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

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24

25 **Abstract**

26

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

39

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

41

42 **Key points**

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

48

49 **Data availability**

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

52 *Dataset name:* Meta-dataset on water demand

53 *Short description:*

54 “Meta-dataset on water demand” is a dataset that contains hand collected data about primary
55 studies published from 1963 to 2013 which have tried to estimate the residential water demand
56 and water price elasticity in particular. Observations are at single estimate level. They are 615,
57 coming from 124 primary studies. The research paper describes the variables included in the

58 dataset with the relative sources. The dataset is useful for replication purposes. Moreover, making
59 it available would facilitate accumulation and processing of future empirical evidence.

60 *Developers:*

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

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

66 *Form of repository:* Spreadsheet

67 *Size of archive:* 188 KB

68 *Software required:* MS Office

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

70 **1. Introduction**

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

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

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

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

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

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

116 study variations in empirical results. In doing so, it may offer suggestions on how to improve
117 primary data, study design, and model specifications and techniques.

118 Three previous meta-analyses provided summary statistics of water price elasticity. Espey et
119 al. (1997) used a sample of 124 price elasticity estimates from 24 journal articles produced
120 between 1967 and 1993. They reported a mean water price elasticity of -0.51. Dalhuisen et al.
121 (2003) extended the previous sample and ran their meta-regression on 296 estimates taken from
122 51 studies produced between 1963 and 2001. They obtained a sample mean of -0.41. Sebri (2014)
123 focused on 100 studies produced between 2002 and 2012 and obtained a mean value of -0.365.
124 The bulk of the literature indicates that water demand is price inelastic, and few studies have
125 reported price elasticity estimates larger than -0.25, i.e. smaller in absolute value (see Renwick &
126 Archibald, 1998; Martínez-Españera & Nauges, 2004).

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

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

140 socio-economic factors, tariff structures, and so on). Our specifications are also robust to the
141 presence of outlier values.

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

155 The rest of the paper is organised as follows. Section 2 reviews the studies conducted on water
156 demand. Section 3 presents the data and describes the methodology for the meta-analysis. Section
157 3 reports the results of our meta-regression model. Then, Section 4 builds on these results to
158 formulate, validate and exploit a scenario simulation approach. Section 5 concludes and discusses
159 the implications of the findings.

160 **2. Meta-analysis: data and methodology**

161 The selection process for the primary studies pertaining to the meta-sample is presented first
162 (Section 2.1). Then, the data (Section 2.2) and methods (Section 2.3) used in the meta-sample are

163 presented and analyzed. This leads to the model used in this meta-analysis, which is then
164 introduced (Section 2.4).

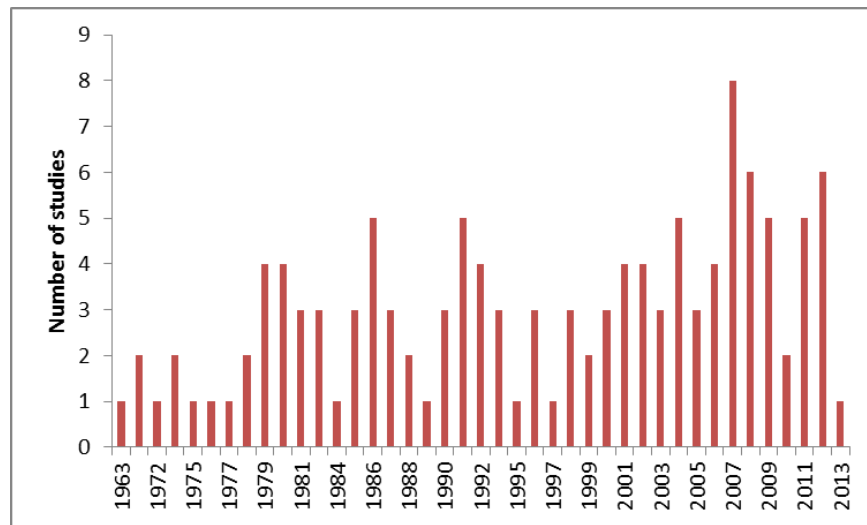
165 ***2.1. Building the meta-sample***

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

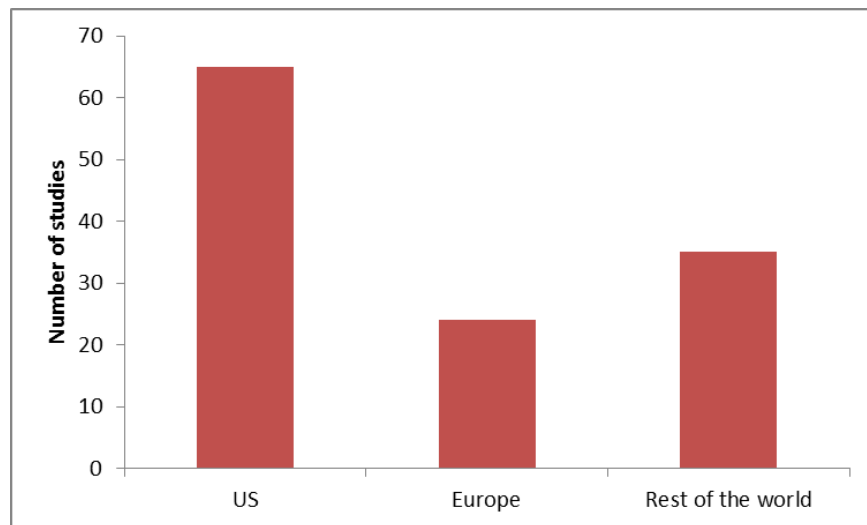
184 The above described screening process yielded 73 articles which were added to the extant
185 sample of 51 studies used by Dalhuisen et al. (2003), which also included 12 unpublished studies

186 that were kept in our sample. Therefore, our final dataset includes 124 papers produced from
187 1963 to 2013 comprising 615 estimates of water price elasticities obtained using data from 31
188 countries (see Figure 1). A coding protocol was designed to operationalise the information
189 gathered from the sampled studies. Two of the coauthors read all the papers to ensure a reliable
190 coding of the effect size and all the meta-analysis explanatory variables. A list of the sampled
191 studies and information coded in the meta-analysis is available upon request.

