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Faculty of Social Sciences
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MASTER'S THESIS

Income Elasticity of Water Demand: A Meta-Analysis

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Declaration of Authorship

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Prague, May 2, 2016

Signature

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Abstract

If policymakers address water scarcity with the demand-oriented approach, the income elasticity of water demand is of pivotal importance. Its estimates, however, differ considerably. We collect 307 estimates of the income elasticity of water demand reported in 62 studies, codify 31 variables describing the estimation design, and employ Bayesian model averaging to address model uncertainty inherent to any meta-analysis. The studies were published between 1972 and 2015, which means that this meta-analysis covers a longer period of time than two previous meta-analyses on this topic combined. Our results suggest that income elasticity estimates for developed countries do not significantly differ from income elasticity estimates for developing countries and that different estimation techniques do not systematically produce different values of the income elasticity of water demand. We find evidence of publication selection bias in the literature on the income elasticity of water demand with the use of both graphical and regression analysis. We correct the estimates for publication selection bias and estimate the true effect beyond bias, which reaches approximately 0.2.

JEL Classification	C52, C81, C83, Q40
Keywords	water demand, income elasticity, meta-analysis, publication selection bias, Bayesian model averaging

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Abstrakt

Pokud tvůrci politik přistoupí k vzácnosti vody ze strany poptávky, důchodová elasticita poptávky po vodě hraje klíčovou roli. Její odhady se ovšem značně liší. Shromáždíme 307 odhadů důchodové elasticity poptávky po vodě obsažených v 62 studiích, definujeme 31 proměnných popisujících design jejich odhadu a aplikujeme metodu Bayesian model averaging, abychom adresovali nejistotu v modelu, která je nedílnou součástí každé meta-analýzy. Studie byly vydány mezi roky 1972 a 2015, což znamená, že tato meta-analýza zahrnuje delší časové období než předchozí dvě meta-analýzy na toto téma dohromady. Výsledky navrhují, že odhady důchodové elasticity pro rozvojové země se výrazně neliší od odhadů důchodové elasticity pro vyspělé země a že rozdílné techniky odhadu neprodukují systematicky rozdílné hodnoty důchodové elasticity poptávky po vodě. Nacházíme důkazy publikační selektivity v literatuře týkající se důchodové elasticity poptávky po vodě s použitím jak grafické, tak regresní analýzy. Opravíme odhady kontaminované publikační selektivitou a odhadneme skutečný efekt, který dosahuje přibližně 0.2.

Klasifikace JEL	C52, C81, C83, Q40
Klíčová slova	poptávka po vodě, důchodová elasticita, meta-analýza, publikační selektivita, Bayesian model averaging

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Contents

List of Tables

List of Figures

Acronyms

BMA Bayesian Model Averaging

FAT Funnel Asymmetry Test

IV Instrumental Variables

MRA Meta-Regression Analysis

OLS Ordinary Least Squares

PET Precision Effect Test

PIP Posterior Inclusion Probability

PMP Posterior Model Probability

Master's Thesis Proposal

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Proposed topic	Income Elasticity of Water Demand: A Meta-Analysis

Topic Characteristics The importance of estimates of the income elasticity of water demand lies in the usage of these estimates by governments. It helps them to determine the percentage change in demand for water if income changes by one percent. This information can be used to improve policy-making, which can help to manage the water demand more effectively; predict changes in the demand and meet consumption needs. During last decades many economists have estimated the income elasticity of water demand, but they came to various results.

Their estimates can be reviewed quantitatively by method called meta-analysis (Stanley 2001). Applications of meta-analysis on similar topic include, among others, Espey *et al.* (1997) on the price elasticity of water demand, Gallet (2007) on price and income elasticities of alcohol demand, and Havranek *et al.* (2012) on the price elasticity of gasoline demand.

There are two big meta-analyses conducted on this topic: Dalhuisen *et al.* (2003) and Sebri (2014). The former analysis did not correct the estimates for publication bias, while the latter addressed the publication bias by inclusion of both published and unpublished studies. According to Doucouliagos & Stanley (2008), however, the difference in magnitudes of publication bias between published and unpublished studies is negligible. Moreover, they did not test the presence of publication bias analytically and omitted between-study heterogeneity.

Hypotheses

1. The literature estimating the income elasticity of water demand is affected by publication bias.

2. The income elasticity of water demand in developing countries is higher than the income elasticity of water demand in developed countries.

3. Numerical estimates of the income elasticity of water demand depend on estimation methods employed to estimate them.

Methodology I aim to use particular estimates from samples by Dalhuisen *et al.* (2003), which start in 1967 and end in 2000, and Sebri (2014), starting in 2002 and ending in 2012. Furthermore, I will search the EconLit, RePEc and Google Scholar for new studies published.

Based on the definition of the income elasticity of water demand it cannot be expected that its value could have a negative sign since water does not have any substitute and, hence, cannot be considered as an inferior goods. Consequently, negative estimates of the income elasticity of water demand are not going to be published, which biases the estimates positively. This is called publication bias (for example, Egger *et al.* 1997). Doucouliagos & Stanley (2013) found that most fields are affected by publication bias. I will try to support their finding by detecting the bias in the literature on the income elasticity of water demand both graphically by funnel and Galbraith plots, and analytically by using funnel asymmetry test. Moreover, I aim to reveal the true effect by correcting the estimates for publication bias. Since it is necessary to account for heteroscedasticity and between-study heterogeneity, I will employ the mixed-effects multilevel meta regression (for example, Stanley 2008), and perform OLS with clustered standard errors as a robustness check. Finally, I will explain the variation of estimates and investigate the influence of study aspects on the results. This contains, among others, water demand specification (e.g., inclusion of household size variable, population density variable), data characteristics (e.g., number of observations, frequency of the data), estimation technique (this will address Hypothesis #3), countries examined (this will address Hypothesis #2), and other study characteristics (e.g., year of publication, number of citations). Since there are many variables which could potentially influence the income elasticity of water demand, the model faces a significant uncertainty. I will address this problem by Bayesian model averaging technique (for example, Kass & Raftery 1995, Eicher *et al.* 2011).

Outline

1. Introduction
2. Literature Review
3. The Data Set of Income Elasticity of Water Demand Estimates
4. Publication Bias
    - Graphical Tests of Publication Bias
    - Regression Tests of Publication Bias
5. Why Do Estimates Vary?
6. Conclusion

Core bibliography

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Chapter 1

Introduction

Growth of population, rapid urbanization, and climate change are the main factors contributing to continuous increases in consumption of water. Although residential water consumption is not the biggest component of total water consumption, it requires the most careful attention since it plays a major role for human life given its impact on survival and hygiene. Residential water has to be easily accessible and supplied regularly and reliably. Moreover, it has to satisfy certain quality standards. In addition, the needs of present and future generations should be taken in consideration from the environmental, social, and economic point of view (Hussain *et al.* 2002).

Dalhuisen *et al.* (2003) distinguishes between two approaches dealing with the problem of water scarcity. The first of them is the supply-oriented approach, which dominated the twentieth century. It focuses on finding new resources of water and improvement of infrastructure. Replacing traditional resources such as the use of surface or ground water by non conventional resources such as desalination of briny water is, however, costly and time-consuming (Ayadi *et al.* 2002). Moreover, the amount of water resources is finite, whereas population growth continuously increases the number of consumers. Consequently, the demand-oriented approach prevailed. It focuses on sustainable and conservative use of water. It encompasses education programs, awareness campaigns, and water-saving plans. Grafton *et al.* (2011) analyze water-saving behavior in a survey of households from ten countries and find out that almost a half of more than eight thousand respondents always turns off water while brushing teeth. Similar fraction always plugs the sink when washing dishes and waits for the coolest part of the day to water the garden. Approximately two thirds of respondents save water by always taking shower instead of bath. Unfortunately, rainwater has never been collected and waste water recycled by around 44% of respondents. Hence, there still exist areas for further enhancement. If water is transported from remote sources, transport and storage losses need to be minimized and leakages in distribution systems reduced (Kostas & Chrysostomos 2006). Furthermore, if water scarcity is addressed with the demand-oriented approach, price and income elasticities of water demand are of pivotal importance. Since the management of water demand needs to be effective and equitable, effects of price and income changes on demand have to be analyzed properly. If the analysis of demand for water uses inadequate tools and avoids modern approaches, outcomes of such analysis are inaccurate and can lead to incorrect conclusions. Consequently, water policy is neither effective, nor equitable, and consequences for environment, society, and economy can be fatal.

The thesis concentrates on the income elasticity of water demand as one of the main components of the demand-oriented approach. We hypothesize that studies estimating the income elasticity of water demand are contaminated by publication selection bias. In other words, researchers or publishers prefer significant estimates of a concrete sign. It uses graphical and as the first meta-analysis in this field regression tests to evaluate the presence of the bias. If the estimates suffer from publication selection bias and the genuine effect remains uncorrected, any analysis produces unreliable results. Next, the thesis assesses the estimation of the water demand equation from two points of view. First, from the point of view of data collection; it investigates whether income elasticity estimates for developing countries are different from income elasticity estimates for developed countries. Second, from the point of view of data estimation; it examines whether different estimation techniques produce different income elasticity estimates. The former can help to determine whether water demand policy in a developing country should substantially differ from water demand policy in a developed country or whether it can be partially adopted. The latter addresses the issue of a choice of an estimator and its consequences. Since the set of determinants of water demand and its income elasticity is large, the estimation faces model uncertainty. We depart from frequentist statistics used in meta-analyses by Dalhuisen *et al.* (2003) and Sebri (2014) and apply Bayesian statistics, namely a method called Bayesian model averaging.

The remainder of the thesis is structured as follows. Chapter 2 reviews and compares previously conducted meta-analyses on the topic of the income elasticity of water demand. Chapter 3 describes the process of collection of estimates, discusses criteria for their inclusion, and presents their properties.

Chapter 4 investigates the presence of publication selection bias in the literature. Chapter 5 deals with heterogeneity in the estimated income elasticity of water demand. Chapter 6 concludes.

Chapter 2

Literature Review

The first meta-analysis of the income elasticity of water demand was conducted by Dalhuisen *et al.* (2003). The authors quantitatively examine 30 studies, which provide 149 income elasticity estimates. They range from -0.9 to +7.8 and are characterized by the mean equal to 0.46 and the median equal to 0.28. Approximately 90% of the estimates are smaller than 1, which suggests that demand for water is inelastic in income. The studies were published between 1972 and 2000. The authors specify their meta-regression model linearly, correct heteroskedasticity with White-adjusted standard errors, and include variables related to microeconomic theory with the prominent role of tariff systems. Since the full sample almost completely lacks explanatory power, Dalhuisen *et al.* (2003) restrict their sample by backward stepwise elimination strategy suggested by Theil (1971).

Regarding water demand specification, there are only two explanatory variables surviving this process. The first one is a variable standing for the inclusion of seasonal dummies; when included, the estimated elasticity significantly decreases. The second one stands for the inclusion of the difference variable.[1] Its effect is, however, insignificant. The data characteristics bring much more information. Somehow ambiguously, the use of winter data affects the elasticity estimates positively. In comparison with time series data, both cross-sectional and panel data yield statistically higher values of the income elasticity. Furthermore, annual data make water demand more elastic when compared with daily data. Dalhuisen *et al.* (2003) find differences among alternative estimation techniques, functional forms of the water demand equations, and price

[1] It represents "[...] the difference between what the consumer actually pays and what he would pay if all water demanded was charged at the marginal rate" (Al-Najjar *et al.* 2011, p. 96).

specifications to be statistically indistinguishable. Although the authors do not observe any evidence for temporal dynamics, they detect spatial dynamics since elasticity estimates for locations in Europe tend to be significantly lower than estimates for locations in the United States. The only difference among tariff rate structures occurs between constant tariffs[2] and unknown tariffs. The latter make water demand more inelastic. Finally, from the point of view of other study characteristics, the application of the discrete-continuous model[3] leads to statistically lower elasticities, and estimates from published studies are more inelastic when compared with estimates from unpublished studies.

