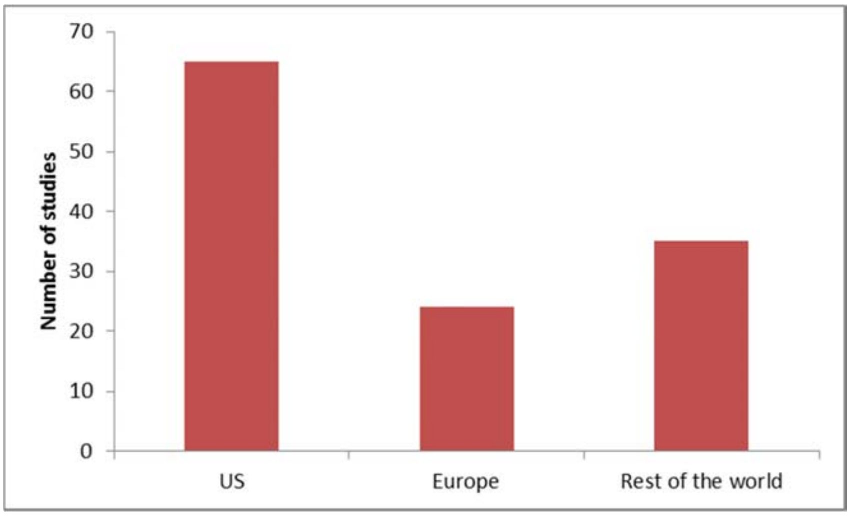


Fig. 1b - Distribution of the sampled water demand studies over demand locations.



2.2. Data used in primary studies

For approximately 64% of the sample, panel data has been used to estimate water demand. Although early water demand studies using panel data date back to the eighties (see Hanke & de Mare, 1982), this approach has become more popular in the last few decades (Dandy et al. 1997; Nauges & Thomas, 2003; Mansur & Olmstead, 2012). Panel data are commonly used to take into account household heterogeneity, and they are essential to estimate long-run price elasticities. Time series data (e.g., Agthe & Billings, 1980; Ruijs et al., 2008) constitute only about 15% of our meta-sample, whereas cross-section data (e.g. Gottlieb, 1963; Foster & Beattie, 1981; Hajispyrou et al., 2002) are used to estimate the remaining 20% of the sampled price elasticities.

Aggregated data hide diverging microeconomic effects, and their use can produce biased estimates, highlighting the interest of data disaggregation over both time and space. Yet, whereas household-level data are needed to control for all relevant household characteristics, only a few studies (Dandy et al., 1997; Olmstead et al., 2007; Mansur & Olmstead, 2012) have actually been able to use them. Most studies resort to aggregated cross-sectional or panel data across a number of municipalities in a region, and then analyze the price elasticity of demand in a spatially disaggregated way. Likewise, daily water consumption data would be ideal to disentangle the effect of price variations on consumption from those of other time-varying determinants such as weather conditions, yet studies using daily data are even more sporadic than those based on household-level data (see Olmstead et al. 2007; Grafton & Ward, 2008). Most primary studies rely on monthly or annual data.

Household-level data has been exploited to estimate only about 36% of the sampled price elasticities, whereas other estimates rely on aggregate data. Daily data are even more uncommon (8% of the estimates), as data is more frequently (53%) disaggregated on a monthly basis.

To estimate residential water demand, the most relevant variable to be measured, together with water consumption, is the price of water. Water tariffs often have complex structures that represent a trade-off between multiple objectives such as equity, public acceptability, transparency and the sustainability of service provision. As far as tariff schemes are concerned, approximately 42% of observations refer to price elasticities estimated in locations where increasing block rates (IBR) were in place. Decreasing block rates (DBR) are far less frequent and account for less than 6% of our observations. When tariff structures are discontinuous, the average and marginal prices generally differ. Some authors assume that what actually defines the price effect is the consumer's perception of it, and that this is best represented by the average price (e.g. Nauges & Thomas, 2000; Gaudin et al., 2001; Schleich & Hillenbrand, 2009). Others prefer marginal prices, and then have to deal with the added difficulty that with IBR and DBR tariffs, marginal prices differ among users according to consumption (Dandy et al., 1997; Hajispyrou et al., 2002; Martínez-Espiñeira, 2002; Nauges & Van Den Berg, 2009). Several ways to tackle challenges linked with price effect estimation consist in introducing an intermediary variable, such as Nordin's difference variable (Nordin, 1976) or Shin's price perception variable (Shin, 1985). Over 36% of price elasticities in the meta-sample are estimated by using the average price (Grafton et al., 2011), whereas the marginal prices are present in 52% of water demand estimates. Almost half of those (24% of the meta-sample) include a difference variable to control for the income effect imposed by discontinuous tariff structures.

In most water demand studies, price elasticity is estimated controlling for other factors that can influence water consumption. The most common among them are climate and seasonal factors, income, household characteristics and urban configuration.

Weather and seasonal factors are taken into account in 73% of the demand estimates through one or more variables measuring temperature (44%), rainfall (61%), evapotranspiration rate (11%)

and season (11%). Indeed, water consumption usually shows a marked seasonal pattern. Summer price elasticities are usually larger than winter ones, as discretionary water uses like outdoor use are more price-sensitive than non-discretionary uses, and they are typically related to summer activities (Billings & Agthe, 1980; Nieswiadomy & Molina, 1989; Griffin & Chang, 1991; Hewitt & Hanemann, 1995; Hoffman et al., 2006). Less than 10% of the price elasticities are obtained using only summer data, while winter data are used in approximately 7% of the cases.

Water bills often represent a small fraction of household income, at least in most developed countries (Arbués et al., 2003). Therefore, although water is considered a normal good (positive income elasticity), the water demand has almost universally been found to be income-inelastic in the literature (see, for instance, Dandy et al., 1997; Gaudin et al., 2001). This remark is accentuated by the difficulty to gather data on household income – provided data themselves are collected at household level – and by the fact that only short-run elasticity values are measured in most studies (approximately 90% of our estimates), whereas retrofitting – the installation of water efficient devices – is a long-run income-related effect of price variations. Furthermore, discontinuous volumetric rates encompass changes in consumer surplus that result in reducing the income effects. Since income is so important in predicting water consumption levels, it is not surprising that it has been controlled for in 79% of our sampled price elasticity estimates.