192
193 **Fig. 1a** - Distribution of the sampled water demand studies over publication year.



194
195 **Fig. 1b** - Distribution of the sampled water demand studies over demand locations.



197

198 **2.2. Data used in primary studies**

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

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

218 Household-level data has been exploited to estimate only about 36% of the sampled price
219 elasticities, whereas other estimates rely on aggregate data. Daily data are even more uncommon
220 (8% of the estimates), as data is more frequently (53%) disaggregated on a monthly basis.

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

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

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

245 (11%) and season (11%). Indeed, water consumption usually shows a marked seasonal pattern.
246 Summer price elasticities are usually larger than winter ones, as discretionary water uses like
247 outdoor use are more price-sensitive than non-discretionary uses, and they are typically related to
248 summer activities (Billings & Agthe, 1980; Nieswiadomy & Molina, 1989; Griffin & Chang,
249 1991; Hewitt & Hanemann, 1995; Hoffman et al., 2006). Less than 10% of the price elasticities
250 are obtained using only summer data, while winter data are used in approximately 7% of the
251 cases.

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

263 Population density and household characteristics are relevant in water demand studies. Per-
264 household consumption increases with household size but per-capita consumption decreases
265 (Arbués et al., 2004). Urban configuration, including land zoning (e.g. single-family residential
266 or commercial), total building area, and density of residential developments, also has an influence
267 on total water consumption (Shandas & Parandvash, 2010). Similarly, household composition is
268 a relevant factor to consider. For instance, both elder and younger inhabitants may exhibit a

269 higher level of water consumption for discretionary uses, gardening for the former, and frequent
270 laundering and more water-intensive outdoor leisure activities for the latter (Nauges & Thomas,
271 2000). Variables that reflect both the proportion of the population over 64 years and under 19
272 years of age can therefore be included (Martínez-Espiñeira, 2003). Household characteristics
273 such as total number of bedrooms, architectural type (i.e., detached or semidetached) and
274 presence of a garden might also impact water demand (Fox et al., 2009). Population and
275 household characteristics are captured by variables measuring population density (in 5% of the
276 estimates) and household size (in more than 41% of the estimates).

277

278 *2.3. Methods used in primary studies*

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

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

293 as vector autoregressive models and co-integration techniques (Martínez-Espiñeira, 2007). OLS
294 is by far the most used estimator in the meta-sample (55% of the estimates).

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

303

304 ***2.4. Model and estimation technique***

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

$$308 \quad pe_{ji} = \beta_j + \sum_{k=1}^K \alpha_k x_{jik} + \sum_{s=1}^S \gamma_s z_{jis} + e_{ji} \quad j=1,2,\dots,L; i=1,2,\dots,N^j \quad (1)$$

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

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

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

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

329
 330 **Table 1** - List of independent variables in MRA and their descriptions.

331

Panel A – Demand specification variables		
Variable category (<i>baseline</i>)	Variable name	Variable description
Type of price elasticity (<i>short-run elasticity</i>)	Long-run	=1 if long-run elasticity is estimated
	Segment	=1 if segment elasticity is estimated
Price measure (<i>average price</i>)	Marginal price	=1 if the marginal price is used as a price measure
	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 (<i>linear</i>)	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

332

Panel B – Data variables

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

333

Panel C – Methodology variables

Variable category (<i>baseline</i>)	Variable name	Variable description
Estimator (<i>OLS</i>)	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

334

Panel D – Publication variables

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

335

Panel E – Location-specific variables

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

336

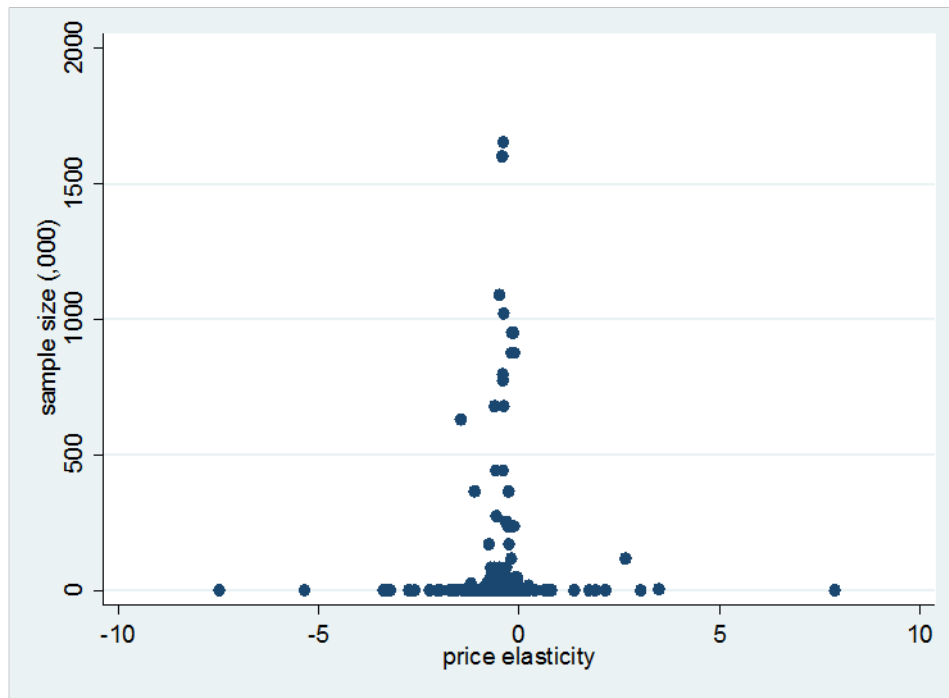
337 3. Results

338 3.1. Descriptive statistics

339 Figure 2 shows the typical funnel plot commonly used in meta-analyses, where the sample
340 size on the y-axis is the number of observations used to estimate the price elasticity (x-axis) in