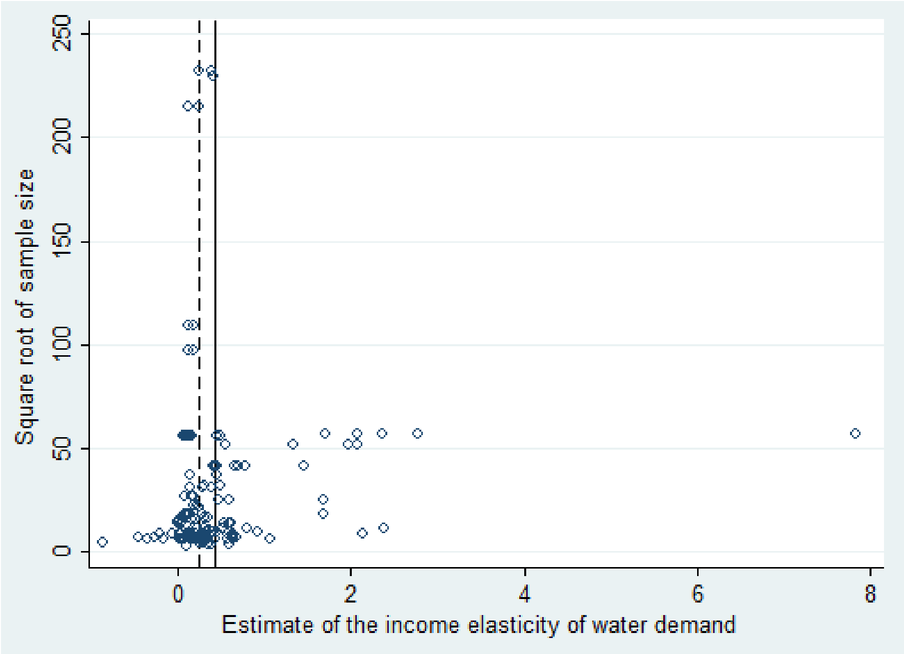
The authors do not, however, provide any test for the presence of publication selection bias, which stems from the preference of researchers and publishers to publish results which are significant, of a concrete sign, or in accordance with theory. In this regard, it concerns positive estimates of the income elasticity of water demand. Consequently, if publication selection bias is present and certain results are omitted, the previously mentioned results cannot be taken at face value.

Figure 2.1 depicts so-called funnel plot, which is a common graphical tool used to investigate the presence of publication selection bias in the literature. Generally, a funnel plot is a scatter plot of the size of an estimate on the horizontal axis against a measure of precision of the estimate on the vertical axis (Sterne & Harbord 2004). Namely, we plot income elasticity estimates (on the horizontal axis) against square root of sample size (on the vertical axis). As a result, we obtain a distribution looks quite symmetrical if we disregard the group of estimates situated in the right-hand part of the figure. Hence, publication selection bias does not seem to be a substantial problem.

[2] The price per unit of water is constant.

[3] A model, proposed by Hewitt & Hanemann (1995), which takes into account the probable nonlinearity and non-convexity of the budget frontier in commodity space.

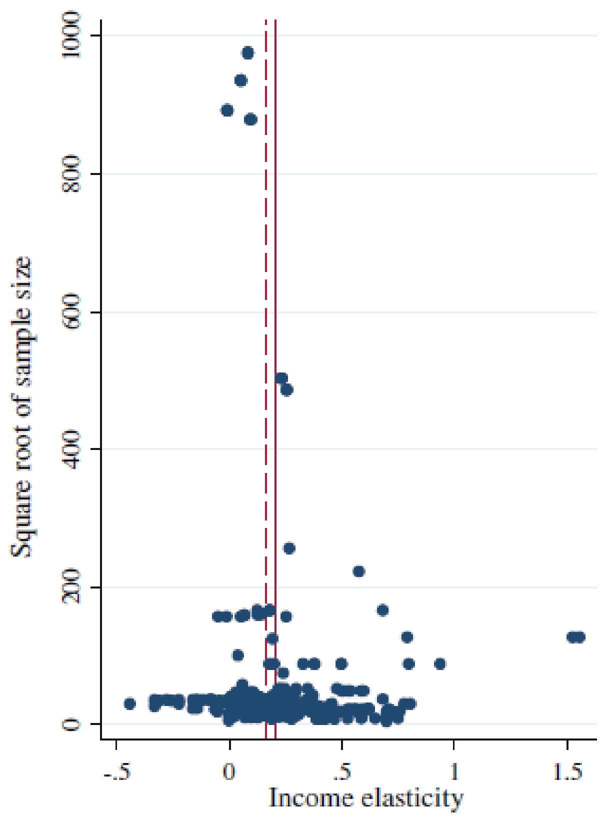
Figure 2.1: Funnel Plot for Estimates from Dalhuisen *et al.* (2003)



Notes: The dashed vertical line indicates the median estimate of the income elasticity of water demand, the solid vertical line indicates the mean estimate of the income elasticity of water demand. When there is no publication selection bias, the estimates should be symmetrically distributed around the hypothetical true effect.
Source: Author's computations using original dataset examined in Dalhuisen *et al.* (2003).

The second meta-analysis of the topic of the income elasticity of residential water demand was conducted by Sebri (2014). Unlike Dalhuisen *et al.* (2003), Sebri (2014) does not pay much attention to the microeconomic background behind consumers' demand for water, but rather concentrates on the issue of publication selection bias. Firstly, the author tries to detect publication selection bias graphically using funnel plot. Identically as in the previous case, income elasticity estimates (on the horizontal axis) are plotted against square root of sample size (on the vertical axis). The resulting distribution, depicted in Figure 2.2, does not show signs of publication selection bias. Secondly, to address publication selection bias, the author includes estimates from both published and unpublished studies. According to Doucouliagos & Stanley (2008) this approach does not, however, help to mitigate publication selection bias. Moreover, although the author addresses publication selection bias, he does not provide any regression test for its presence.

Figure 2.2: Funnel Plot for Estimates from Sebri (2014)



Notes: The dashed vertical line indicates the median estimate of the income elasticity of water demand, the solid vertical line indicates the mean estimate of the income elasticity of water demand. When there is no publication selection bias, the estimates should be symmetrically distributed around the hypothetical true effect.
Source: Sebri (2014).

The author quantitatively examines 72 studies, which provide 332 income elasticity estimates. They range from -0.44 to +1.56 and are characterized by the mean equal to 0.207 and the median equal to 0.159. The studies were published between 2002 and 2013. The author estimates his meta-regression model by weighted least squares with cluster-robust standard errors. He performs a bootstrap ordinary least squares (OLS), a robust OLS with White-corrected standard errors, and a random effect maximum likelihood as robustness checks. He enlarges the set of explanatory variables by a dummy variable differentiating between developing and developed countries, and dummy variables reflecting whether water is used for indoor or outdoor purposes.

Unlike Dalhuisen *et al.* (2003), the specification of water demand plays an important role in affecting values of income elasticity estimates. When included, each of following variables has a significantly negative effect on estimated elasticity: population density, lagged dependent variable, rainfall, seasonal dummies. The effect of population density and lagged dependent variable is, however, not robust across specifications. Lower elasticity caused by the inclusion of seasonal dummies supports finding from Dalhuisen *et al.* (2003). The same holds for the insensitivity to the inclusion of the household size variable. The presence of the difference variable and temperature has no effect in the baseline model. For alternative estimators, however, the difference variable takes significantly negative effect and temperature significantly positive effect. It sounds reasonable since higher temperature triggers an increase in demand for water, which can be addressed by spending a higher proportion of income on water. Given the relationship between the indoor use of water and winter it can be expected that the indoor water use deflates elasticity values. Similarly, the connection between the outdoor use of water and summer suggests that the outdoor water use inflates the values. On the one hand, both the use of winter data and the indoor water use have expected signs. On the other hand, both the use of summer data and the outdoor water use do not conform to the expectations. Sebri (2014) reaches the same finding as Dalhuisen *et al.* (2003) in the insensitivity of results to the use of household or aggregate data, but opposes in the comparison of time series and cross-sectional data, in which higher values for time series data are found, and in the comparison of annual and daily data. Rather than annual data, Sebri (2014) finds that monthly data produce significantly lower elasticities than daily data. The values of income elasticity estimates are not affected by the choice of an estimation technique. Although there exist slight differences among price specifications, they are not robust to changes of the estimator. This means that it does not matter whether average, marginal, or Shin price[4] is used. Sebri (2014) does not find either temporal or spatial dynamics. Moreover, elasticity estimated for developing countries does not significantly differ from that estimated for developed countries. Regarding tariff rate structures, the effect of constant tariffs is statistically indistinguishable from the effect of unknown tariff structures. On the other

[4] Also known as so-called perceived price (Shin 1985). It takes the following form: $P^* = MP \times \left(\frac{AP}{MP}\right)^k$, where P^* denotes Shin price, MP denotes marginal price, AP denotes average price, and k denotes price perception parameter. If $k = 0$, then Shin price is equal to marginal price. If $k = 1$, then Shin price is equal to average price. For further details see Nieswiadomy & Molina (1991).

hand, and with comparison to the same baseline group, decreasing tariffs[5] deflate observed elasticities. Values connected to the use of increasing tariffs[6] are not robust. Last but not least, Sebri (2014) supports Dalhuisen *et al.* (2003) in the negative effect of the use of the discrete-continuous model, but contradicts the comparison of published and unpublished studies. In this case, published studies affect elasticity estimates positively when compared to its baseline category.

[5]The price is constant within discrete intervals of use, but decreasing between different intervals of use.

[6]"[T]he price is constant within discrete intervals of use, but increasing between different intervals [...]" (Dalhuisen *et al.* 2003, p. 4).

Chapter 3

The Data Set of Income Elasticity of Water Demand Estimates

To estimate the income elasticity of water demand, researchers usually assess the water demand equation:

$$Q_{it} = \alpha + \pi P_{it} + \theta I_{it} + \sum_j \delta_j Z_{jit} + \nu_{it}, \tag{3.1}$$

where Q_{it} denotes the water consumption of a consumer i in a period t, P_{it} denotes price of water, I_{it} denotes income of the consumer, Z_{it} denotes a set of other control variables such as household size, rainfall, or temperature, α, π, θ, and δ denote regression coefficients, and ν_{it} denotes a disturbance term.

Any meta-analysis starts with the collection of studies providing estimates of variables of interest. We refer to them as primary studies and, in our case, they encompass studies examined in Dalhuisen *et al.* (2003), Sebri (2014), and those found in the Google Scholar database using words *residential*, *water*, and *demand* as a search query. The search was stopped on March 6, 2016.

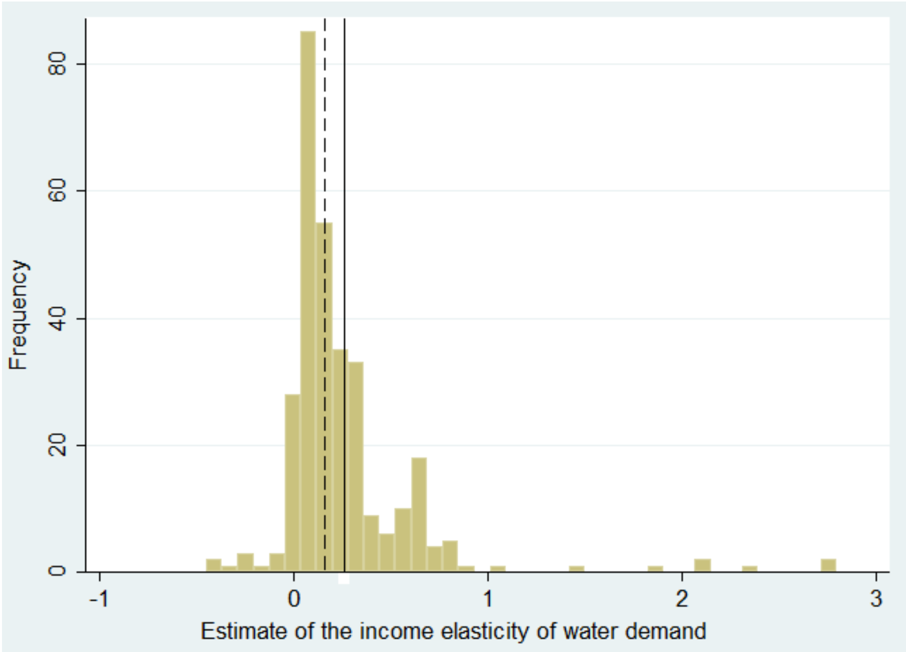
Three inclusion criteria are applied. First, the study must estimate the water demand equation and report an empirical estimate of the regression coefficient on income, that is, γ in Equation 3.1. Second, the study must estimate the log-log functional form of the water demand equation. In other words, data on Q_{it} and I_{it} in Equation 3.1 must be log-transformed, which means that the regression coefficient on income can be directly interpreted as elasticity. Several estimates cannot be used since they do not conform to this condition. It regards the level-level functional form, in which data on neither of the two variables are log-transformed (for example, estimates from Schefter

& David 1985), the log-level functional form, in which only data on the water consumption are log-transformed (for example, estimates from Gibbs 1978), and the level-log functional form, in which only data on income are log-transformed (for example, several estimates from Jones & Morris 1984). Third, studies which do not provide a statistics from which standard errors can be computed, or the standard errors themselves, are excluded from the meta-analysis (for example, estimates from Gaudin *et al.* 2001 or several estimates from Nieswiadomy 1992).