Population density and household characteristics are relevant in water demand studies. Per-household consumption increases with household size but per-capita consumption decreases (Arbués et al., 2004). Urban configuration, including land zoning (e.g. single-family residential or commercial), total building area, and density of residential developments, also has an influence on total water consumption (Shandas & Parandvash, 2010). Similarly, household composition is a relevant factor to consider. For instance, both elder and younger inhabitants may exhibit a higher level of water consumption for discretionary uses, gardening for the former, and frequent laundering and more water-intensive outdoor leisure activities for the latter (Nauges & Thomas, 2000). Variables that reflect both the proportion of the population over 64 years and under 19 years of age can therefore be included (Martínez-Espiñeira, 2003). Household characteristics such as total number of bedrooms, architectural type (i.e., detached or semidetached) and presence of a garden might also impact water demand (Fox et al., 2009). Population and household characteristics are captured by variables measuring population density (in 5% of the estimates) and household size (in more than 41% of the estimates).

2.3. Methods used in primary studies

Recall that our meta-sample only contains studies that use econometric modeling to estimate water demand. The functional forms used are diverse, but even though the most natural approach is to estimate a linear water demand model (Chicoine & Ramamurthy, 1986; Nieswiadomy & Molina, 1989), the most recurrent functional form is the double-log, where both water consumption and price are log-transformed. The log-transformation is a convenient way to deal with skewed variables; what is more, the coefficient of the price variable in a log-log model is the price elasticity of the water demand. Models where only water consumption or price is log-transformed are also used (Hughes, 1980; Arbués et al., 2004).

The estimation methodologies present in the meta-sample include ordinary least squares (OLS; e.g., Billings & Agthe, 1980; Chicoine et al., 1986; Hewitt & Hanemann, 1995; Martínez-Espiñeira, 2003; Schleich & Hillenbrand, 2009) and several instrumental variable approaches (IV), with specific emphasis on two- and three-stage least squares (2SLS and 3SLS). All of these techniques can be used with data collected at one or at a few points in time, such as cross-sectional and panel data. Time series, instead, may require more sophisticated approaches, such as vector autoregressive models and co-integration techniques (Martínez-Espiñeira, 2007). OLS is by far the most used estimator in the meta-sample (55% of the estimates).

An innovative approach, used in three sampled primary studies is the discrete/continuous choice (DCC) model (Hewitt & Hanemann, 1995; Olmstead et al., 2007; Olmstead, 2009). DCC is a methodology that deals with the endogeneity of price to water consumption arising in discontinuous tariff schedules such as IBR or DBR. It models the observed demand of water as the outcome of 1) a discrete choice of the block in which consumption takes place and 2) a perception error which may place consumption on a different block than intended by the consumer if it is large. Its main weakness is the assumption that consumers are well-informed about the tariff structure.

2.4. Model and estimation technique

The dependent variable of our empirical meta-regression model is represented by the water price elasticities (pe_{ji}) reported in each study. We use two vectors of study- and location-level characteristics as independent variables. The resulting model is as follows:

$$pe_{ji} = \beta_j + \sum_{k=1}^{K} \alpha_k \mathrm{x}_{jik} + \sum_{s=1}^{S} \gamma_s \mathrm{z}_{jis} + e_{ji} \qquad j=1,2,\ldots,L;\ i=1,2,\ldots,N^j \qquad (1)$$

where β_j is the baseline value of the residential water price elasticity, net of any study- and location-specific effect, $\mathbf{x}_{ij}$ and $\mathbf{z}_{ij}$ encompass the K study-specific and S location-specific characteristics, the j indexes L included studies and the i indexes N^j estimates reported in each study, respectively. The baseline β_j is indexed by j because we allow for heterogeneity across studies. e_{ji} is a stochastic disturbance.

Price elasticity estimates may vary considerably in precision leading to heteroskedasticity issues. Therefore, applying conventional ordinary least squares (OLS) to the estimation of equation

(1) can potentially lead to biased estimates of the coefficients' standard errors. To mitigate heteroskedasticity, weighted least squares (WLS) have been adopted. When using WLS, inverse variances should be used as weights in the estimation procedure. Unfortunately, since our data miss most of the standard errors that are needed to compute the inverse variance matrix, we use a standard approach in meta-regression analysis whereby we proxy standard errors with a monotonic transformation of the sample size associated to each reported price elasticity estimate (Horowitz & McConnell 2002; Stanley & Rosenberger 2009).

The study- and location-specific characteristics included in the meta-analysis model of equation (1) are those identified as relevant in explaining variations in price elasticity estimates, such as demand specification and functional form, data characteristics, estimation techniques, and so on. The complete list of the independent variables used in the MRA and their descriptions are presented in Table 1. The operationalization of most of these variables is analogous to those of previous meta-analyses in the field (Dalhuisen et al., 2003; Sebri, 2014).

Table 1 - List of independent variables in MRA and their descriptions.

Panel A – Demand specification variables		
Variable category (*baseline*)	Variable name	Variable description
Type of price elasticity	Long-run	=1 if long-run elasticity is estimated
(*short-run elasticity*)	Segment	=1 if segment elasticity is estimated
Price measure	Marginal price	=1 if the marginal price is used as a price measure
(*average price*)	Shin price	=1 if the Shin price is used as a price measure
Conditioning variables	Number of variables	Number of conditioning variables
	Lagged consumption	=1 if lagged consumption included in demand specification
	Evapotranspiration rate	=1 if evapotranspiration rate included in demand specification
	Season	=1 if season is controlled for in the demand specification
	Household size	=1 if household size included in demand specification
	Population density	=1 if population density included in demand specification
	Income	=1 if income level included in demand specification
	Commercial uses	=1 if commercial use is controlled for in demand specification
	Temperature	=1 if temperature included in demand specification
	Rainfall	=1 if rainfall included in demand specification