341 each primary study. In the absence of publication bias, studies based on larger samples have near-
342 average elasticity, whereas studies based on smaller samples are spread on both sides of the
343 average, creating a roughly funnel-shaped distribution. In this respect, it is worth recalling that
344 we have included also unpublished studies in our meta-sample.¹ The funnel plot justifies the
345 adoption of WLS to mitigate the heteroskedasticity that arises from differences in precision
346 associated with the price elasticity estimates.

347
348 **Fig. 2** - Funnel plot of price elasticity over sample size.

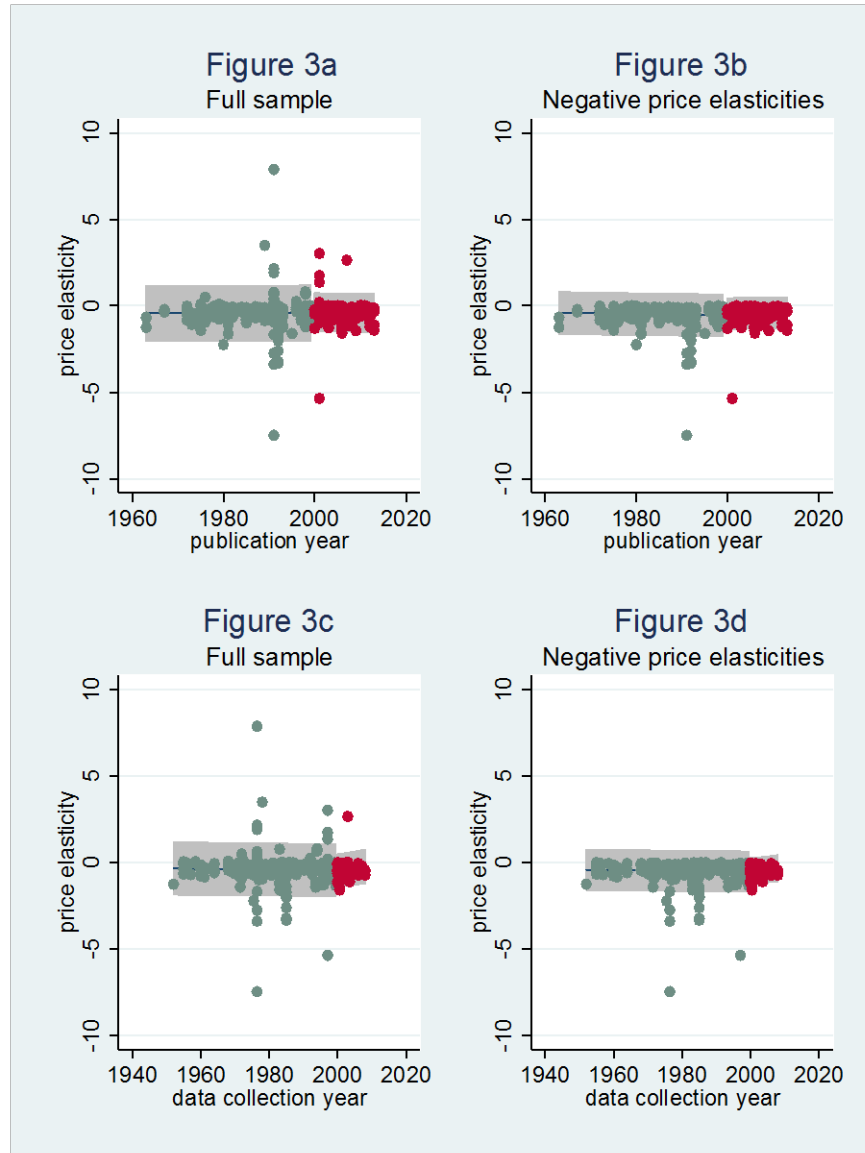


349
350 The average water price elasticity estimate is -0.40, with a standard deviation of 0.72 and a
351 median of -0.34. Fifty-three out of 615 estimates are smaller than -1, i.e. refer to elastic water
352 demands. The most price-elastic estimated water demand reports a price elasticity of -7.47.
353 Thirty-two out of 615 observations are positive, indicating that demand increases with price.

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.

354 These positive values will be carefully handled in the MRA because they are not consistent with
355 standard micro-economic theory.

356
357 **Fig. 3** - Estimated price elasticities over the publication year (Figure 5a-b) and over the data
358 collection year (Figure 5c-d) with 95% confidence interval bands computed before and after the
359 year 2000.



360
361 Price elasticity estimates from the post-2000 studies are closer to the overall mean value
362 (Figure 3a-b). This convergence in the most recent estimates is also confirmed when the price

363 elasticities are plotted against the data collection years (see Figure 3c-d). The use of more
 364 standardized estimation techniques partly explains this decrease in inter-study variance.

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

370
 371 **Table 2** - Descriptive statistics.