The author quantitatively examines 62 studies satisfying the inclusion criteria. Of these, 52 come from peer-reviewed journals and 10 are non-refereed articles. They are listed in Appendix B. The studies were published between 1972 and 2015, which means that this meta-analysis covers a longer period of time than the two previous meta-analyses combined. The publication year of the median study is 2005, which suggests that the literature estimating the income elasticity of water demand does not stop attracting attention of researchers. The studies provide 307 income elasticity estimates. For each estimate, we gather 31 variables describing the estimation design. The estimates range from -0.450 to +2.801 and are characterized by the mean equal to 0.261 and the median equal to 0.157. Less than 3% of the estimates are higher than 1, which suggests that demand for water is inelastic in income. More than 94% of the estimates is higher than 0, which supports the common microeconomic view that water cannot be considered as an inferior good since it does not have any substitute.

Figure 3.1 shows a histogram of the estimates of the income elasticity of water demand. First, the median of the data is smaller than the mean of the data and the distribution seems to be skewed to the right. Second, and in addition to the deviation from the shape of normal distribution, there are several estimates situated far from the mean. The issue of outliers may lead to biased results, hence, we approach it in two ways. On the one hand, we include all estimates in the meta-analysis. This measure can be explained by the existence of a group of estimates in the right-hand part of the figure, which can potentially be produced by certain study aspects. On the other hand, when conducting a regression analysis, we winsorize the seven highest estimates to control for their potential contribution to bias in results. Third, the histogram is double-peaked, which suggests that the estimates are heterogeneous. This aspect can be attributed to a high variety of reasons, which are investigated in Section 5.

Figure 3.1: Histogram of the Estimates of the Income Elasticity of Water Demand



Notes: The dashed vertical indicates the median estimate of the income elasticity of water demand. The solid vertical indicates the mean estimate of the income elasticity of water demand.
Source: Author's computations.

To take a closer look on the causes of heterogeneity, we compute mean values of the income elasticity estimates conditional on different characteristics. Table 3.1 reports the results both for unweighted estimates and for estimates weighted by the inverse of the number of estimates per study which assigns each study the same importance. First, short-run estimates are on average much larger than long-run estimates, by about 0.1. This difference, however, almost disappears when we weight the estimates. Hence, the decision about the existence of temporal dynamics is rather inconclusive. Second, sample means for estimates for different parts of the world show that spatial dynamics may be present. More specifically, both unweighted and weighted specifications suggest that estimates are highest for the United States, lower for Europe, and lowest for any other location. Third, studies employing aggregate data yield slightly higher estimates of the income elasticity of water demand than household data, they differ approximately by 0.02. When weights are assigned, the situation is reversed and the difference is doubled. Fourth, unpublished studies tend to inflate the income elasticity estimates in comparison with published studies. This result is robust to weighting and fluctuates around 0.1.

Table 3.1: Income Elasticity Estimates for Different Subsets of Data

	Unweighted			Weighted			
	Mean	5%	95%	Mean	5%	95%	No of est.
All estimates	0.261	-0.008	0.760	0.270	-0.004	0.753	307
Temporal dynamics							
SR estimates	0.291	-0.025	0.783	0.275	0.003	0.760	216
LR estimates	0.189	0.022	0.684	0.256	-0.004	0.753	91
Spatial dynamics							
US	0.324	-0.028	1.450	0.323	-0.012	1.450	136
EUR	0.261	0.053	0.753	0.252	0.027	0.753	51
Other loc.	0.188	0.002	0.675	0.220	0.003	0.650	120
Aggregation level							
Household	0.254	0.004	0.779	0.289	0.020	0.753	194
Aggregate	0.273	-0.060	0.760	0.243	-0.012	0.640	113
Publication status							
Unpublished	0.345	0.020	1.450	0.358	0.045	1.185	68
Published	0.237	-0.025	0.684	0.254	-0.008	0.683	239

Notes: The table reports mean values of the income elasticity estimates for different subsets of data. 5% and 95% represent the corresponding percentiles. SR = short-run. LR = long-run. US = data from the United States are used to produce estimates. EUR = data from Europe are used to produce estimates. Other loc. = data from a location other than already mentioned are used to produce estimates. Household = household data are used to produce estimates. Aggregate = aggregate data are used to produce estimates. Unpublished = estimates from non-refereed articles. Published = estimates published in peer-reviewed journals. Weighted = estimates are weighted by the inverse of the number of estimates per study.
Source: Author's computations.

We turn the attention to the two main subsamples of interest involving the level of development of a country and estimation techniques employed to obtain income elasticity estimates. Table 3.2 summarizes the results. First, studies of developed countries report higher estimates than those of developing countries. This pattern is retained even after the estimates have been weighted and clearly contradicts one of the hypotheses of this thesis. The basic assumption for the hypothesis is that inhabitants in developing countries consume lower amount of water than they would potentially consume if they had sufficient income. And, similarly, water consumption of individuals living in developed countries is assumed to be on a sufficient level implying no need to increase it noticeably after a rise in income. Consequently, individuals from developing countries are expected to dedicate a relatively higher proportion of their additional income to expenditures on water than those from developed countries. This assumption, however, showed to be incorrect. If income of an individual from a developed country increases by 1%, it triggers an increase in demand for water roughly by 0.3%. The increase of demand for the same change of income for an individual from a developing country is around 0.2%. It can be explained by an analysis of expenditure structures of both groups. The income elasticity of consumers from developed countries may be higher since they are more likely to use water for activities during which it serves rather as a luxury good. It regards, for example, filling up of swimming pools, washing cars, and irrigation of lawns. Similarly, the income elasticity of consumers from developing countries may be lower since they tend to assign a higher proportion of their income to other necessities. Therefore, they do not increase their water consumption as one would expect. It encompasses, for example, food and health.

Table 3.2: Income Elasticity Estimates for Different Levels of Development and Estimation Techniques

	Unweighted			Weighted			
	Mean	5%	95%	Mean	5%	95%	No of est.
Development level							
Developing	0.195	0.004	0.700	0.227	0.003	0.650	106
Developed	0.295	-0.009	0.781	0.290	-0.004	0.753	201
Estimation technique							
OLS	0.268	-0.012	0.685	0.285	0.010	0.685	142
IV	0.324	-0.025	2.364	0.347	-0.009	2.364	56
Panel	0.201	0.040	0.683	0.238	0.050	0.683	75
Other est.	0.258	-0.028	0.783	0.212	-0.028	0.662	34

Notes: The table reports mean values of the income elasticity estimates for different levels of development and estimation techniques. 5% and 95% represent the corresponding percentiles. Developing = estimates for developing countries. Developed = estimates for developed countries. OLS = the method of ordinary least squares is employed for estimation. IV = the method of instrumental variables is employed for estimation. Panel = a panel technique (fixed effects, random effects) is employed for estimation. Other est. = an estimator other than already mentioned is employed for estimation. Weighted = estimates are weighted by the inverse of the number of estimates per study.
Source: Author.

Second, and as hypothesized, different estimation techniques lead to different values of estimates of the income elasticity of water demand. Namely, the use of the method of instrumental variables IV produces on average higher estimates than the use of a panel technique and the method of OLS, approximately by 0.12 and 0.05, respectively. The analysis of weighted data yields almost identical differences. Estimators other than already mentioned lead to similar values as the method of OLS in the unweighted specification, but thy are the only estimators whose corresponding estimates decrease in the weighted specification. In other words, estimated elasticities seems to depend on whether a researcher addresses problem of endogeneity by employing the method of IV, takes the advantage of a panel structure of available data by employing a panel technique, or decides for a different estimator.

To sum up, we find some evidence for the differences between income elasticity estimates for developing and developed countries and among different estimation techniques. In other words, the comparison of sample averages sheds some light on the sources of heterogeneity of the estimates. It does not, however, have to necessarily reflect the genuine effect if the estimates are subject to publication selection bias.

Chapter 4

Publication Selection Bias

Based on the definition of the income elasticity of water demand, its value is not expected to be negative since water does not have any adequate substitute and, hence, cannot be considered as an inferior good. Consequently, negative estimates of the income elasticity of water demand are less likely to be published, which biases the mean estimate positively. This phenomenon is commonly referred to as publication selection bias. If an estimate is selected because of its desirable sign, it is type I selection. Besides the sign of an estimate, its statistical significance takes part in determination whether the estimate is put into a file drawer (Rosenthal 1979), or reported despite its insignificance. In such a case, we deal with type II selection (Stanley 2005). Doucouliagos & Stanley (2013) found that most fields are affected by publication selection bias. For instance, Espey *et al.* (1997) detected selection efforts in the topic of the price elasticity of water demand estimates, Ashenfelter *et al.* (1999) among estimates of returns to education, and Havranek *et al.* (2012) in the field of the gasoline elasticity with respect to its price.

4.1 Graphical Tests of Publication Selection Bias

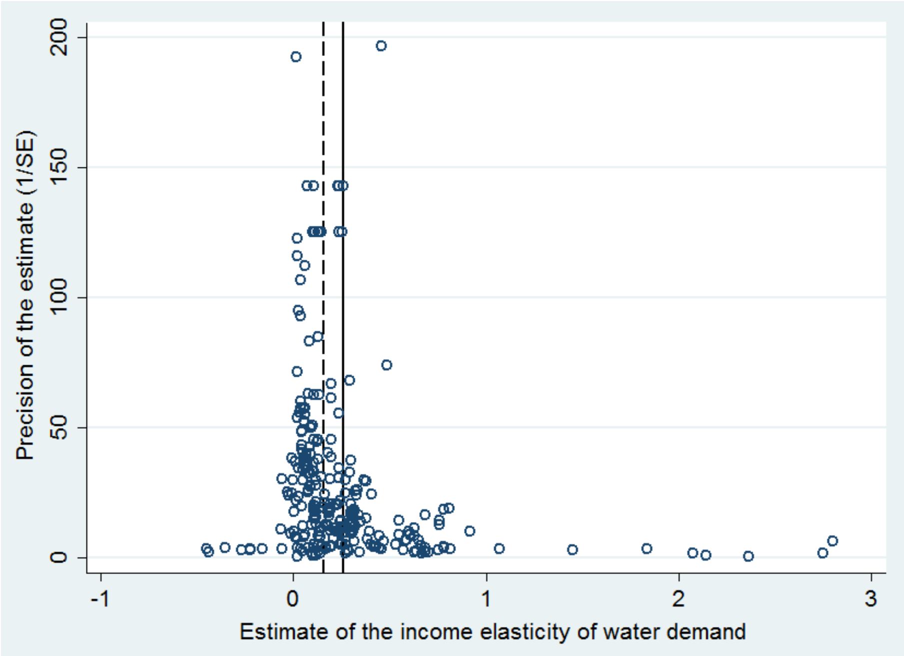
4.1.1 Funnel Plot

One of the most commonly used graphical tests for investigation of the presence of publication selection bias in the literature is the visual examination of funnel plot (Egger *et al.* 1997). Generally, a funnel plot is a scatter plot of the non-standardized size of an estimate on the horizontal axis against a measure of precision of the estimate on the vertical axis (Sterne & Harbord 2004). Precision of the estimate is usually determined by the sample size, by the square root of the sample size, or by the inverse of the standard error of the estimate. In an ideal case, the plot should result into an inverted funnel, where estimates with highest precision are situated close to each other and estimates with lower precision are somehow dispersed (Havranek *et al.* 2015a). Furthermore, estimates should be symmetrically distributed around the true effect since a small imprecise estimate should be published with the same probability as a large imprecise estimate (Havranek *et al.* 2015b). Consequently, asymmetric (type I selection) or hollow (type II selection) funnel plots suggest selection efforts.

It is worth pointing out that asymmetric or hollow funnel plots do not necessarily imply the presence of publication selection bias. The deviations from symmetry can be caused by a variety of other reasons. Among the most frequent belong, for instance, misspecification biases, which arise from modeling choices, or spatial and temporal heterogeneity of true effects.