	Difference variable	=1 if difference variable included in demand specification
Functional form (*linear*)	Log price	=1 if the specification is semi-logarithmic (x is logarithmic)
	Log consumption	=1 if the specification is semi-logarithmic (y is logarithmic)
	Double log	=1 if the specification is double logarithmic
	Flexible	=1 if the specification is flexible

Panel B – Data variables

Variable category (*baseline*)	Variable name	Variable description
Disaggregation overtime (*annual data*)	Daily data	=1 if the primary study relies on daily data
	Monthly data	=1 if the primary study relies on monthly data
Disaggregation overusers (*aggregate data*)	Household data	=1 if the primary study relies on household-level data
Data period (*cross-season data*)	Summer data	=1 if the primary study uses summer data
	Winter data	=1 if the primary study uses winter data
Data structure (*cross-section data*)	Time-series data	=1 if the primary study relies on time-series data
	Panel data	=1 if the primary study relies on panel data

Panel C – Methodology variables

Variable category (*baseline*)	Variable name	Variable description
Estimator (*OLS*)	IV	=1 if the instrumental variable (IV) approach is used
	2SLS	=1 if the two stages least squares (2SLS) approach is used
	3SLS	=1 if the three stages least squares (3SLS) approach is used
	DCC	=1 if the discrete-Continuous choice approach is used

Panel D – Publication variables

Variable category	Variable name	Variable description
Publication status	Published	=1 if the primary study is published
	Publication year	Publication year

Panel E – Location-specific variables

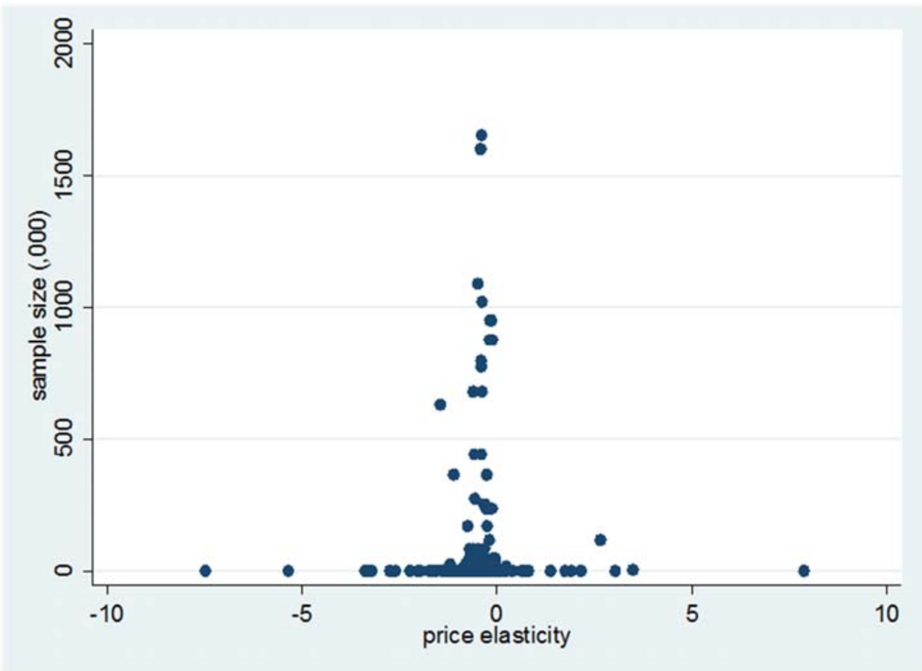
Variable category (*baseline*)	Variable name	Variable description
Socio-economic indicator	GDP per capita	Gross Domestic Product per capita
Water tariff scheme (*flat rate*)	IBR	=1 if customers are subjected to increasing block rates (IBR)
	DBR	=1 if customers are subjected to decreasing block rates (DBR)
Location (*other parts of the world*)	US	=1 if the location is in the United States
	Europe	=1 if the location is in Europe

3. Results

3.1. Descriptive statistics

Figure 2 shows the typical funnel plot commonly used in meta-analyses, where the sample size on the y-axis is the number of observations used to estimate the price elasticity (x-axis) in each primary study. In the absence of publication bias, studies based on larger samples have near-average elasticity, whereas studies based on smaller samples are spread on both sides of the average, creating a roughly funnel-shaped distribution. In this respect, it is worth recalling that we have included also unpublished studies in our meta-sample.[1] The funnel plot justifies the adoption of WLS to mitigate the heteroskedasticity that arises from differences in precision associated with the price elasticity estimates.

Fig. 2 - Funnel plot of price elasticity over sample size.