372

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

373

374 **3.2. Main results from the meta-analysis model**

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

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

385

386 **Table 3 - WLS and panel GLS estimates.**

	WLS			Panel GLS
	(1)	(2)	(3)	(4)
GDP per capita			.0088 (.0115)	.0040** (.0018)
US			-.0521 (.3235)	-.0531 (.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 (.4049)	.3772 (.4229)	.3715 (.4154)	.4569*** (.1294)
Double log	-.2587 (.2188)	-.2027 (.2020)	-.1777 (.2188)	-.1252*** (.0378)
Flexible	-.0204 (.1935)	-.0075 (.1966)	.0001 (.2427)	-.0205 (.0543)
Daily data	-.0441 (.3646)	.0141 (.3434)	.0089 (.3451)	-.0114 (.0612)
Monthly data	-.2064 (.2262)	-.1988 (.2145)	-.1593 (.2126)	-.0194 (.0506)
Household data	.0844 (.1045)	.0685 (.1879)	.0256 (.2005)	-.0696* (.0379)
Summer data	-.2380 (.1454)	-.2711* (.1388)	-.2715* (.1526)	-.1054*** (.0373)
Winter data	.0867 (.1345)	.0543 (.1274)	.0538 (.1452)	.1137*** (.0380)
Time-series data	.0518 (.4651)	.0295 (.4465)	.2093 (.4785)	.1462** (.0680)
Panel data	-.2262 (.3688)	-.1770 (.3654)	-.0634 (.2971)	.0014 (.0652)
IV	-1.437* (.8012)	-1.441* (.8013)	-1.512* (.8131)	-.1983 (.1604)
2SLS	-.2410 (.2174)	-.2133 (.2076)	-.2229 (.2167)	-.0946* (.0488)
3SLS	1.791** (.8164)	1.253 (.8506)	1.262 (.8640)	.5108* (.2780)
DCC	-.5121** (.2448)	-.5060** (.2425)	-.5577** (.2478)	-.2291** (.1068)
Published	-.0940 (.2948)	-.1321 (.2663)	-.2073 (.3053)	-.1348*** (.0497)
Constant	-.3712 (.6997)	-.3600 (.6895)	-.6642 (.8140)	-.3325*** (.1080)
Observations	615	615	598	598
Studies	122	122	117	117

387 The table reports the results of the WLS (columns 1-3) and panel GLS (column 4) estimations obtained using the
388 square root of the sample size as analytical weights. The dependent variable is the price elasticity reported in each
389 estimate of each primary study included in the meta-analysis. Depending on the specification, the models control for

390 study-level characteristics, tariff schemes, location of the water demand and gross domestic product per capita.
391 Standard errors (clustered by studies) are reported in parentheses. *, **, and *** denote significance at 10%, 5% and
392 1%, respectively.

393
394 Column (1) reports the estimates that refer to a specification which includes only study-level
395 characteristics. The variables that control for the tariff scheme faced by customers, i.e. *IBR* and
396 *DBR*, are included in the specification reported in column (2). The location (*US* and *Europe*) and
397 *GDP per capita* are also added in column (3).

398 The results reported in Table 3 provide some insights into the sources of variation in price
399 elasticity estimates. If the most thorough specification in column (3), which was obtained through
400 WLS, is considered, three variables show highly statistically significant coefficients. First, the
401 *Number of variables* employed in the specification of the water demand is found to have a
402 positive effect on the estimated price elasticity. The coefficient is statistically significant at the
403 1% level, since when more variables are included in the model specification, the analyst obtains a
404 less elastic water demand. Second, the presence of *Commercial uses* also results in a less elastic
405 water demand, with statistical significance at the 1% level. Third, consistently with Dalhuisen
406 et al. (2003), other things being equal, primary studies that rely upon the DCC approach – always
407 applied to cases with IBR in our sample – show a more price-elastic water demand. In this case,
408 the coefficient is negative and statistically significant at the 5% level. The three coefficients are
409 also statistically significant in the specifications reported in columns (1) and (2). The statistical
410 significance at the 5% level of DCC suggests that as far as DCC can be considered as the most
411 sophisticated methodology available to estimate water demand under discontinuous prices, IBR
412 should be considered an effective tool for water conservation.

413 The application of the DCC approach remains statistically significant in the panel GLS
414 estimates (column 4) along with the number of variables included in the specification and the

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

432

433 **3.3. Outlier analysis**

434 As shown in Section 3.1, the range of price elasticity estimates from primary studies is very
435 large. There are observations whose price elasticity is positive in contradiction of basic micro-
436 economic theory, and others that show an extremely elastic water demand. These outliers raise
437 concerns both about the reliability of these estimates, and about their potential influence on the
438 meta-regression results. Therefore, we estimate a probit model that predicts the probability of

439 belonging to the outliers' group and find evidence that using panel data significantly decreases
 440 the odds of obtaining an outlier price elasticity estimate, whereas the water demand location (i.e.
 441 location-specific features) does not have any statistically significant impact (results are
 442 untabulated but available upon request).

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

448
 449 **Table 4 – Outlier-robust estimates.**

	Outliers excluded		
	(1)	(2)	(3)
GDP per capita	.0032 (.0057)	-.0001 (.0058)	-.0008 (.0058)
US	.2723 (.2023)	.3078 (.1989)	.3217 (.1979)
Europe	.5073** (.2221)	.4635* (.2213)	.4732** (.2187)
IBR	-.0102 (.0370)	-.0082 (.0367)	-.0098 (.0372)
DBR	.2466** (.1244)	.2511* (.1284)	.2537* (.1315)
Long-run	.0568 (.0835)	.0591 (.0843)	.0554 (.0825)
Segment	-.2171 (.1489)	-.2051 (.1655)	-.2042 (.1677)
Marginal price	.0212 (.0706)	.0390 (.0678)	.0426 (.0671)
Shin price	.0983 (.1301)	.1169 (.1352)	.1156 (.1374)
Number of variables	.0031***	.0028***	.0028***