Figure 4.1 depicts funnel plot for 307 non-standardized estimates of the income elasticity of water demand with the inverse of the standard error of an estimate used as a measure of precision. Two points are worth mentioning. First, estimates do not form a symmetrical distribution, the left-hand part of the funnel is essentially absent. This asymmetry suggests that the literature on the income elasticity of water demand is contaminated by publication selection bias; namely, type I selection. Researchers omit negative values of the elasticity since they assume that such results have a lower probability of being accepted by publishers. Moreover, they would have difficulties to explain such results given the lack of microeconomic theories justifying income elasticity of water demand lower than zero. This biases the estimate of the true effect upwards and can have severe consequences for policies relying on an analysis of incorrect data. Second, the visual examination detects a group of seven estimates located in the bottom of the right-hand part of the figure. Since graphical tests of publication selection bias are rather subjective, we will address the issue of outliers in the regression analysis of its presence.

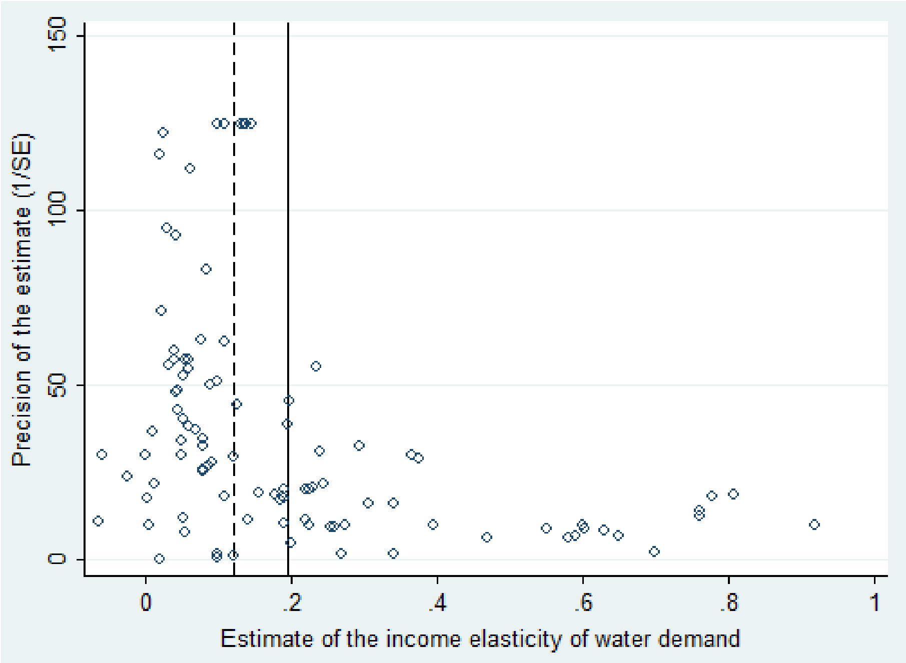
Figure 4.1: Funnel Plot Suggests Publication Selection Bias



Notes: The dashed vertical line indicates the median estimate of the income elasticity of water demand, the solid vertical line indicates the mean estimate of the income elasticity of water demand. When there is no publication selection bias, the estimates should be symmetrically distributed around the true effect.
Source: Author's computations.

Funnel plots for estimates for developing and developed countries are presented in Figure 4.2 and Figure 4.3, respectively. The decision about the presence of publication selection bias within studies estimating the income elasticity of water demand in developing countries may be complicated by a relatively low number of observations. The funnel, however partly symmetric, suggests little publication selection bias given the existence of its right-hand fat tail. Funnel plot for estimates from developed countries is visually identical to funnel plot for all estimates, hence, the conclusion needs to be the same: studies producing estimates of the income elasticity of water demand for developed countries suffer from publication selection bias.

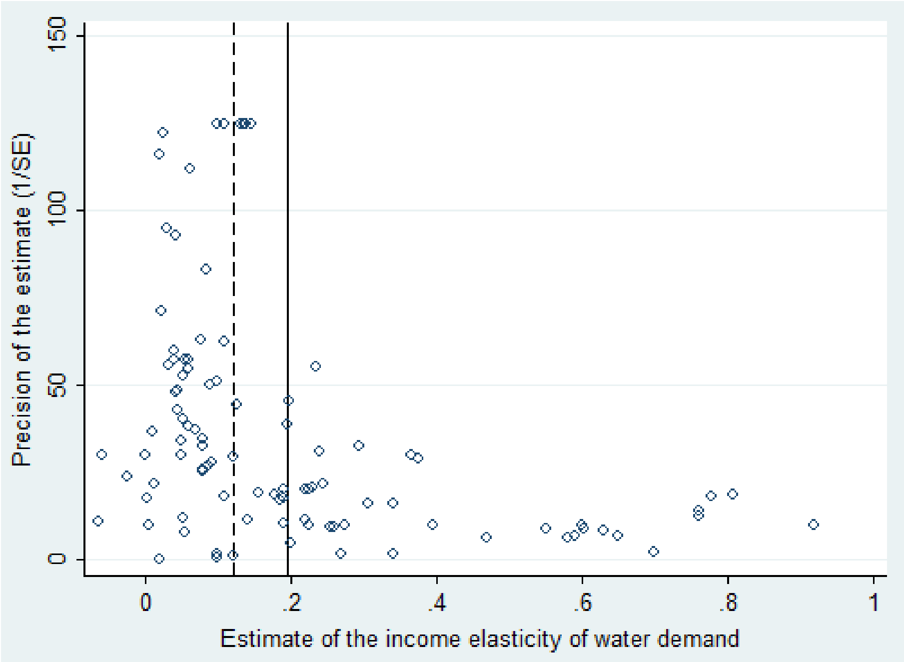
Figure 4.2: Funnel Plot for Developing Countries



Notes: The dashed vertical line indicates the median estimate of the income elasticity of water demand, the solid vertical line indicates the mean estimate of the income elasticity of water demand.
Source: Author's computations.

We do not present funnel plots for different estimation techniques since low number of observations, mainly for the method of IV and the group called other estimators, makes the graphical analysis of publication selection bias complicated.

Figure 4.3: Funnel Plot for Developed Countries



Notes: The dashed vertical line indicates the median estimate of the income elasticity of water demand, the solid vertical line indicates the mean estimate of the income elasticity of water demand.
Source: Author's computations.

4.1.2 Galbraith Plot

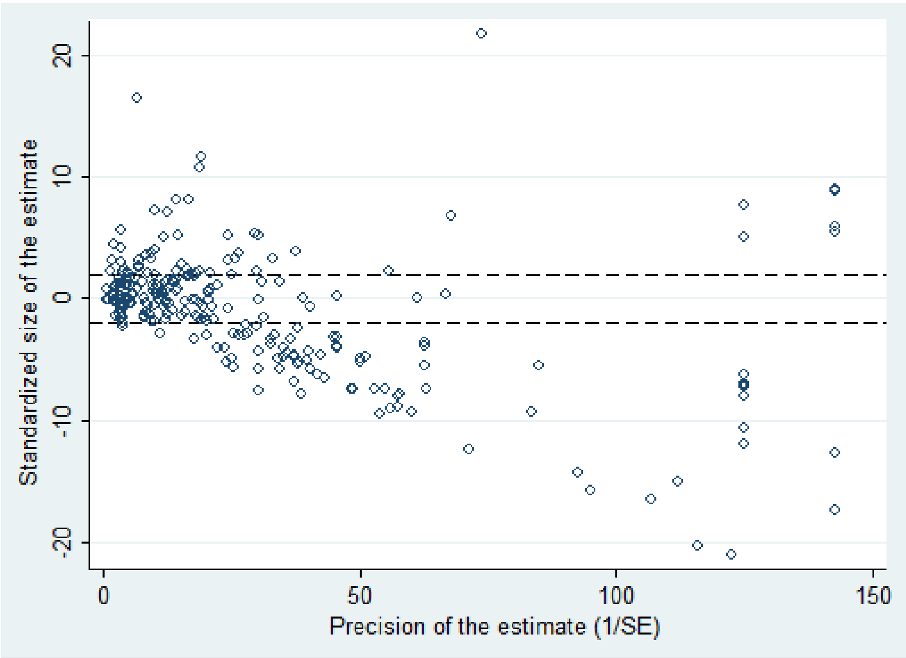
Galbraith plots serve as another graphical test for investigation of the presence of publication selection bias in the literature, namely type II selection. Generally, a Galbraith plot is a scatter plot of precision of an estimate on the horizontal axis against the standardized size of the estimate on the vertical axis (Galbraith 1990). Authors who prefer significant results and disregard insignificant results will overreport high t-values (in absolute terms). Galbraith plots help to find out whether significant estimates with high t-values are reported with higher probability than insignificant estimates with low t-values; again, in absolute terms. Namely, if we select 5% as the natural level, which decides about the significance or insignificance of estimates, then the statistics

$$\left| \frac{e_i - TE}{SE_i} \right|,$$

where e_i denotes the i-th estimated effect of a study, SE_i denotes its standard error, and TE denotes the true effect, should be smaller than 1.96[1] in 95% of cases (Stanley 2005). The true effect can be estimated either by FAT-PET (discussed in the next section) or with the use of funnel plot.

Galbraith plot for 307 standardized estimates of the income elasticity of water demand is depicted in Figure 4.4. Again, the inverse of the standard error

Figure 4.4: Galbraith Plot Suggests Publication Selection Bias



Notes: The dashed upper horizontal line indicates the positive critical value of t-statistics with the significance level of 5%, that is, 1.96. The dashed lower horizontal line indicate the negative critical value of t-statistics with the significance level of 5%, that is, -1.96. Less than 95% of points lie between the two horizontal lines, which suggests that there is type II selection.
Source: Author's computations.

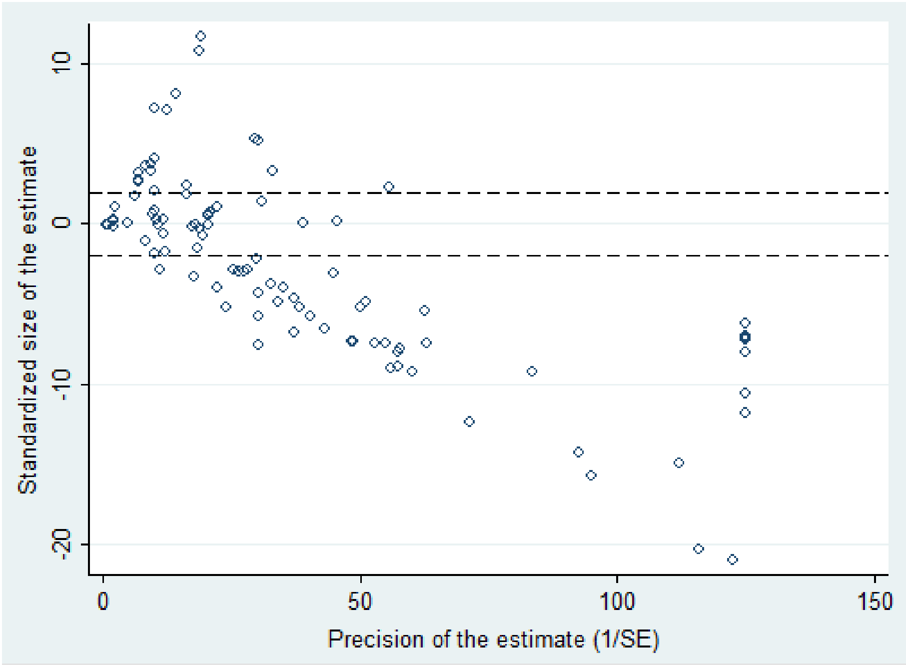
of an estimate is used as a measure of precision. On the one hand, a majority of the estimates are situated between the two lines denoting critical values of t-statistics for 5% significance level. On the other hand, they are rather imprecise, and the higher the precision, the higher the number of estimates outside the area defined by the two dashed lines. Put another way, Galbraith plot shows excess variation of reported t-values since only 43% of the estimates fall into the area of interest, which leads us to the conclusion that the literature on the income elasticity of water demand suffers from type II selection. Researchers

[1] Critical value of t-statistics associated with the significance level of 5%.

are more likely to prefer significant results over insignificant and may conduct a specification search in order to produce desired results.

Galbraith plots for estimates for developing and developed countries are presented in Figure 4.5 and 4.6, respectively.