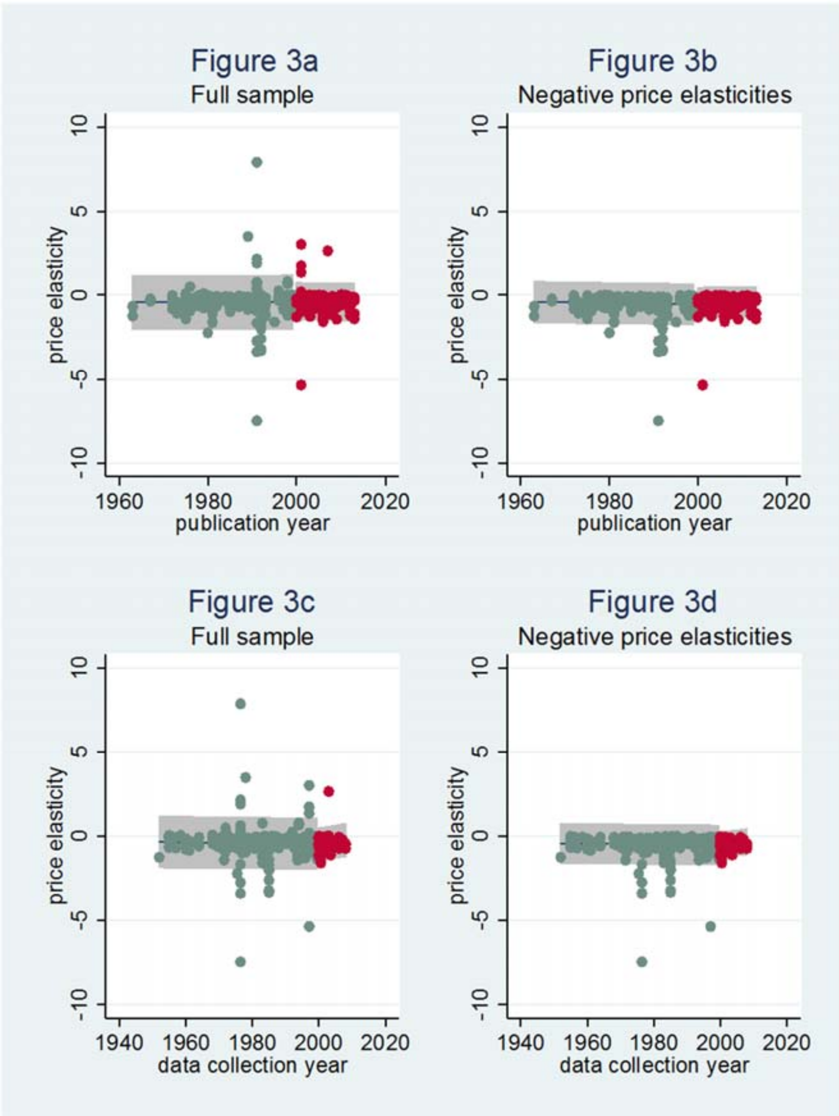


The average water price elasticity estimate is -0.40, with a standard deviation of 0.72 and a median of -0.34. Fifty-three out of 615 estimates are smaller than -1, i.e. refer to elastic water

[1] Unpublished studies include working papers that have not been accepted for publication yet. When existing, we have always included a published version of the study.

demands. The most price-elastic estimated water demand reports a price elasticity of -7.47. Thirty-two out of 615 observations are positive, indicating that demand increases with price. These positive values will be carefully handled in the MRA because they are not consistent with standard micro-economic theory.

Fig. 3 - Estimated price elasticities over the publication year (Figure 5a-b) and over the data collection year (Figure 5c-d) with 95% confidence interval bands computed before and after the year 2000.



Price elasticity estimates from the post-2000 studies are closer to the overall mean value (Figure 3a-b). This convergence in the most recent estimates is also confirmed when the price elasticities are plotted against the data collection years (see Figure 3c-d). The use of more standardized estimation techniques partly explains this decrease in inter-study variance.

Table 2 reports the descriptive statistics of the independent variables included in the model described in equation (1). Sixty-eight primary studies (397 observations) used data collected in the United States, whereas 26 studies (111 observations) are based on European datasets.[2] On average, water demand is estimated in high income locations (the mean value of *GDP per capita* is 25,300 US dollars).

Table 2 - Descriptive statistics.

Variable	Mean	Sd	Max	Min
Long-run	.0992	.2992	1	0
Segment	.0425	.2019	1	0
Marginal price	.5213	.4999	1	0
Shin price	.0236	.1520	1	0
Number of variables	8.169	13.67	206	0
Lagged consumption	.1497	.3570	1	0
Evapotranspiration rate	.1035	.3049	1	0
Season	.1083	.3110	1	0
Household size	.4189	.4938	1	0
Population density	.0525	.2233	1	0
Income	.7898	.4078	1	0
Commercial uses	.0350	.1840	1	0
Temperature	.4350	.4962	1	0
Rainfall	.6035	.4896	1	0
Difference variable	.2299	.4211	1	0
Log price	.0252	.1568	1	0
Log consumption	.0173	.1306	1	0
Double log	.5423	.4986	1	0
Flexible	.0835	.2768	1	0
Daily data	.0835	.2768	1	0
Monthly data	.5260	.4997	1	0

Household data	.3669	.4823	1	0
Summer data	.0945	.2927	1	0
Winter data	.0677	.2515	1	0
Time-series data	.1480	.3554	1	0
Panel data	.6346	.4819	1	0
IV	.0457	.2089	1	0
2SLS	.0756	.2646	1	0
3SLS	.0094	.0968	1	0
DCC	.0205	.1417	1	0
Published	.8976	.3034	1	0
GDP per capita	25,086	9,929	59,065	762.1
IBR	.4031	.4909	1	0
DBR	.0567	.2314	1	0
US	.6520	.4767	1	0
Europe	.1748	.3801	1	0

3.2. Main results from the meta-analysis model

Table 3 presents the results of the model referring to equation (1). The dependent variable is the price elasticity reported in each estimate of each primary study included in the meta-sample.

The table reports the results of the WLS (columns 1-3) and panel generalised least squares (GLS, column 4) estimations obtained using the square root of the sample size as analytical weights (Stanley & Rosenberger, 2009). In fact, the studies included in the meta-dataset report multiple estimates, depending on whether they use different subsamples, specifications, estimators and so on. We correct the standard errors by clustering the estimates within studies (columns 1-3) to account for data dependency across estimates from the same study. An alternative approach applies panel data estimators to a panel that observes multiple estimates for single studies (Rosenberger & Loomis 2000; Stanley & Doucouliagos 2012).

Table 3 - WLS and panel GLS estimates.