	(.0010)	(.0010)	(.0010)
Lagged consumption	-.1322 (.0807)	-.1293 (.0823)	-.1237 (.0807)
Evapotranspiration rate	.2064** (.0960)	.1680* (.0882)	.1502* (.0862)
Season	.2915*** (.0914)	.2900*** (.0897)	.3028*** (.0870)
Household size	.1087 (.0997)	.1225 (.1025)	.1348 (.1036)
Population density	.2254 (.2302)	.1919 (.2195)	.2017 (.2203)
Income	-.0253 (.1394)	-.0914 (.1492)	-.0978 (.1506)
Commercial uses	.8610*** (.1822)	.8277*** (.1841)	.8195*** (.1840)
Temperature	-.1555* (.0809)	-.1832** (.0810)	-.1924** (.0813)
Rainfall	.1695 (.1239)	.1949* (.1170)	.2093* (.1145)
Difference variable	-.3338** (.1288)	-.2853** (.1245)	-.2671** (.1209)
Log price	-.5236*** (.1531)	-.5606*** (.1580)	-.5568*** (.1600)
Log consumption	.0610 (.2222)	.0908 (.2279)	.1071 (.2311)
Double log	-.3548*** (.0885)	-.3194*** (.0870)	-.3040*** (.0860)
Flexible	-.0790 (.1186)	-.0413 (.1180)	-.0269 (.1172)
Daily data	-.2492 (.1565)	-.2308 (.1526)	-.2205 (.1530)
Monthly data	-.0263 (.1220)	-.0760 (.1210)	-.0736 (.1199)
Household data	-.1161 (.1183)	-.1106 (.1191)	-.1092 (.1197)
Summer data	-.2601** (.1110)	-.2587** (.1088)	-.2447** (.1066)

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

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

456
457 Results reported in Table 4 make our main findings more robust. Applying the DCC approach,
458 including more variables in the specification, and controlling for the commercial uses, are three
459 methodological features that retain statistical significance on estimated water price elasticities. In
460 addition, some coefficients that are statistically significant in our panel estimations (but not in our
461 full sample WLS estimations) are proved to be so in the outlier-robust WLS estimates as well.
462 This is the case of *Double log*, *Time-series data* and *Published*, for which the outlier-robust
463 estimates are even stronger than in the panel model; the *Double log* and *Published* specifications

464 are associated with a more elastic water demand whereas the opposite is true for *Time-series*
465 *data*. Concerning the *Published* specification, this is a clear evidence of publication bias that we
466 were not able to discern through the visual aid provided by the funnel plot, simply because we
467 had no way to distinguish between published and unpublished studies. On the contrary, after
468 having dropped less reliable estimates that were likely to significantly drive our main results, the
469 preference for studies that found a more elastic water demand has been detected.

470 **4. Simulation approach**

471 *4.1. Rationale and description*

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

483 We cannot directly propose a meta-regression model as a simulation tool. Given the large
484 number of included regressors, overfitting would be a concern when using such a model for
485 predictive purposes (see e.g., Harrell, 2015: p. 72). For that reason, we use a three-step procedure
486 aimed at taking advantage of our meta-sample in a scenario simulation setting. First, starting

487 from the outlier-robust meta-model of Section 3.3, we eliminate the least relevant variables to
488 select a more parsimonious linear model. Second, we validate the obtained restricted model.
489 Finally, we use the validated model to obtain scenario simulations exploring the combined
490 impacts of tariff structure, seasonality, and estimation methodology.

491

492 ***4.2. Model selection and validation***

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

503 The selected model has been cross-validated by using studies published before 2000 as
504 “training set” and those published after 2000 as “test set” (Arlot & Celisse, 2010). This procedure
505 entails the following sub-steps: i) estimating the predictive model using the training set; ii)
506 obtaining model predictions relative to observations in the test set; iii) regressing observed price
507 elasticities against predictions using the test set; iv) testing that predictions are able to explain the
508 observed values, i.e., the relative coefficient is statistically significant at the conventional
509 significance level. In order to cope with heteroskedasticity we use WLS both in steps i) and iii).
510 The model is validated at a 5% statistically significance level. This suggests that the selected

511 model exhibits good predictive performance and can be accordingly used to produce reliable
 512 scenario simulations. Table 5 shows the estimates of the predictive model.

513
 514
 515
 516 **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)
<hr/>	
Observations	572
<hr/>	
Studies	122
<hr/>	

517 The table reports the results of the WLS estimations obtained using the square root of the sample size as analytical
518 weights after having dropped positive price elasticities and trimmed 2% of the observations on the left tail of the
519 price elasticity distribution. The dependent variable is the price elasticity reported in each estimate of each primary
520 study included in the meta-analysis. Standard errors (clustered by studies) are reported in parentheses. *, **, and ***
521 denote significance at 10%, 5% and 1%, respectively.
522

523 ***4.3. Insights from the simulation approach***

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

531
 532
 533
 534
 535
 536
 537

Table 6 – Scenario simulations.

Predicted variable: Price elasticity			
	Price elasticity	Standard error	95% conf. inter.
<i>All seasons</i>			
Linear	-.3692***	.0194	[-.4075;-.3308]
DBR	-.0211	.1060	[-.2309;.1888]
IBR	-.3941***	.0236	[-.4408;-.3473]
IBR (with DCC)	-.6615***	.1188	[-.8967;-.4263]
<i>Summer</i>			
Linear	-.5913***	.0763	[-.7423;-.4403]
DBR	-.2432**	.1226	[-.4859;-.0005]
IBR	-.6162***	.0798	[-.7743;-.4581]
IBR (with DCC)	-.8837***	.1341	[-1.149;-.6182]
<i>Winter</i>			
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

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

542

543 The validated model simulates price elasticities across seasons under linear DBR and IBR
544 tariff schedules. In the latter case, we compare estimates obtained with and without the DCC
545 approach, which, on the one hand, properly deals with the endogeneity of price with respect to
546 water demand, but, on the other hand, rests on the assumption that households are fully informed
547 about the tariff structure, including block sizes and prices within each block (Olmstead et al,
548 2007).