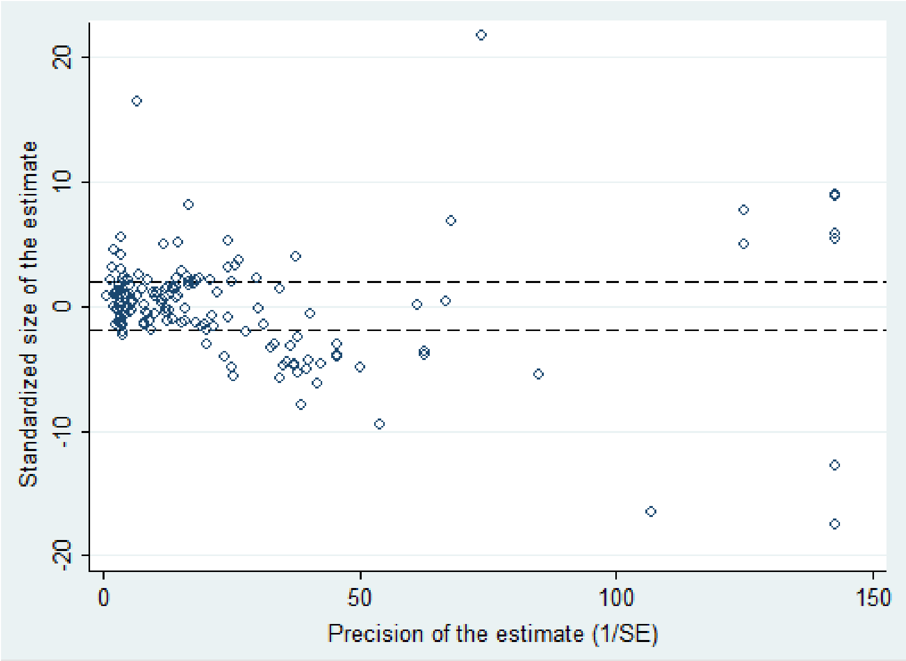
Figure 4.5: Galbraith Plot for Developing Countries



Notes: The dashed upper horizontal line in indicates the positive critical value of t-statistics with the significance level of 5%, that is, 1.96. The dashed lower horizontal line in indicate the negative critical value of t-statistics with the significance level of 5%, that is, −1.96.
Source: Author's computations.

Galbraith plots for both levels of a country's development show excess variation of reported t-values. For the case of developing countries, only approximately one third of the estimates falls between the two horizontal lines. For the case of developed countries, the share of estimates in the area of interest is about one half. Hence, the literature on the income elasticity of water demand for developed countries suffers not only from type I selection, but also from type II selection. Interestingly, studies estimating the income elasticity for developing countries are contaminated only by type II selection.

Figure 4.6: Galbraith Plot for Developed Countries



Notes: The dashed upper horizontal line in indicates the positive critical value of t-statistics with the significance level of 5%, that is, 1.96. The dashed lower horizontal line in indicate the negative critical value of t-statistics with the significance level of 5%, that is, −1.96.
Source: Author's computations.

As in the case of funnel plots, given the lack of a sufficient number of observations for the method of IV and the group of other estimators, we do not conduct the graphical analysis of publication selection bias with the use of Galbraith plots for estimates produced by different estimation techniques.

4.2 Regression Tests of Publication Selection Bias

The examination of funnel and Galbraith plots, however, serves only as an informal and subjective evaluation of publication selection bias. Hence, although both graphical tests provide the same conclusion about its presence, a formal and objective tool is needed. Doucouliagos & Stanley (2009) address this problem by employing meta-regression analysis (MRA), which connects study's estimated effect and a standard error of this effect:

$$e_{ij} = e_0 + \beta \times SE(e_{ij}) + \mu_{ij}, \tag{4.1}$$

where e_{ij} denotes i-th effect estimated in j-th study, $SE(e_{ij})$ denotes its standard error, e_0 and β denote regression coefficients, and μ_{ij} denotes a disturbance term. This disturbance term can be decomposed into study-level random effects, ζ_j, and estimate-level disturbances, ϵ_{ij}. This leads to (Havranek *et al.* 2012):

$$e_{ij} = e_o + \beta \times SE(e_{ij}) + \zeta_j + \epsilon_{ij}, \tag{4.2}$$

where $\zeta_j \mid SE(e_{ij}) \sim N(0, \psi)$ and $\epsilon_{ij} \mid SE(e_{ij}), \zeta_j \sim N(0, \theta)$. Under the assumption of no publication selection bias, estimated effects should be independent of their standard errors; in terms of econometrics, β should be indistinguishable from zero, and each estimated effect should equal the true effect, e_0, plus the disturbance term. On the other hand, if authors publish only statistically significant estimates, publication selection bias will be present. Consequently, estimated effects will depend on their standard errors; in terms of econometrics, β will be significantly different from zero. We employ the method of OLS to find out whether there is a relationship between e_{ij} and $SE(e_{ij})$. Within a given study, it can be expected that each author produces estimates which are dependent. This problem is known as between-study heterogeneity and can be addressed by the means of fixed-effects estimator. We prefer fixed-effects estimator to mixed-effects estimator since the latter one assumes that independent variables and study-level random effects are uncorrelated, which is rarely satisfied in practice. Moreover, it is usually preferred in fields where each study provides a single estimate, which dos not concern the estimation of the water demand equation. On the top of between-study heterogeneity, different authors examine different sample sizes, specify their models differently, and apply different techniques to estimate these models causing Equation 4.2 to be very likely heteroskedastic. Hence, before employing the method of OLS or the fixed-effects estimator, we approach this problem by weighting Equation 4.2 by the inverse of the number of estimates per study. This procedure assigns each study the same weight irrespective of the number of estimates it reports. As a robustness check, we weight Equation 4.2 by the inverse of the standard error an estimate. With such weights precise estimates are given more importance.

Once the model is described by Equation 4.2, hypotheses can be formed. Firstly, the analysis of $H_0 : \beta = 0$ against its alternative ($H_1 : \beta \neq 0$) is an objective test for the presence of publication selection bias. This test is called the funnel asymmetry test (FAT). Secondly, testing $H_2 : e_0 = 0$ against its alternative ($H_3 : e_0 \neq 0$) enables to investigate the mean value of income elasticity estimates after they have been corrected for publication selection bias. This test is called the precision effect test (PET).

Table 4.1 reports results of FAT and PET. Results in Panel A are based on the original sample without any modifications. Results in Panel B serve as a robustness check and are based on a sample with winsorized outliers. It regards seven observations with notably higher values of the income elasticity of water demand. Both panels present estimates of the unweighted version of the MRA model and of versions weighted by the inverse of the number of estimates per study or by the inverse of the standard error of an estimate. Within each of these approaches, the MRA model is estimated by the method of OLS or by fixed-effects estimator.

Table 4.1: Funnel Asymmetry Tests Detect Publication Selection Bias

Panel A: Original Sample	Unweighted		Study		Precision	
	OLS	FE	OLS	FE	OLS	FE
SE (publication selection bias)	0.676**	0.551*	0.884***	0.644***	1.280***	1.514
	(0.305)	(0.301)	(0.132)	(0.161)	(0.369)	(1.176)
Constant (effect beyond bias)	0.178***	0.193***	0.155***	0.187***	0.103***	0.121***
	(0.029)	(0.037)	(0.022)	(0.021)	(0.012)	(0.045)
Observations	307	307	307	307	307	307
Prob > F	0.0303	0.0716	0.0000	0.0002	0.0010	0.2027
Panel B: Winsorized Sample	Unweighted		Study		Precision	
	OLS	FE	OLS	FE	OLS	FE
SE (publication selection bias)	0.338**	0.228*	0.438***	0.247**	1.039***	0.659
	(0.154)	(0.129)	(0.082)	(0.093)	(0.283)	(0.484)
Constant (effect beyond bias)	0.193***	0.207***	0.190***	0.215***	0.107***	0.130***
	(0.024)	(0.016)	(0.022)	(0.012)	(0.011)	(0.019)
Observations	307	307	307	307	307	307
Prob > F	0.0314	0.0824	0.0000	0.0101	0.0005	0.1783

Notes: The table reports the results of regression $e_{ij} = e_o + \beta \times SE(e_{ij}) + \zeta_j + \epsilon_{ij}$, where e_{ij} denotes i-th effect estimated in j-th study and $SE(e_{ij})$ denotes its standard error. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered at the study level. Unweighted = the MRA model is not weighted. Study = the MRA model is weighted by the inverse of the number of estimates per study. Precision = the MRA model is weighted by the inverse of the standard error of an estimate. The results of the regressions in Panel B are based on the winsorized sample.
Source: Author's computations.

Regression tests replicate the outcomes both from the funnel plot and Galbraith plot and confirm the contamination of the income elasticity of water demand literature by publication selection bias. The bias has a positive sign, which means that the true effect is lower than what researchers tend to report. Moreover, this conclusion is robust to winsorizing outliers. The value of the true effect, although similar across samples, somehow varies across specifications of the MRA model. First, it is considerably lower for the model weighted by the inverse of the standard error of an estimate when compared to the other two specifications. Second, according to F-tests, application of the fixed-effects estimator is not suitable if we use the inverse of the standard error of an estimate as weight. This leads us to the conclusion that such a model estimates the effect beyond bias to be somewhere around 0.1. Third, and in a sharp contrast to the previous case, MRA model weighted by the inverse of the number of estimates per study should be estimated by the fixed-effects estimator rather than by the method of OLS. The decision regarding the choice of a relevant estimator in the unweighted model is mixed. Altogether, these two models produce income elasticity estimates ranging approximately from 0.18 to 0.21, which contains the mean estimate from Sebri (2014), but is more than two times lower than the mean estimate from Dalhuisen *et al.* (2003).

The contamination of the literature on the income elasticity of water demand creates a need to reassess conclusions about our hypotheses drawn by comparing averages for different subsamples. For this reassessment, we restrict the analysis only to the level of development of countries and to the comparison of estimation techniques while using the winsorized sample. Table 4.2 summarizes the results for developing and developed countries. Firstly, FAT detects publication selection bias only among estimates for developed countries. This means that the literature on the income elasticity of water demand in developing countries is not contaminated by publication selection bias. Second, for all possible combinations of model specifications and estimators employed, the difference between effect beyond bias for developing and developed countries is lower than the one suggested by sample averaging; that is, 0.1. Moreover, the difference is less than 0.01 for a half of the estimates produced by the PET. Finally, disregarding the “Precision” specification, the true effect in developing and developed countries varies somewhere between 0.19 and 0.21. This is very close to the mean estimate for developing countries, which supports the previous finding of no publication selection bias in studies of developing countries, but it is still much lower than the mean estimate for developed countries underlying the presence of publication selection bias in the literature on developed countries. To sum up, after controlling for publication selection bias, we find no difference between income elasticity estimates for developing and developed countries.

Table 4.2: No Effect of a Development Level After Controlling For Publication Selection Bias

Panel A: Developing Countries	Unweighted		Study		Precision	
	OLS	FE	OLS	FE	OLS	FE
SE (publication selection bias)	0.041	0.018	0.207	0.065	1.018	0.050
	(0.087)	(0.026)	(0.224)	(0.071)	(0.718)	(0.062)
Constant (effect beyond bias)	0.191***	0.193***	0.207***	0.221***	0.092***	0.132***
	(0.046)	(0.003)	(0.048)	(0.007)	(0.021)	(0.002)
Observations	106	106	106	106	106	106
Prob > F	0.6434	0.4958	0.3685	0.3678	0.1730	0.4268
Panel B: Developed Countries	Unweighted		Study		Precision	
	OLS	FE	OLS	FE	OLS	FE
SE (publication selection bias)	0.511***	0.406*	0.477***	0.288**	1.056***	1.355***
	(0.131)	(0.210)	(0.095)	(0.132)	(0.292)	(0.434)
Constant (effect beyond bias)	0.187***	0.201***	0.187***	0.214***	0.114***	0.116***
	(0.029)	(0.028)	(0.027)	(0.019)	(0.015)	(0.017)
Observations	201	201	201	201	201	201
Prob > F	0.0003	0.0605	0.0000	0.0355	0.0008	0.0032

Notes: Results of regression $e_{ij} = e_o + \beta \times SE(e_{ij}) + \zeta_j + \epsilon_{ij}$, where e_{ij} denotes i-th effect estimated in j-th study and $SE(e_{ij})$ denotes its standard error, are reported for developing countries in Panel A and for developed countries in Panel B. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered at the study level. Unweighted = the MRA model is not weighted. Study = the MRA model is weighted by the inverse of the number of estimates per study. Precision = the MRA model is weighted by the inverse of the standard error of an estimate. Winsorized sample is used.
Source: Author's computations.