	WLS			Panel GLS
	(1)	(2)	(3)	(4)
GDP per capita			.0088	.0040**

			(.0115)	(.0018)
US			-.0521	-.0531
			(.3235)	(.0624)
Europe			.0405	.0395
			(.3574)	(.0542)
IBR		-.0528	-.0456	-.1130**
		(.0600)	(.0505)	(.0445)
DBR		.5569*	.5567	.0401
		(.3334)	(.3432)	(.1105)
Long-run	-.0084	-.0129	-.0361	-.0768
	(.1028)	(.0963)	(.0738)	(.0657)
Segment	-.0036	.0464	.0477	.0696
	(.4936)	(.4848)	(.4957)	(.1954)
Marginal price	.1963	.1777	.1852	.1262***
	(.1281)	(.1200)	(.1228)	(.0390)
Shin price	1.022**	.7647	.8143	.0576
	(.4216)	(.4838)	(.5531)	(.1746)
Number of variables	.0112***	.0117***	.0123***	.0054***
	(.0021)	(.0021)	(.0022)	(.0014)
Lagged consumption	-.0503	-.0454	-.0274	-.0711
	(.1056)	(.1008)	(.0801)	(.0556)
Evapotranspiration rate	-.0006	-.0291	-.0277	.0099
	(.2345)	(.2100)	(.2263)	(.0617)
Season	.3009**	.2697**	.2684*	.0280
	(.1331)	(.1267)	(.1424)	(.0528)
Household size	-.2367	-.1923	-.1575	-.0316
	(.2659)	(.2455)	(.2635)	(.0305)
Population density	.0959	.0872	.1421	.0631
	(.2651)	(.2549)	(.3074)	(.0595)
Income	.2917	.2124	.2721	.0635
	(.3631)	(.3474)	(.3219)	(.0472)
Commercial uses	.7604***	.6964***	.6816***	.3192***
	(.2330)	(.2007)	(.2052)	(.0783)
Temperature	-.0247	-.0558	-.0854	.0216
	(.1871)	(.1692)	(.1918)	(.0366)
Rainfall	.1630	.1994	.1247	.0191
	(.2256)	(.2000)	(.2032)	(.0436)

Difference variable	.2364	.2542	.2704	.0247
	(.3048)	(.2948)	(.3198)	(.0516)
Log price	.8797	.9449	1.078	.0661
	(.8271)	(.8004)	(.8294)	(.1517)
Log consumption	.3716	.3772	.3715	.4569***
	(.4049)	(.4229)	(.4154)	(.1294)
Double log	-.2587	-.2027	-.1777	-.1252***
	(.2188)	(.2020)	(.2188)	(.0378)
Flexible	-.0204	-.0075	.0001	-.0205
	(.1935)	(.1966)	(.2427)	(.0543)
Daily data	-.0441	.0141	.0089	-.0114
	(.3646)	(.3434)	(.3451)	(.0612)
Monthly data	-.2064	-.1988	-.1593	-.0194
	(.2262)	(.2145)	(.2126)	(.0506)
Household data	.0844	.0685	.0256	-.0696*
	(.1045)	(.1879)	(.2005)	(.0379)
Summer data	-.2380	-.2711*	-.2715*	-.1054***
	(.1454)	(.1388)	(.1526)	(.0373)
Winter data	.0867	.0543	.0538	.1137***
	(.1345)	(.1274)	(.1452)	(.0380)
Time-series data	.0518	.0295	.2093	.1462**
	(.4651)	(.4465)	(.4785)	(.0680)
Panel data	-.2262	-.1770	-.0634	.0014
	(.3688)	(.3654)	(.2971)	(.0652)
IV	-1.437*	-1.441*	-1.512*	-.1983
	(.8012)	(.8013)	(.8131)	(.1604)
2SLS	-.2410	-.2133	-.2229	-.0946*
	(.2174)	(.2076)	(.2167)	(.0488)
3SLS	1.791**	1.253	1.262	.5108*
	(.8164)	(.8506)	(.8640)	(.2780)
DCC	-.5121**	-.5060**	-.5577**	-.2291**
	(.2448)	(.2425)	(.2478)	(.1068)
Published	-.0940	-.1321	-.2073	-.1348***
	(.2948)	(.2663)	(.3053)	(.0497)
Constant	-.3712	-.3600	-.6642	-.3325***
	(.6997)	(.6895)	(.8140)	(.1080)
Observations	615	615	598	598

Studies	122	122	117	117

The table reports the results of the WLS (columns 1-3) and panel GLS (column 4) estimations obtained using the square root of the sample size as analytical weights. The dependent variable is the price elasticity reported in each estimate of each primary study included in the meta-analysis. Depending on the specification, the models control for study-level characteristics, tariff schemes, location of the water demand and gross domestic product per capita. Standard errors (clustered by studies) are reported in parentheses. *, **, and *** denote significance at 10%, 5% and 1%, respectively.

Column (1) reports the estimates that refer to a specification which includes only study-level characteristics. The variables that control for the tariff scheme faced by customers, i.e. *IBR* and *DBR,* are included in the specification reported in column (2). The location (*US* and *Europe*) and *GDP per capita* are also added in column (3).

The results reported in Table 3 provide some insights into the sources of variation in price elasticity estimates. If the most thorough specification in column (3), which was obtained through WLS, is considered, three variables show highly statistically significant coefficients. First, the *Number of variables* employed in the specification of the water demand is found to have a positive effect on the estimated price elasticity. The coefficient is statistically significant at the 1% level, since when more variables are included in the model specification, the analyst obtains a less elastic water demand. Second, the presence of *Commercial uses* also results in a less elastic water demand, with statistically significance at the 1% level. Third, consistently with Dalhuisen et al. (2003), other things being equal, primary studies that rely upon the DCC approach – always applied to cases with IBR in our sample – show a more price-elastic water demand. In this case, the coefficient is negative and statistically significant at the 5% level. The three coefficients are also statistically significant in the specifications reported in columns (1) and (2). The statistical significance at the 5% level of DCC suggests that as far as DCC can be considered as the most sophisticated methodology available to estimate water demand under discontinuous prices, IBR should be considered an effective tool for water conservation.

The application of the DCC approach remains statistically significant in the panel GLS estimates (column 4) along with the number of variables included in the specification and the inclusion of a variable that takes into consideration the commercial uses. In addition, the results in column (4) suggest that the use of the *Marginal price* as a price measure may lead to a less elastic water demand, compared with those obtained using average prices. This suggests that users are more sensitive to average than marginal price. As far as the functional form is concerned, the double-logarithmic (*Double log*) specification is associated with a more elastic water demand, whereas the *Semi logarithmic specification* is conducive to lower price elasticities. All of the aforementioned effects are statistically significant at the 1% level. Reliance on *Time-series data* leads to smaller price elasticity estimates (more inelastic water demand) with a statistical significance level of 5%. A possible explanation is the impossibility to exploit household-level heterogeneity in the water demand estimation. According to the panel results, the season in which the data were collected is statistically significant in explaining variations in the price elasticity estimates. In particular, studies relying on *Summer data* show a more elastic water demand, whereas *Winter data* are more likely to be associated with a less elastic water demand. As far as the location-specific variables are concerned, *GDP per capita* is found to be statistically significant at the 5% level in explaining a less elastic water demand, as economic theory would predict. Moreover, *IBR* is found to be conducive to a more elastic water demand (with statistical significance at the 5% level).