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

560 **5. Discussion**

561 This analysis extends previous meta-analyses in two respects. First, it exploits a larger sample
562 of primary studies (more than double than that of Dalhuisen et al., 2003, 20% larger than that of
563 Sebri, 2014) spanning over a longer time period and includes recent analyses that make use of
564 more advanced methods and better datasets. Second, it uses the resulting meta-regression model
565 to implement a simulation approach to explore price elasticities under different scenarios. A

566 salient finding from this approach is that the more sophisticated the statistical analysis methods -
567 i.e. when they deal with the endogeneity of price to water consumption – the more elastic the
568 water demand in IBRs schemes. This finding suggests that IBRs may be more effective than
569 traditional ones in bringing about water savings. It also stresses the importance of the estimation
570 methodology. In fact, endogeneity issues are relevant when estimating water demand under non-
571 linear pricing: price elasticities estimated using OLS can be shown to be positively (negatively)
572 biased under IBRs (DBRs) schemes (see Hewitt & Hanemann, 1995). This result is so far based
573 on a limited number of observations (13) as only three primary studies in the sample used DCC.

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

590 from periods of peak demand in the morning and evening, leading to substantial financial savings
591 for water utilities (Rougé et al., *in press*). In that latter case, the possibility to substitute peak uses
592 with off-peak uses may lead to a more price-elastic peak demand (Cole et al., 2012).

593 Besides, the assumption that consumers have appropriate information about tariff structure,
594 essential for the DCC model, is bound to see its validity increase with smart metering, as it brings
595 about new ways for utilities to engage with their customers (Fraternali et al., 2012; Harou et al.,
596 2014; Koutiva & Makropoulos, 2016). More generally, the high-resolution data generated by
597 smart metering may also enable to verify the assumptions behind estimation methodologies, and
598 to propose even more sophisticated model that would be able to provide more accurate price
599 elasticity estimates.

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

608 This meta-analysis offers several guidelines for future research on the price response of water
609 demand. First, it highlights the importance of using panel data, which significantly reduce the
610 probability of obtaining outlier values when estimating water price elasticity. Second, it shows
611 that water price elasticities differ significantly depending on the season. This underscores the
612 importance of using cross-season data, and of controlling for the season during which data have
613 been collected. Third, it stresses the value of using disaggregated data, both over time and across

614 users. Finally, it draws attention to the relevance of considering the non-linearity of the price
615 structure when estimating water demands.

616 **6. Conclusions**

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

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

633

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645 **References**

- 646 1) Agthe, D. E., & Billings, R. B. (1980). Dynamic models of residential water demand. *Water*
647 *Resources Research*, 16(3), 476-480.
- 648 2) Arbués, F., Barberán, R., & Villanúa, I. (2004). Price impact on urban residential water
649 demand: A dynamic panel data approach. *Water Resources Research*, 40(11), 1-9.
- 650 3) Arbués, F., Garcia-Valiñas, M. Á., & Martínez-Espiñeira, R. (2003). Estimation of residential
651 water demand: a state-of-the-art review. *The Journal of Socio-Economics*, 32(1), 81-102.
- 652 4) Arlot, S., & Celisse, A. (2010). A survey of cross-validation procedures for model selection.
653 *Statistics Surveys*, 4, 40-79.
- 654 5) Billings, R. B., & Agthe, D. E. (1980). Price elasticities for water: a case of increasing block
655 rates. *Land Economics*, 56(1), 73-84.
- 656 6) Chicoine, D.L., Deller, S. C., & Ramamurthy, G. (1986). Water demand estimation under
657 block rate pricing: A simultaneous equation approach. *Water Resources Research*, 22(6),
658 859-863.
- 659 7) Chicoine, D. L., & Ramamurthy, G. (1986). Evidence on the specification of price in the
660 study of domestic water demand. *Land Economics*, 62(1), 26-32.
- 661 8) Cole, G., O'Halloran, K., Stewart, R. A. (2012). Time of use tariffs: implications for water
662 efficiency. *Water Science and Technology: Water Supply*, IWA Publishing, 12, 90-100.
- 663 9) Cominola, A., Giuliani, M., Piga, D., Castelletti, A., & Rizzoli, A. E. (2015). Benefits and
664 challenges of using smart meters for advancing residential water demand modeling and
665 management: A review. *Environmental Modelling & Software*, 72, 198-214.
- 666 10) Dalhuisen, J. M., Florax, R. J., de Groot, H. L., & Nijkamp, P. (2003). Price and income
667 elasticities of residential water demand: a meta-analysis. *Land Economics*, 79(2), 292-308.
- 668 11) Dandy, G., Nguyen, T., & Davies, C. (1997). Estimating residential water demand in the
669 presence of free allowances. *Land Economics*, 125-139.
- 670 12) EC (2012). Communication from the Commission to the European Parliament, the Council,
671 the European Economic and Social Committee and the Committee of the Regions. A
672 Blueprint to Safeguard Europe's Water Resources /* COM/2012/0673 final */
- 673 13) Escriva-Bou, A., Lund, J. R., & Pulido-Velazquez, M. (2015). Optimal residential water
674 conservation strategies considering related energy in California. *Water Resources Research*,
675 51(6), 4482-4498.