Table 4.3 presents results of FAT and PET for different estimation techniques. We detect publication selection bias among estimates produced by the method of instrumental variables and by a panel technique. In addition, we conclude that the publication selection bias is not present in studies using the method of OLS to estimate the income elasticity of water demand. The situation among other estimators is mixed, only a half of FAT results considers publication selection bias as a problem. PET considerably changes the previous comparisons of the mean estimates for alternative methods producing income elasticity estimates. Since the specification with the inverse of the standard error of an estimate used as a weight leads to generally lower estimates of the effect beyond bias in a majority of cases, we do not comment on it. For the remaining couple of specifications, two notable patterns emerge. First, if the method of OLS is

Table 4.3: Different Estimation Techniques Produce Different Estimates

Panel A: OLS	Unweighted		Study		Precision	
	OLS	FE	OLS	FE	OLS	FE
SE (publication selection bias)	0.133	0.152	0.354	0.267	0.897**	0.164
	(0.165)	(0.141)	(0.288)	(0.205)	(0.352)	(0.157)
Constant (effect beyond bias)	0.233***	0.230***	0.220***	0.232***	0.115***	0.152***
	(0.033)	(0.022)	(0.039)	(0.027)	(0.013)	(0.007)
Observations	142	142	142	142	142	142
Prob > F	0.4264	0.2884	0.2268	0.2024	0.0155	0.3040
Panel B: IV	Unweighted		Study		Precision	
	OLS	FE	OLS	FE	OLS	FE
SE (publication selection bias)	0.449***	0.362	0.399***	0.266***	1.032**	1.631***
	(0.131)	(0.208)	(0.075)	(0.082)	(0.406)	(0.461)
Constant (effect beyond bias)	0.163***	0.175***	0.183***	0.209***	0.079***	0.076***
	(0.049)	(0.030)	(0.053)	(0.016)	(0.016)	(0.024)
Observations	56	56	56	56	56	56
Prob > F	0.0035	0.1011	0.0001	0.0051	0.0218	0.0027
Panel C: Panel	Unweighted		Study		Precision	
	OLS	FE	OLS	FE	OLS	FE
SE (publication selection bias)	1.578***	1.314***	1.409***	1.310***	2.012**	1.378***
	(0.391)	(0.252)	(0.256)	(0.115)	(0.841)	(0.363)
Constant (effect beyond bias)	0.130***	0.142***	0.137***	0.144***	0.110***	0.117***
	(0.036)	(0.011)	(0.030)	(0.008)	(0.030)	(0.008)
Observations	75	75	75	75	75	75
Prob > F	0.0012	0.0273	0.0000	0.0000	0.0001	0.0007
Panel D: Other Estimator	Unweighted		Study		Precision	
	OLS	FE	OLS	FE	OLS	FE
SE (publication selection bias)	1.211*	0.519	0.919**	0.667	1.248**	1.022
	(0.581)	(0.455)	(0.353)	(0.526)	(0.534)	(0.901)
Constant (effect beyond bias)	0.087*	0.178***	0.081*	0.116	0.082***	0.110**
	(0.043)	(0.060)	(0.041)	(0.072)	(0.028)	(0.049)
Observations	34	34	34	34	34	34
Prob > F	0.0535	0.2708	0.0193	0.2229	0.0326	0.2734

Notes: Results of regression $e_{ij} = e_o + \beta \times SE(e_{ij}) + \zeta_j + \epsilon_{ij}$, where e_{ij} denotes i-th effect estimated in j-th study and $SE(e_{ij})$ denotes its standard error, are reported for estimates produced by the method of ordinary least squares in Panel A, by the method of instrumental variables in Panel B, by a panel technique in Panel C, and by an estimator other than already mentioned in Panel D. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered at the study level. Unweighted = the MRA model is not weighted. Study = the MRA model is weighted by the inverse of the number of estimates per study. Precision = the MRA model is weighted by the inverse of the standard error of an estimate. Winsorized sample is used.
Source: Author's computations.

employed for estimation of the water demand equation, the true effect fluctuates approximately around 0.23, while the use of the method of IV leads to estimates approximately between 0.16 and 0.21. Hence, the preference for certain values among estimates produced by the method of IV biased outcomes of the analysis of sample means. Second, the application of a panel technique or of any other estimator not already mentioned brings the lowest estimates, from 0.13 to 0.14 and with one exception from 0.08 to 0.12, respectively. This is an already known result, the means of these two groups were the lowest as well. Altogether, even if we address publication selection bias, we find differences in estimates of the true effect among estimation techniques.

To sum up, on the one hand, publication selection bias contaminates the literature on the income elasticity of water demand as a whole. On the other hand, certain groups of estimates are not contaminated; for example, estimates for developing countries or estimates produced by the method of OLS. Regarding values of the genuine effect beyond bias, we do not detect heterogeneity among estimates for developed and developing countries. We do, however, detect heterogeneity for different estimators. Unfortunately, the results of FAT and PET may be an incorrect approximation of the reality if the omitted variable bias is present. The decision about which variables should be included in the regression equation and which should not is, however, a hardly approachable econometric issue.

Chapter 5

Why Do Estimates Vary?

The estimates of the income elasticity of water demand cover a substantial range of values. The problem with the explanation of this heterogeneity is the existence of a high number of variables which can potentially have an effect on the values. This can be addressed with the inclusion of all such explanatory variables into the regression equation. This approach, however, leads to many insignificant variables and inefficient estimators. Alternatively, the so-called sequential t-testing can be applied. The caveat with this technique is the threat of losing an important variable during the process. Another possibility is to run many OLS regressions with different subsets and weight them by adjusted R^2. In reality, there can be, however, billions of subsets.

To overcome the above mentioned problems, this thesis employs so-called Bayesian Model Averaging (BMA), which is able to account for model uncertainty in the sense that the subset of explanatory variables is the most effective, and to identify the determinants of the variable of interest. The idea of BMA was proposed by Draper (1995), but the name firstly appears in Raftery *et al.* (1997).

5.1 Explanatory Variables

Water demand specification The specification of water demand can play an important role in affecting values of the income elasticity estimates. Hence, we collect information about the inclusion of the following variables: household size, population density, temperature, rainfall, evaporation, difference variable, and lagged dependent variable. Hewitt & Hanemann (1995) suggest to use the discrete-continuous model in order to avoid misspecification bias caused by ignoring positions of consumers on the demand curve. Hence, we control for the impact of the application of this model.

Price specification One of the most important explanatory variables used in the water demand equation is, besides income, price of water. Nevertheless, different authors prefer different types of prices. For this reason, we specify whether the study uses average, marginal, or any other price. The reference category for this group of dummy variables is the average price specification.

Data characteristics From each study we gather the period of examination and compute its midpoint. This enables us to take a closer look at the temporal dynamics of the income elasticity of water demand. Next, we determine whether the obtained estimate is short-term or long-term. Moreover, we take into account whether the study uses household or aggregate data. Another characteristics we focus on is the frequency of data, whether it is yearly, monthly, or daily. The reference category for the frequency of data is the use of quarterly data for estimation. Last but not least, we distinguish between time series, cross-sectional, and panel data while using panel data as the reference category.

Estimation technique The application of different estimation techniques may lead to different outcomes. In this part, we explore whether these outcomes are affected systematically in the field of the income elasticity of water demand. The most commonly used estimation techniques are OLS, IV, and a panel technique. The reference category for this group of dummy variables including any other estimator is the use of the method of IV.

Tariff structure Tariff structures serve as a suitable tool for policymakers, helping them to control demand for water. Hence, the investigation of the impacts of different tariff structures is of pivotal importance. Unfortunately, expectations about changes in water demand caused by a particular tariff structure create a complicated issue. For example, increasing tariff structure may decrease consumption of water, which leads to higher real income. If the income elasticity of water demand is positive, higher real income results in higher demand for water. It is not known, however, which of these two effects prevails. To address such problems, we include information on the use of flat, increasing, and decreasing tariff structures. The reference category for this group of dummy variables is the situation in which the used tariff structure is not available.

Countries examined Data from different countries can lead to strikingly different estimates of the income elasticity of water demand. The main reasons for this heterogeneity can be differences in consumption habits, culture, climate, or can be given historically. Moreover, Dalhuisen *et al.* (2003) find a significant difference between income elasticity estimates for the US and Europe, while Sebri (2014) argues that this difference is insignificant. Hence, for these reasons, the spatial dynamics is definitely worth examining. We focus on locations in the US, Europe, and any location outside the US and Europe. The reference category for this group of dummy variables is the estimation of the income elasticity of water demand for a location in the US. Next, we make a distinction between whether the study estimates elasticity for a developed or a developing country.

Publication characteristics Finally, we investigate methodological advances by collecting the year of publication of each study. To address the quality of the study, we use the average yearly number of citations and RePEc recursive discounted impact factor for journals. Dalhuisen *et al.* (2003) find that published studies decrease estimates of income elasticity, while Sebri (2014) finds the opposite. Hence, we distinguish between published and unpublished studies.

Table 5.1 provides a summary statistics for the response variable, its standard error, and 31 previously mentioned explanatory variables.

Table 5.1: Description and Summary Statistics of Regression Variables

Variable	Description	Mean	SD	WM
Income elasticity	The estimate of the income elasticity of water demand.	0.261	0.377	0.270
SE	The standard error of the estimate of the income elasticity of water demand.	0.123	0.232	0.130
Water demand specification				
Household size	= 1 if the demand equation contains household size.	0.518	0.500	0.533
Population density	= 1 if the demand equation contains population density.	0.107	0.310	0.099
Temperature	= 1 if the demand equation contains temperature.	0.489	0.501	0.427
Rainfall	= 1 if the demand equation contains rainfall.	0.632	0.483	0.535
Evaporation	= 1 if the demand equation contains evaporation.	0.130	0.337	0.161

Continued on next page

Table 5.1: Description and summary statistics of regression variables (continued)

Variable	Description	Mean	SD	WM
Difference variable	= 1 if the demand equation contains the difference variable.	0.156	0.364	0.218
Lagged	= 1 if the demand equation contains lagged dependent variable.	0.085	0.279	0.124
Discrete-continuous	= 1 if the demand equation is build under the discrete-continuous model.	0.107	0.310	0.125
Price specification				
Marginal	= 1 if marginal price is used for estimation (reference category for this group of dummy variables is the use of average price for estimation).	0.401	0.491	0.462
Other price	= 1 if price other than marginal or average is used for estimation.	0.130	0.337	0.198
Data characteristics				
Mid-year	The midpoint of the period of examination (the base year is the sample minimum: 1956).	36.09	13.13	37.23
Long-term	= 1 if estimated elasticity is long-term.	0.296	0.457	0.237
Household data	= 1 if household data are used for estimation.	0.632	0.483	0.597
Annual	= 1 if the frequency of data used for estimation is annual (reference category for this and the two following variables is the use of quarterly data for estimation).	0.235	0.424	0.242
Monthly	= 1 if the frequency of data used for estimation is monthly.	0.394	0.489	0.483
Daily	= 1 if the frequency of data used for estimation is daily.	0.189	0.392	0.161
Time series	= 1 if time series data are used for estimation (reference category for this and the following variable is the use of panel data for estimation).	0.029	0.029	0.086
Cross section	= 1 if cross-sectional data are used for estimation.	0.293	0.456	0.334
Estimation technique				
OLS	= 1 if the method of ordinary least squares is employed for estimation (reference category for this group of dummy variables is the use of the method of instrumental variables).	0.463	0.499	0.411
Panel technique	= 1 if a panel technique (fixed effects, random effects) is employed for estimation.	0.244	0.430	0.212
Other estimator	= 1 if an estimation technique not listed here is employed for estimation.	0.111	0.314	0.208
Tariff structure				
Flat	= 1 if flat tariff structure is used for estimation (reference category for this group of dummy variables is the situation when the used tariff structure is not available).	0.078	0.269	0.121
Increasing	= 1 if increasing tariff structure is used for estimation.	0.485	0.501	0.526

Continued on next page

Table 5.1: Description and summary statistics of regression variables (continued)

Variable	Description	Mean	SD	WM
Decreasing	= 1 if decreasing tariff structure is used for estimation.	0.023	0.150	0.031
Countries examined				
Europe	= 1 if the income elasticity of water demand is estimated for a location in Europe (reference category for this and the following variable is the estimation of the income elasticity of water demand for a location in the US).	0.166	0.373	0.226
Other location	= 1 if the income elasticity of water demand is estimated for a location not listed here.	0.391	0.489	0.355
Developed	= 1 if the income elasticity of water demand is estimated for a developed country.	0.655	0.476	0.693
Publication characteristics				
Publication year	The year of the appearance of the study in Google Scholar (the base year is the sample minimum: 1972).	30.28	11.36	30.02
Citations	The average yearly number of citations the study received in Google Scholar since its appearance there.	4.494	6.724	4.385
Impact	RePEc recursive discounted impact factor for journals	0.106	0.199	0.088
Published	= 1 if the study is published.	0.799	0.416	0.839

Notes: SD = standard deviation, WM = mean weighted by the inverse of the number of estimates per study.