3.3. Outlier analysis

As shown in Section 3.1, the range of price elasticity estimates from primary studies is very large. There are observations whose price elasticity is positive in contradiction of basic micro-economic theory, and others that show an extremely elastic water demand. These outliers raise concerns both about the reliability of these estimates, and about their potential influence on the meta-regression results. Therefore, we estimate a probit model that predicts the probability of belonging to the outliers' group and find evidence that using panel data significantly decreases the odds of obtaining an outlier price elasticity estimate, whereas the water demand location (i.e. location-specific features) does not have any statistically significant impact (results are untabulated but available upon request).

In order to rule out the possibility that our estimates may be biased considerably by the presence of these outlier values, we re-estimate the model on different subsamples. Table 4 reports the results of WLS estimations after having dropped positive price elasticities (column 1), and after having dropped positive price elasticities and trimmed 1% (column 2) and 2% (column 3) of the observations on the left tail of the price elasticity distribution.

Table 4 – Outlier-robust estimates.

	Outliers excluded		
	(1)	(2)	(3)
GDP per capita	.0032	-.0001	-.0008
	(.0057)	(.0058)	(.0058)
US	.2723	.3078	.3217
	(.2023)	(.1989)	(.1979)
Europe	.5073**	.4635*	.4732**
	(.2221)	(.2213)	(.2187)
IBR	-.0102	-.0082	-.0098
	(.0370)	(.0367)	(.0372)
DBR	.2466**	.2511*	.2537*
	(.1244)	(.1284)	(.1315)
Long-run	.0568	.0591	.0554
	(.0835)	(.0843)	(.0825)
Segment	-.2171	-.2051	-.2042
	(.1489)	(.1655)	(.1677)
Marginal price	.0212	.0390	.0426
	(.0706)	(.0678)	(.0671)
Shin price	.0983	.1169	.1156

	(.1301)	(.1352)	(.1374)
Number of variables	.0031***	.0028***	.0028***
	(.0010)	(.0010)	(.0010)
Lagged consumption	-.1322	-.1293	-.1237
	(.0807)	(.0823)	(.0807)
Evapotranspiration rate	.2064**	.1680*	.1502*
	(.0960)	(.0882)	(.0862)
Season	.2915***	.2900***	.3028***
	(.0914)	(.0897)	(.0870)
Household size	.1087	.1225	.1348
	(.0997)	(.1025)	(.1036)
Population density	.2254	.1919	.2017
	(.2302)	(.2195)	(.2203)
Income	-.0253	-.0914	-.0978
	(.1394)	(.1492)	(.1506)
Commercial uses	.8610***	.8277***	.8195***
	(.1822)	(.1841)	(.1840)
Temperature	-.1555*	-.1832**	-.1924**
	(.0809)	(.0810)	(.0813)
Rainfall	.1695	.1949*	.2093*
	(.1239)	(.1170)	(.1145)
Difference variable	-.3338**	-.2853**	-.2671**
	(.1288)	(.1245)	(.1209)
Log price	-.5236***	-.5606***	-.5568***
	(.1531)	(.1580)	(.1600)
Log consumption	.0610	.0908	.1071
	(.2222)	(.2279)	(.2311)
Double log	-.3548***	-.3194***	-.3040***
	(.0885)	(.0870)	(.0860)
Flexible	-.0790	-.0413	-.0269
	(.1186)	(.1180)	(.1172)
Daily data	-.2492	-.2308	-.2205
	(.1565)	(.1526)	(.1530)
Monthly data	-.0263	-.0760	-.0736
	(.1220)	(.1210)	(.1199)
Household data	-.1161	-.1106	-.1092
	(.1183)	(.1191)	(.1197)

Summer data	-.2601**	-.2587**	-.2447**
	(.1110)	(.1088)	(.1066)
Winter data	.0673	.0684	.0821
	(.1046)	(.1015)	(.0982)
Time-series data	.8271***	.7256**	.7428**
	(.2878)	(.2944)	(.2928)
Panel data	.0347	-.0014	-.0008
	(.1671)	(.1674)	(.1688)
IV	.2789**	.2586*	.2502*
	(.1324)	(.1363)	(.1359)
2SLS	.0180	.0016	-.0034
	(.0732)	(.0728)	(.0730)
3SLS	.1220	.1736	.1929
	(.2326)	(.2486)	(.2512)
DCC	-.2245*	-.2524*	-.2619**
	(.1321)	(.1291)	(.1272)
Published	-.6516***	-.6335***	-.6324***
	(.1218)	(.1236)	(.1249)
Constant	-.1493	-.0072	-.0300
	(.2804)	(.3111)	(.3089)
Observations	567	560	555
Studies	117	117	117

The table reports the results of the WLS estimations obtained using the square root of the sample size as analytical weights after having dropped positive price elasticities (column 1), and after having dropped positive price elasticities and trimmed 1% (column 2) and 2% (column 3) of the observations on the left tail of the price elasticity distribution. The dependent variable is the price elasticity reported in each estimate of each primary study included in the meta-analysis. Standard errors (clustered by studies) are reported in parentheses. *, **, and *** denote significance at 10%, 5% and 1%, respectively.

Results reported in Table 4 make our main findings more robust. Applying the DCC approach, including more variables in the specification, and controlling for the commercial uses, are three methodological features that retain statistical significance on estimated water price elasticities. In addition, some coefficients that are statistically significant in our panel estimations (but not in our full sample WLS estimations) are proved to be so in the outlier-robust WLS estimates as well. This is the case of *Double log*, *Time-series data* and *Published*, for which the outlier-robust estimates are even stronger than in the panel model; the *Double log* and *Published* specifications are associated with a more elastic water demand whereas the opposite is true for *Time-series data*. Concerning the *Published* specification, this is a clear evidence of publication bias that we were not able to discern through the visual aid provided by the funnel plot, simply because we had no way to distinguish between published and unpublished studies. On the contrary, after having dropped less reliable estimates that were likely to significantly drive our main results, the preference for studies that found a more elastic water demand has been detected.