- 676 14) Espey, M., Espey, J., & Shaw, W. D. (1997). Price elasticity of residential demand for water:
677 A meta-analysis. *Water Resources Research*, 33(6), 1369-1374.
- 678 15) Foster, H. S., & Beattie, B. R. (1981). On the specification of price in studies of consumer
679 demand under block price scheduling. *Land Economics*, 624-629.
- 680 16) Fox, C., McIntosh, B. S., & Jeffrey, P. (2009). Classifying households for water demand
681 forecasting using physical property characteristics. *Land Use Policy*, 26(3), 558-568.
- 682 17) Fraternali, P., Castelletti, A., Soncini-Sessa, R., Ruiz, C. V., & Rizzoli, A. E. (2012). Putting
683 humans in the loop: Social computing for Water Resources Management. *Environmental*
684 *Modelling & Software*, 37, 68-77.
- 685 18) Gaudin, S., Griffin, R. C., & Sickles, R. C. (2001). Demand specification for municipal water
686 management: evaluation of the Stone-Geary form. *Land Economics*, 77(3), 399-422.
- 687 19) Geyskens, I., Krishnan, R., Steenkamp, J. B. E., & Cunha, P. V. (2009). A review and
688 evaluation of meta-analysis practices in management research. *Journal of*
689 *Management*, 35, 393-419.
- 690 20) Gottlieb, M. (1963). Urban domestic demand for water: A Kansas case study. *Land*
691 *Economics*, 39(2), 204-210.
- 692 21) Grafton, R. Q., & Kompas, T. (2007). Pricing sydney water. *Australian Journal of*
693 *Agricultural and Resource Economics*, 51(3), 227-241
- 694 22) Grafton, R. Q., & Ward, M. B. (2008). Prices versus rationing: Marshallian surplus and
695 mandatory water restrictions*. *Economic Record*, 84(s1), S57-S65.
- 696 23) Grafton, R. Q., Ward, M. B., To, H., & Kompas, T. (2011). Determinants of residential water
697 consumption: Evidence and analysis from a 10-country household survey. *Water Resources*
698 *Research*, 47(8).
- 699 24) Griffin, R. C., & Chang, C. (1991). Seasonality in community water demand. *Western*
700 *Journal of Agricultural Economics*, 207-217.
- 701 25) Hajispyrou, S., Koundouri, P., & Pashardes, P. (2002). Household demand and welfare:
702 implications of water pricing in Cyprus. *Environment and Development Economics*, 7(04),
703 659-685.
- 704 26) Hanke, S. H., & de Mare, L. (1982). Residential water demand: A pooled, time series, cross
705 section study of Malmo, Sweden. *Journal of the American Water Resources Association*,
706 18(4), 621-626.

- 707 27) Harou, J. J., Garrone, P., Rizzoli, A. E., Maziotis, A., Castelletti, A., Fraternali, P., ... &
708 Ceschi, P. A. (2014). Smart metering, water pricing and social media to stimulate residential
709 water efficiency: Opportunities for the SmartH2O project. *Procedia Engineering*, 89, 1037-
710 1043.
- 711 28) Harrell, F. (2015). Regression modeling strategies: with applications to linear models, logistic
712 and ordinal regression, and survival analysis. Springer.
- 713 29) Hewitt, J. A., & Hanemann, W. M. (1995). A discrete/continuous choice approach to
714 residential water demand under block rate pricing. *Land Economics*, 173-192.
- 715 30) Hocking, R. R. (1976). The analysis and selection of variables in linear regression.
716 *Biometrics*, 32(1), 1-49.
- 717 31) Hoffman, M., Worthington, A., & Higgs, H. (2006). Urban water demand with fixed
718 volumetric charging in a large municipality: the case of Brisbane, Australia*. *Australian*
719 *Journal of Agricultural and Resource Economics*, 50(3), 347-359.
- 720 32) Horowitz, J. K., & McConnell, K. E. (2002). A review of WTA/WTP studies. *Journal of*
721 *Environmental Economics and Management*, 44(3), 426-447.
- 722 33) House-Peters, L. A., & Chang, H. (2011). Urban water demand modeling: Review of
723 concepts, methods, and organizing principles. *Water Resources Research*, 47(5).
- 724 34) Howe, C. W., & Linaweaver, F. P. (1967). The impact of price on residential water demand
725 and its relation to system design and price structure. *Water Resources Research*, 3(1), 13-32.
- 726 35) Hughes, T.C. (1980). Peak period design standards for small Western U.S. water supply
727 systems. *Journal of the American Water Resources Association*, 16(4), 661-667.
- 728 36) Kennedy, W. J., & Bancroft, T. A. (1971). Model building for prediction in regression based
729 upon repeated significance tests. *The Annals of Mathematical Statistics*, 42(4), 1273-1284.
- 730 37) Koutiva, I., & Makropoulos, C. (2016). Modelling domestic water demand: An agent based
731 approach. *Environmental Modelling & Software*, 79, 35-54.
- 732 38) Kummu, M., Ward, P. J., de Moel, H., & Varis, O. (2010). Is physical water scarcity a new
733 phenomenon? Global assessment of water shortage over the last two millennia.
734 *Environmental Research Letters*, 5(3), 034006.
- 735 39) MacDonald, G. M. (2010). Water, climate change, and sustainability in the Southwest.
736 *Proceedings of the National Academy of Sciences*, 107(50), 21256-21262.