5.2 Estimation and Results

To address the heterogeneity of estimates of the income elasticity of water demand we augment Equation 4.2 by including 31 variables mentioned above:

$$e_{ij} = e_o + \beta \times SE(e_{ij}) + \sum_{k=1}^{31} \gamma_k \times X_{ijk} + \zeta_j + \epsilon_{ij}, \tag{5.1}$$

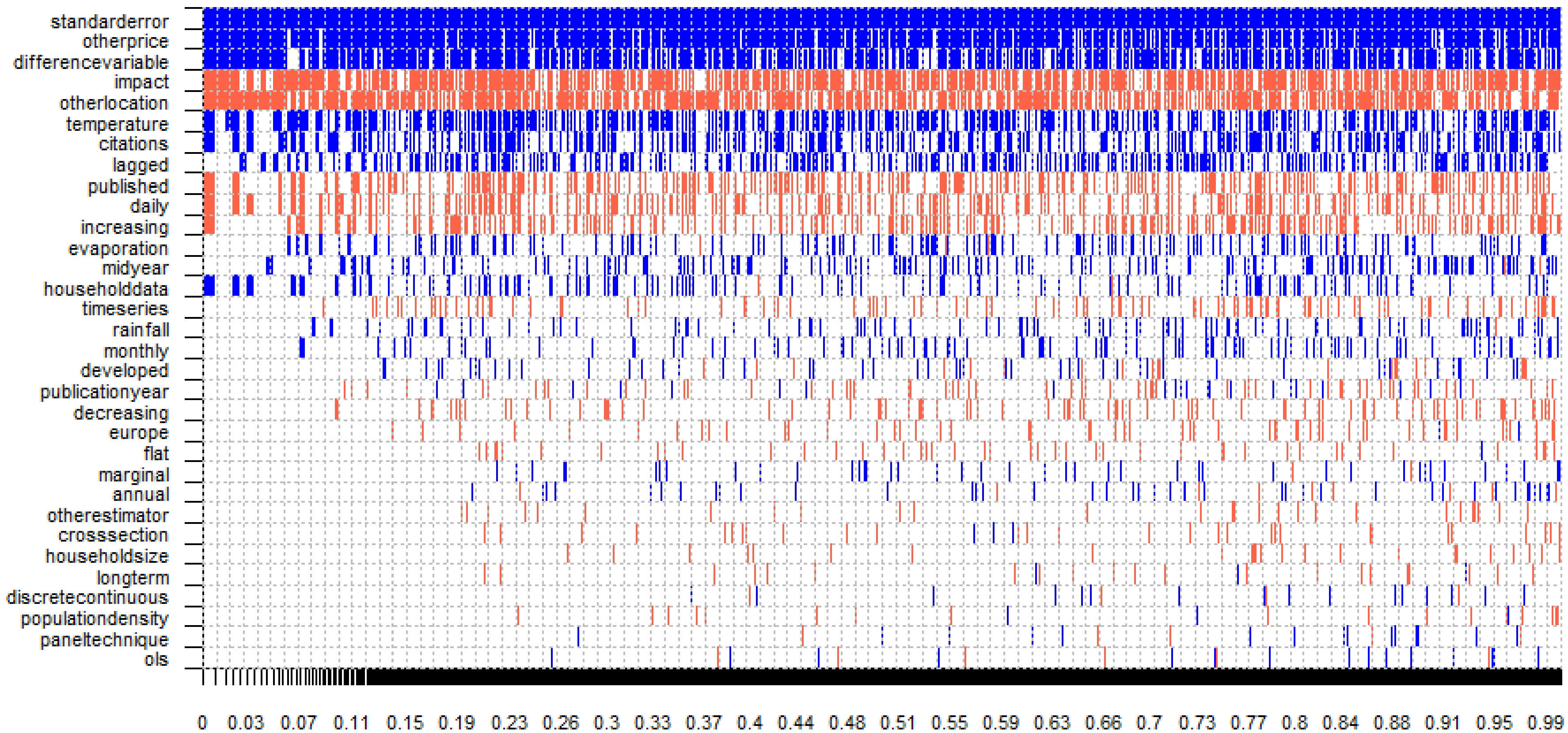
where X_{ijk} denotes a set of explanatory variables.

In Bayesian statistics, the specification of priors is a common issue which has to be dealt with. Namely, before employing BMA, parameter and model priors have to be specified. Although the results of BMA are sensitive to the choice of priors, Eicher *et al.* (2011) consider the unit information prior as an appropriate default parameter prior. The amount of information contained in such a prior is approximately equivalent to the amount of information contained in a single typical observation. Furthermore, they recommend the use of the uniform model prior as a default model prior. Under such setting, each model is assigned with the same prior probability.

Having priors specified, BMA estimates many regressions with different subsets of the 32 explanatory variables while relying on Markov chain Monte Carlo model composition (Madigan *et al.* 1995). Each model is assigned with the posterior model probability (PMP), which reflects the degree to which the model fits the data. It is an analogy to the adjusted coefficient of determination commonly used in frequentist statistics. Next, each variable is assigned with the posterior inclusion probability (PIP), which reflects the probability of the inclusion of the variable in the true model. It is computed by summing up each PMP conditional on the variable being included in the model. Following the rule of thumb suggested by Jeffreys (1961) and applied, among others, by Eicher *et al.* (2012), PIP lower than 0.5 is considered as evidence *against an effect*, while PIP exceeding 0.5 is considered as evidence for an effect. This evidence is *weak* if PIP lies between 0.5 and 0.75, *positive* if it lies between 0.75 and 0.95, *strong* if it lies between 0.95 and 0.99, or *decisive* if it is higher than 0.99.

Figure 5.1 depicts the results of BMA applied on Equation 5.1. The explanatory variables on the vertical axis are ranked according to their PIPs from the highest at the top to the lowest at the bottom. Values of cumulative PMP are denoted on the horizontal axis. If a cell is colored in blue (darker in greyscale), then the corresponding explanatory variable is included in the model and its effect on the response variable is positive. Red color (lighter in greyscale) is connected to a negative effect, no color implies no effect on the response variable. The most important explanatory variables occur to be *standard error*, *other price*, *difference variable*, *impact*, *other location*, and *temperature*. The sign of regression coefficient for each listed variable is robust across different models. With the exception of *impact* and *other location* all of them inflate estimates of the income elasticity of water demand. Only a single variable shows decisive evidence for an effect since its PIP is higher than 0.99. It regards the standard error of an estimate of the income elasticity of water demand. This finding corresponds to the conclusion drawn with the use of the graphical and regression tests of the presence of publication selection bias, hence, the magnitude of the standard error influences the value of the income elasticity of water demand. Put another way, even after controlling for omitted variable bias, the decision about the contamination of the literature on

Figure 5.1: Model Inclusion in Bayesian Model Averaging: Unweighted Specification



Notes: The figure depicts the results of BMA applied on Equation 5.1. Vertical axis: the explanatory variables ranked according to their PIPs from the highest at the top to the lowest at the bottom. Horizontal axis: values of cumulative PMP. Blue color (darker in greyscale) = the corresponding explanatory variable is included in the model and its effect on the response variable is positive. Red color (lighter in greyscale) = the corresponding explanatory variable is included in the model and its effect on the response variable is negative. No color = the corresponding explanatory variable is not included in the model. Numerical results are reported in Table 5.2. All variables are described in Table 5.1.
Source: Author's computations.

the income elasticity of water demand by publication selection bias remains unchanged. Two variables, *other price* and *difference variable*, can be classified as having positive evidence, evidence of the remaining three variables is weak. More importantly, the dummy variable standing for developed countries is not included in the most effective subset of explanatory variables conforming to the results of the PET. Similarly, variables for estimation techniques are excluded from the subset as well. This finding, however, contradicts the heterogeneity of estimates produced by the choice of a particular estimation technique observed in the previous chapter. Hence, if we control for omitted variable bias, different estimators do not systematically yield significantly different estimates of the income elasticity of water demand.

Table 5.2 reports results of an OLS regression while using variables with PIP higher than 0.5 as explanatory variables. All variables have the same sign of corresponding regression coefficients as in the BMA exercise. Furthermore, the magnitude of the regression coefficients is quite robust as well. The frequentist check, however, assigns *temperature* and *difference variable* an insignificant regression coefficient. The income elasticity of water demand estimated for a location other than Europe and the US tends to be approximately by 0.1 lower when compared to the elasticity estimated for the US and holding other factors fixed. Given this is the only spatial dynamics detected in our model, we contradict Dalhuisen *et al.* (2003), who find differences between income elasticity estimates for Europe and the US, and Sebri (2014), who observes no spatial dynamics at all. If price other than average or marginal is used in the water demand equation, the income elasticity estimates are on average 0.181 higher than if average price specification is employed, *ceteris paribus*. Also this result opposes the outcomes of the analyses by Dalhuisen *et al.* (2003) and Sebri (2014) since both studies find differences among price specifications to be statistically indistinguishable.

Figure 5.2 shows the results of BMA applied on Equation 5.1 weighted by the inverse of the number of estimates per study. In this exercise, the group of the most influential explanatory variables includes *standard error*, *evaporation*, *other price*, *temperature*, *daily*, *lagged*, *household size*, and *increasing*. As in the previous case, the regression coefficient for each variable retains the same sign across different models. A majority of explanatory variables influence income elasticity estimates positively, only *daily*, *household size*, and *increasing* tend to deflate the estimates. In accordance with previous findings, the standard error of an estimate of the income elasticity of water demand has a crucial role in

Table 5.2: Explaining Heterogeneity in the Estimates of the Income Elasticity of Water Demand: Unweighted Specification

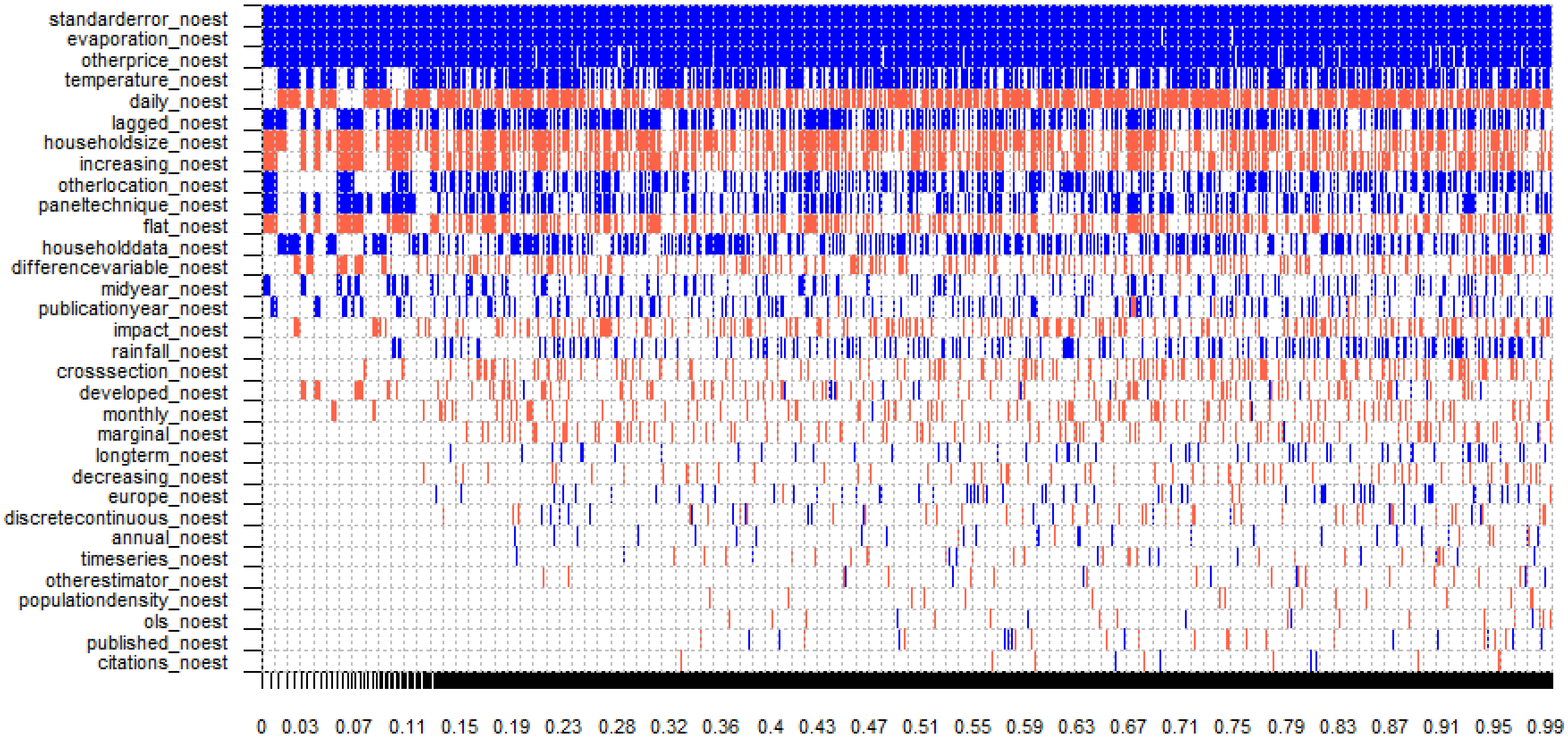
Response variable:	Bayesian model averaging			Frequentist check (OLS)		
Income elasticity	Post. mean	Post. st. dev.	PIP	Coef.	Std. er.	p-value
Constant	-0.830	NA	1.000	0.186	0.046	0.000
Standard error	0.649	0.083	1.000	0.339	0.130	0.012
Water demand specification						
Household size	-0.001	0.011	0.035			
Population density	-0.001	0.013	0.029			
Temperature	0.070	0.076	0.539	0.065	0.058	0.260
Rainfall	0.010	0.032	0.122			
Evaporation	0.038	0.092	0.196			
Difference variable	0.132	0.092	0.756	0.088	0.065	0.181
Lagged	0.082	0.113	0.410			
Discrete-continuous	0.002	0.018	0.031			
Price specification						
Marginal	0.003	0.017	0.050			
Other price	0.200	0.087	0.921	0.181	0.075	0.018
Data characteristics						
Mid-year	0.001	0.004	0.194			
Long-term	-0.001	0.012	0.035			
Household data	0.024	0.057	0.190			
Annual	0.002	0.021	0.047			
Monthly	0.009	0.031	0.117			
Daily	-0.063	0.107	0.323			
Time series	-0.027	0.082	0.134			
Cross section	-0.001	0.012	0.038			
Estimation technique						
OLS	0.000	0.007	0.025			
Panel technique	0.000	0.013	0.027			
Other estimator	-0.003	0.021	0.047			
Tariff structure						
Flat	-0.005	0.030	0.057			
Increasing	-0.034	0.060	0.297			
Decreasing	-0.016	0.066	0.081			
Countries examined						
Europe	-0.005	0.027	0.063			
Other location	-0.125	0.095	0.730	-0.099	0.048	0.046
Developed	0.004	0.047	0.101			
Publication characteristics						
Publication year	-0.001	0.003	0.098			
Citations	0.004	0.006	0.417			
Impact	-0.260	0.194	0.734	-0.223	0.107	0.042
Published	-0.042	0.068	0.333			
Studies	62			62		
Observations	307			307		