4. Simulation approach

4.1. Rationale and description

Our meta-sample can be also exploited through the formulation of scenarios aimed at obtaining predictions of water price elasticity in different contexts and under alternative pricing policies. In what follows, a scenario simulation is a model prediction obtained using the estimated coefficients and setting the independent variables at values corresponding to the scenario’s assumptions. The justification for developing this methodology is two-fold. On one hand, it can inform demand management policies by providing quantitative estimates of price elasticity for well-defined scenarios. On the other hand, scenarios can explore the combined impact of several variables on price elasticity. Although individual coefficients of meta-regressions may not be statistically significant, changes in the corresponding variables used as inputs to the simulation of the scenario may still play a significant role when jointly implemented.

We cannot directly propose a meta-regression model as a simulation tool. Given the large number of included regressors, overfitting would be a concern when using such a model for predictive purposes (see e.g., Harrell, 2015: p. 72). For that reason, we use a three-step procedure aimed at taking advantage of our meta-sample in a scenario simulation setting. First, starting from the outlier-robust meta-model of Section 3.3, we eliminate the least relevant variables to select a more parsimonious linear model. Second, we validate the obtained restricted model. Finally, we use the validated model to obtain scenario simulations exploring the combined impacts of tariff structure, seasonality, and estimation methodology.

4.2. Model selection and validation

Model selection has been performed via stepwise regression technique with a backward elimination approach, which is a part of the broad family of the General-to-Specific modelling approaches (Hocking, 1976). Backward elimination starts with the full meta-regression model, then iteratively drops independent variables whose p-values are higher than a chosen threshold and re-estimates the resulting restricted model, until all p-values are under the threshold (Kennedy & Bancroft, 1971). We chose 0.2 as our p-value threshold, and eliminated the independent variable with the highest p-value at each iteration. The stepwise regression led to dropping the following variables in this order: *Longrun*, *Segment*, *Marginal Price*, *Shin Price*, *Income*, *Population Density*, *Log Consumption*, *Flexible*, *Monthly data*, *Household data*, *Panel data*, *2SLS*, *3SLS* and *GDP per capita*.

The selected model has been cross-validated by using studies published before 2000 as "training set" and those published after 2000 as "test set" (Arlot & Celisse, 2010). This procedure entails the following sub-steps: i) estimating the predictive model using the training set; ii) obtaining model predictions relative to observations in the test set; iii) regressing observed price elasticities against predictions using the test set; iv) testing that predictions are able to explain the observed values, i.e., the relative coefficient is statistically significant at the conventional significance level. In order to cope with heteroskedasticity we use WLS both in steps i) and iii). The model is validated at a 5% statistically significance level. This suggests that the selected model exhibits good predictive performance and can be accordingly used to produce reliable scenario simulations. Table 5 shows the estimates of the predictive model.

Table 5 – Predictive model estimates.

Dependent variable: Price elasticity	
IBR	-.0235
	(.0429)
DBR	.3495***
	(.1078)
Summer data	-.2828***
	(.1026)
Winter data	.0441
	(.0959)
US	.1963
	(.1680)
Europe	.4184**
	(.1933)
Number of variables	.0026***
	(.0009)
Lagged consumption	-.0731***
	(.0140)
Evapotranspiration rate	.1395*
	(.0798)
Season	.2635***
	(.0839)
Household size	.0737
	(.0535)
Commercial uses	.8922***
	(.0811)
Temperature	-.1785**
	(.0786)
Rainfall	.1657**
	(.0837)
Difference variable	-.2424**

	(.1200)
Log price	-.4273***
	(.1270)
Double log	-.2630***
	(.0769)
Daily data	-.1201
	(.1035)
Time-series data	.6615***
	(.2163)
IV	.2103**
	(.0905)
DCC	-.2689**
	(.1207)
Published	-.6011***
	(.0587)
Constant	-.1078
	(.2219)
Observations	572
Studies	122

The table reports the results of the WLS estimations obtained using the square root of the sample size as analytical weights after having dropped positive price elasticities and trimmed 2% of the observations on the left tail of the price elasticity distribution. The dependent variable is the price elasticity reported in each estimate of each primary study included in the meta-analysis. Standard errors (clustered by studies) are reported in parentheses. *, **, and *** denote significance at 10%, 5% and 1%, respectively.

4.3. Insights from the simulation approach

After having validated the predictive model, we illustrate the approach by simulating selected scenarios and comparing the relative price elasticities. Scenarios are simulated by setting all the independent variables at their means, except for those measuring the tariff structure and the season during which the water demand has been estimated. Thereafter, we exploit meta-data variation to produce simulated price elasticities conditional on tariff structure, season, and estimation methodology – focusing on the use of DCC. Table 6 shows the scenario simulation results.

Table 6 – Scenario simulations.

Predicted variable: Price elasticity	Price elasticity	Standard error	95% conf. inter.
All seasons			
Linear	-.3692***	.0194	[-.4075;-.3308]
DBR	-.0211	.1060	[-.2309;.1888]
IBR	-.3941***	.0236	[-.4408;-.3473]
IBR (with DCC)	-.6615***	.1188	[-.8967;-.4263]
Summer			
Linear	-.5913***	.0763	[-.7423;-.4403]
DBR	-.2432**	.1226	[-.4859;-.0005]
IBR	-.6162***	.0798	[-.7743;-.4581]
IBR (with DCC)	-.8837***	.1341	[-1.149;-.6182]
Winter			
Linear	-.2644***	.0691	[-.4012;-.1276]
DBR	.0837	.1440	[-.2013;.3687]
IBR	-.2893***	.0664	[-.4207;-.1578]
IBR (with DCC)	-.5567***	.1200	[-.7943;-.3192]
Observations	555	555	555
Studies	117	117	117

The table reports the results of scenario simulations based on the validated predictive model. The predicted price elasticities are obtained by setting all the variables at their means, except for those measuring the tariff structure and the season. Standard errors (clustered by studies) and 95% confidence intervals are also reported. ** and *** denote significance at 5% and 1%, respectively.