- 737 40) Macián-Sorribes, H., Pulido-Velazquez, M., Tilmant, A., 2015. Definition of efficient
738 scarcity-based water pricing policies through stochastic programming. *Hydrol. Earth Syst.*
739 *Sci.* 19, 3925–3935.
- 740 41) Mansur, E. T., & Olmstead, S. M. (2012). The value of scarce water: Measuring the
741 inefficiency of municipal regulations. *Journal of Urban Economics*, 71(3), 332-346.
- 742 42) Martínez-Españeira, R. (2002). Residential water demand in the Northwest of
743 Spain. *Environmental and Resource Economics*, 21(2), 161-187.
- 744 43) Martínez-Españeira, R. (2003). Estimating water demand under increasing-block tariffs using
745 aggregate data and proportions of users per block. *Environmental and Resource*
746 *Economics*, 26(1), 5-23.
- 747 44) Martínez-Españeira, R., & Nauges, C. (2004). Is all domestic water consumption sensitive to
748 price control? *Applied Economics*, 36(15), 1697-1703.
- 749 45) Martínez-Españeira, R. (2007). An estimation of residential water demand using co-
750 integration and error correction techniques. *Journal of Applied Economics*, 10(1), 161-184.
- 751 46) Moeltner, K., Boyle, K. J., & Paterson, R. W. (2007). Meta-analysis and benefit transfer for
752 resource valuation-addressing classical challenges with Bayesian modeling. *Journal of*
753 *Environmental Economics and Management*, 53(2), 250-269.
- 754 47) Moncur, J. E. (1987). Urban water pricing and drought management. *Water Resources*
755 *Research*, 23(3), 393-398.
- 756 48) Nauges, C., & Thomas, A. (2000). Privately operated water utilities, municipal price
757 negotiation, and estimation of residential water demand: the case of France. *Land Economics*,
758 68-85.
- 759 49) Nauges, C., & Thomas, A. (2003). Long-run study of residential water
760 consumption. *Environmental and Resource Economics*, 26(1), 25-43.
- 761 50) Nauges, C., & Van Den Berg, C. (2009). Demand for piped and non-piped water supply
762 services: Evidence from southwest Sri Lanka. *Environmental and Resource*
763 *Economics*, 42(4), 535-549.
- 764 51) Nauges, C., & Whittington, D. (2009). Estimation of water demand in developing countries:
765 An overview. *The World Bank Research Observer*, lkp016.

- 766 52) Nelson, J. P., & Kennedy, P. E. (2009). The use (and abuse) of meta-analysis in
767 environmental and natural resource economics: an assessment. *Environmental and Resource*
768 *Economics*, 42(3), 345-377.
- 769 53) Nieswiadomy, M. L., & Molina, D. J. (1989). Comparing residential water demand estimates
770 under decreasing and increasing block rates using household data. *Land Economics*, 65(3),
771 280-289.
- 772 54) Nordin, J. A. (1976). A proposed modification of Taylor's demand analysis: comment. *The*
773 *Bell Journal of Economics*, 719-721.
- 774 55) Olmstead, S. M. (2009). Reduced-form versus structural models of water demand under
775 nonlinear prices. *Journal of Business & Economic Statistics*, 27(1), 84-94.
- 776 56) Olmstead, S. M., Hanemann, W. M., & Stavins, R. N. (2007). Water demand under
777 alternative price structures. *Journal of Environmental Economics and Management*, 54(2),
778 181-198.
- 779 57) Olmstead, S. M., & Stavins, R. N. (2009). Comparing price and nonprice approaches to urban
780 water conservation. *Water Resources Research*, 45(4).
- 781 58) Pulido-Velazquez, M., Alvarez-Mendiola, E., & Andreu, J. (2012). Design of efficient water
782 pricing policies integrating basinwide resource opportunity costs. *Journal of Water Resources*
783 *Planning and Management*, 139(5), 583-592.
- 784 59) Renwick, M. E., & Archibald, S. O. (1998). Demand side management policies for residential
785 water use: who bears the conservation burden? *Land Economics*, 343-359.
- 786 60) Rogers, P., Silva, R.D., Bhatia, R., 2002. Water is an economic good. How to use prices to
787 promote equity, efficiency, and sustainability. *Water Policy*, 4: 1-17.
- 788 61) Rosenberger, R.S. & Loomis, J.B. (2000). Panel stratification in meta-analysis of economic
789 studies: an investigation of its effects in the recreation valuation literature. *Journal of*
790 *Agricultural and Applied Economics*, 32: 459-70.
- 791 62) Rougé, C., Harou, J.J., Pulido-Velazquez, M., Matrosov, E.S., Garrone, P., Marzano, R.,
792 Lopez-Nicolas, A., Castelletti, A., Rizzoli, A.-E. (2017). Assessment of smart-meter-enabled
793 dynamic pricing at the utility and basin scales. Resubmitted to *Journal of Water Resources*
794 *Planning and Management* following revisions.
- 795 63) Ruijs, A., Zimmermann, A., & Van den Berg, M. (2008). Demand and distributional effects
796 of water pricing policies. *Ecological Economics*, 66(2), 506-516.

- 797 64) Schleich, J., & Hillenbrand, T. (2009). Determinants of residential water demand in
798 Germany. *Ecological Economics*, 68(6), 1756-1769.
- 799 65) Sebri, M. (2014). A meta-analysis of residential water demand studies. *Environment,*
800 *Development and Sustainability*, 16(3), 499-520.
- 801 66) Shandas, V., & Parandvash, G. H. (2010). Integrating urban form and demographics in water-
802 demand management: an empirical case study of Portland, Oregon. *Environment and*
803 *Planning B: Planning and Design*, 37(1), 112-128.
- 804 67) Shin, J. (1985). Perception of price when price information is costly: evidence from
805 residential electricity demand. *The Review of Economics and Statistics*, 67, 591–598.
- 806 68) Stanley, T. D. & Doucouliagos, H. (2012). *Meta-regression Analysis in Economics and*
807 *Business*. Routledge.
- 808 69) Stanley, T. D., & Jarrell, S. B. (1989). Meta-Regression analysis: A quantitative method of
809 literature surveys. *Journal of Economic Surveys*, 3(2), 161-170.
- 810 70) Stanley, T. D. & R. S. Rosenberger. (2009). Are recreation values systematically
811 underestimated? Reducing publication selection bias for benefit transfer. MAER-Net
812 Colloquium, Corvallis Oregon.
- 813 71) Tunçel, T., & Hammitt, J. K. (2014). A new meta-analysis on the WTP/WTA
814 disparity. *Journal of Environmental Economics and Management*, 68(1), 175-187.
- 815 72) Worthington, A. C., & Hoffman, M. (2008). An empirical survey of residential water demand
816 modelling. *Journal of Economic Surveys*, 22(5), 842-871.
- 817