The validated model simulates price elasticities across seasons under linear DBR and IBR tariff schedules. In the latter case, we compare estimates obtained with and without the DCC approach, which, on the one hand, properly deals with the endogeneity of price with respect to water demand, but, on the other hand, rests on the assumption that households are fully informed about the tariff structure, including block sizes and prices within each block (Olmstead et al, 2007).

Simulated results lead to the following conclusions. First, predicted price elasticities are close to the sample mean value reported in the Section 3.1 overall, particularly under the linear tariff schedule (-0.37). Second, the water demand is found to be more price-elastic during summer than winter months. Price elasticity goes up (in absolute value) by 0.33 when switching from winter to summer periods. Third, DBR makes water demand less price-elastic. Under DBR the water consumption seems not to respond to price unless we focus on summer months. Fourth, IBR is associated with more elastic water demand, provided that water demand is estimated using a DCC approach. According to our simulations, price elasticity reaches the value of -0.88 when DCC is employed to estimate the water demand in locations exposed to IBR. This means that under IBR, if the water demand is properly estimated (and customers are fully informed about the functioning of the tariff mechanism), it turns out to be price elastic or close to.

5. Discussion

This analysis extends previous meta-analyses in two respects. First, it exploits a larger sample of primary studies (more than double than that of Dalhuisen et al., 2003, 20% larger than that of Sebri, 2014) spanning over a longer time period and includes recent analyses that make use of more advanced methods and better datasets. Second, it uses the resulting meta-regression model to implement a simulation approach to explore price elasticities under different scenarios. A salient finding from this approach is that the more sophisticated the statistical analysis methods - i.e. when they deal with the endogeneity of price to water consumption – the more elastic the water demand in IBRs schemes. This finding suggests that IBRs may be more effective than traditional ones in bringing about water savings. It also stresses the importance of the estimation methodology. In fact, endogeneity issues are relevant when estimating water demand under non-linear pricing: price elasticities estimated using OLS can be shown to be positively (negatively) biased under IBRs (DBRs) schemes (see Hewitt & Hanemann, 1995). This result is so far based on a limited number of observations (13) as only three primary studies in the sample used DCC.

This finding highlights the effectiveness of managing water demand using pricing schemes more sophisticated than a two-part tariff with a uniform volumetric charge. On the one hand, the reasons for this finding should be investigated. Previous studies have shown that differences in the average magnitude of prices across locations adopting IBRs and uniform rates are not responsible for differences in observed elasticities (see Olmstead et al., 2007). Behavioral reaction to the water price structure, for instance due to increased attention to price, could be a more plausible explanation. On the other hand, the result is interesting because technological innovations, most notably smart meters that can measure consumption at a sub-hourly timescale and provide real-time feedback to the users through online consumer portals, are bound to increase interest in more complex pricing schemes (Cominola et al., 2015). Such tariffs would be dynamic, i.e., prices could vary over short time intervals (Rougé et al., *in press*). For instance, scarcity pricing could help manage demand when water becomes scarce (e.g. linked to available reservoir storage) by adjusting prices on a weekly or monthly basis, thus sending users a signal of the true resource value (Grafton & Kompas, 2007; Pulido-Velazquez et al., 2013; Macian-Sorribes et al., 2015); residential prices would be adjusted every week or month as the situation evolves. Similarly, peak pricing could modulate sub-daily prices to help shift consumption away from periods of peak demand in the morning and evening, leading to substantial financial savings for water utilities (Rougé et al., *in press*). In that latter case, the possibility to substitute peak uses with off-peak uses may lead to a more price-elastic peak demand (Cole et al., 2012).

Besides, the assumption that consumers have appropriate information about tariff structure, essential for the DCC model, is bound to see its validity increase with smart metering, as it brings about new ways for utilities to engage with their customers (Fraternali et al., 2012; Harou et al., 2014; Koutiva & Makropoulos, 2016). More generally, the high-resolution data generated by smart metering may also enable to verify the assumptions behind estimation methodologies, and to propose even more sophisticated model that would be able to provide more accurate price elasticity estimates.

Conversely, when the tariff includes a uniform volumetric charge, the finding from previous meta-analyses that residential water demand is price inelastic is confirmed, even though the study also confirms that the elasticity of demand is always significantly different from zero. In addition, price elasticity is likely to increase for higher prices. Our meta-dataset does not include data on water prices charged in locations where the water demand has been estimated, but there are reasons to expect a certain degree of heterogeneity in price elasticity across price levels. This highlights the need for further study of the potential role of dynamic residential water pricing for managing water scarcity and promoting water conservation in urban water supply.

This meta-analysis offers several guidelines for future research on the price response of water demand. First, it highlights the importance of using panel data, which significantly reduce the probability of obtaining outlier values when estimating water price elasticity. Second, it shows that water price elasticities differ significantly depending on the season. This underscores the importance of using cross-season data, and of controlling for the season during which data have been collected. Third, it stresses the value of using disaggregated data, both over time and across users. Finally, it draws attention to the relevance of considering the non-linearity of the price structure when estimating water demands.

6. Conclusions

Meta-analysis is a powerful tool to summarise previous statistical evidence on water price elasticity, and to get an overall picture of the impacts of heterogeneity in study designs and study characteristics on the variations of empirical estimates. This study confirmed this; for instance, its results stressed that including more variables in the specification and controlling for the commercial uses of water lead to a less elastic water demand, suggesting that the specification choices are not neutral with respect to price elasticity estimates.

Yet, meta-analyses are not fit for answering direct questions on the range of plausible price elasticities under given conditions. These are relevant questions when it comes to summarising previous demand studies to inform demand management policies, as debate rages on the potential role on water pricing. This is why this work has also validated and demonstrated a simulation tool designed to serve just that purpose. It has shown that when customers face IBRs and the water demand is estimated by relying on state-of-the-art methodological approaches, the predicted water price elasticity is higher in absolute value. Yet, the DCC methodology that leads to these more elastic estimates also has weaknesses. This stresses the policy implications of understanding which methodologies are the most appropriate to evaluate the price response, and in which circumstances.

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Data are described as thoroughly as possible in the dedicated section of the paper. The authors are in charge of curating the data and are fully committed to make the data available to anyone upon request.

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