Notes: PIP = posterior inclusion probability. Only variables providing at least weak evidence for an effect are included in the frequentist check. Standard errors are clustered at the study level. All variables are described in Table 5.1. Additional details on the BMA exercise can be found in Table A.1 of Appendix A.
Source: Author's computations.

affecting its values. Besides the standard error, evidence for an effect is decisive for evaporation. Furthermore, it is strong for any price specification other than marginal and average. All the five remaining variables provide only weak evidence for an effect. There are three variables in the most effective subset of explanatory variables which are robust to weighting, which suggests that they systematically affect the estimates of the income elasticity of water demand. It encompases *standard error*, *other price*, and *temperature*. Similarly, the conclusion about the omission of the variable differentiating between developed and developing countries, and variables for different estimation techniques is robust to weighting. Hence, neither of the variables of interest contributes to significantly different estimates of the income elasticity of water demand, which is consistent with outcomes of meta-analyses by Dalhuisen *et al.* (2003) and Sebri (2014).

Table 5.3 summarizes results of a frequentist check with the use of the method of OLS while weighting the estimates by the inverse of the number of estimates per study. Again, an estimate of the income elasticity of water demand is regressed on a set of explanatory variables having at least weak evidence for an effect. With only one exception the signs of the regression coefficients correspond to those suggested by the BMA method. The size of the regression coefficients, however, differs from the results of BMA much more than for the unweighted specification. The most pronounced difference occurs for the standard error, its regression coefficient assigned by frequentist statistics is less than a half of the coefficient assigned by Bayesian statistics. If the variable for the amount of evaporation is included in the water demand equation and other factors are held fixed, the estimates of the income elasticity of water demand are on average 0.133 higher than if it is not included. This meta-analysis is the first one to detect the effect of evaporation on the income elasticity estimates. Its positive sign conforms to expectations since it represents the depletion of water resources caused by a change of state of water from liquid to vapor. The lost resources have to be replaced by new resources, which require increase in expenditures. It is worth noting that the inclusion of the lagged dependent variable into the set of explanatory variables can violate classical linear model assumptions. Hence, the method of OLS does not necessarily bring reliable results.

Figure 5.2: Model Inclusion in Bayesian Model Averaging: Study-Weighted Specification



Notes: The figure depicts the results of BMA applied on Equation 5.1 weighted by the inverse of the number of estimates per study. Vertical axis: the explanatory variables ranked according to their PIPs from the highest at the top to the lowest at the bottom. Horizontal axis: values of cumulative PMP. Blue color (darker in greyscale) = the corresponding explanatory variable is included in the model and its effect on the response variable is positive. Red color (lighter in greyscale) = the corresponding explanatory variable is included in the model and its effect on the response variable is negative. No color = the corresponding explanatory variable is not included in the model. Numerical results are reported in Table 5.3. All variables are described in Table 5.1.
Source: Author's computations.

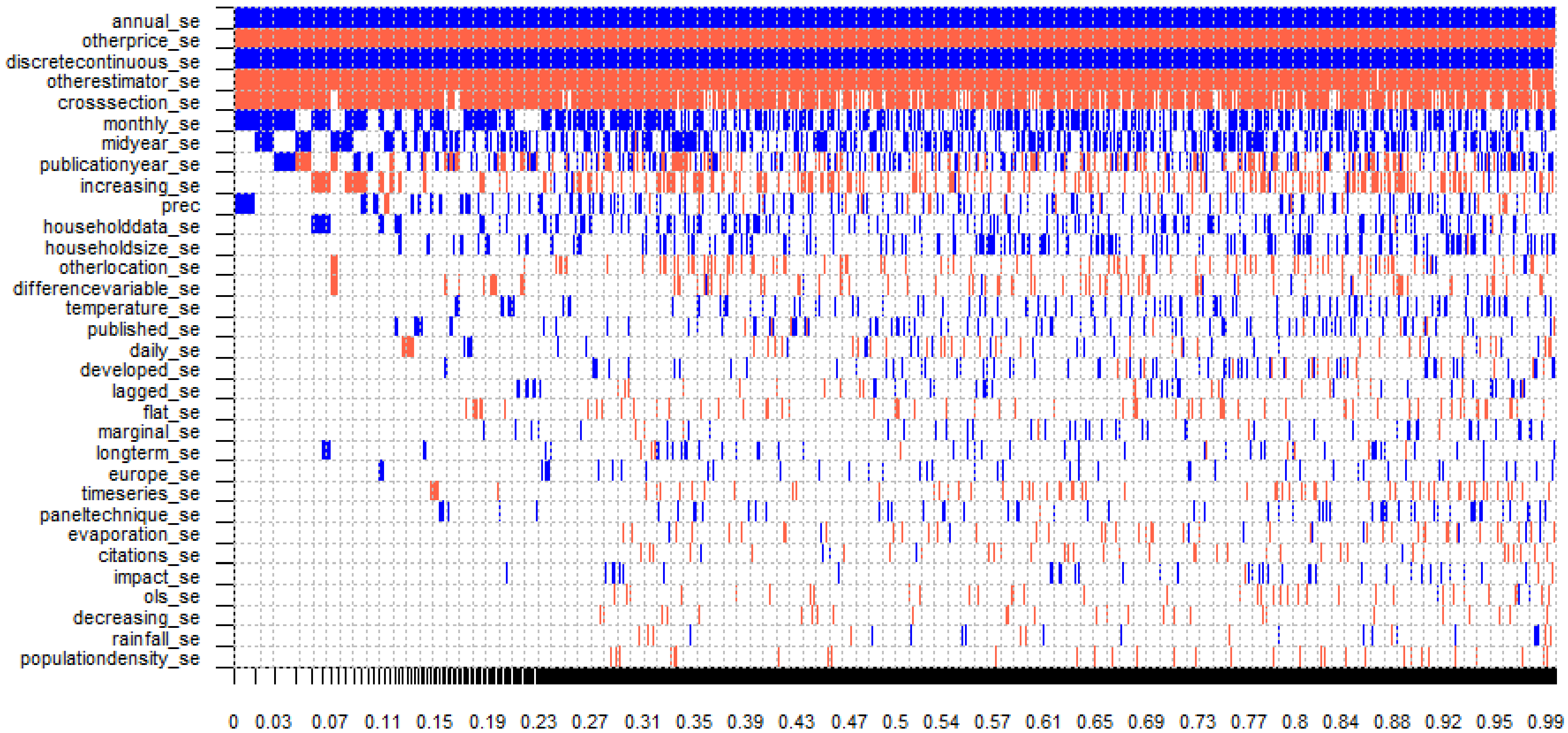
Results of BMA applied on Equation 5.1 while using the inverse of the standard error of an estimate as a weight are depicted in Figure 5.3. If the most precise estimates are given the highest importance, leading explanatory variables occur to be *annual*, *other price*, *discrete continuous*, *other estimator*, and *cross section*. All of them have a sign which is robust across different models. In contrast to the two previous specification, a majority of mentioned variables have a negative impact on the estimates of the income elasticity of water demand. It regards *other price*, *other estimator*, and *cross section*. It is worth mentioning that any price specification of the water demand equation other than marginal and average systematically affects the income elasticity estimates since its corresponding coefficient offers at least weak evidence for an effect according to all the BMA results. The coefficient is not, however, the same in all cases; it is positive twice and negative once. Another mentionable feature of the precision-weighted specification is that out of the five most important variables four of them provide decisive evidence for an effect. The only exception is the use of cross-sectional data for estimation connected with positive evidence for an effect. Again, as *developed* is not included in the subset of the most effective explanatory variables, no difference among estimates for developed and developing countries is found. Next, the results support the hypothesis that different estimation techniques lead to different values of the estimates of the income elasticity of water demand. Specifically, and when compared to the method of IV, an estimation technique using a method different from the method of OLS, IV, and a panel technique leads on average to lower income elasticity estimates *ceteris paribus*. Last but not least, in accordance with results of meta-analyses by Dalhuisen *et al.* (2003) and Sebri (2014), all three BMA exercises argue that the estimates of the income elasticity of water demand are insensitive to the use of household or aggregate data. In contrast, the omission of the variable *published* from the subset of the most effective explanatory variables in each of the results of BMA contradicts results from both Dalhuisen *et al.* (2003) and Sebri (2014). The former finds that published studies affect the elasticity estimates negatively when compared to its baseline category, the latter finds the opposite.

Table 5.3: Explaining Heterogeneity in the Estimates of the Income Elasticity of Water Demand: Study-Weighted Specification

Response variable:	Bayesian model averaging			Frequentist check (OLS)		
Income elasticity	Post. mean	Post. st. dev.	PIP	Coef.	Std. er.	p-value
Constant	0.009	NA	1.000	0.209	0.045	0.000
Standard error	0.815	0.077	1.000	0.365	0.104	0.001
Water demand specification						
Household size	-0.064	0.063	0.589	-0.051	0.043	0.246
Population density	-0.001	0.013	0.035			
Temperature	0.080	0.062	0.692	0.079	0.044	0.082
Rainfall	0.016	0.038	0.203			
Evaporation	0.186	0.049	0.998	0.133	0.062	0.035
Difference variable	-0.015	0.029	0.264			
Lagged	0.068	0.065	0.602	-0.014	0.058	0.806
Discrete-continuous	0.000	0.016	0.065			
Price specification						
Marginal	-0.007	0.024	0.122			
Other price	0.172	0.049	0.974	0.126	0.060	0.041
Data characteristics						
Mid-year	0.000	0.000	0.224			
Long-term	0.004	0.017	0.083			
Household data	0.030	0.040	0.419			
Annual	0.001	0.013	0.054			
Monthly	-0.009	0.026	0.145			
Daily	-0.114	0.094	0.673	-0.064	0.056	0.259
Time series	0.000	0.016	0.053			
Cross section	-0.011	0.028	0.184			
Estimation technique						
OLS	0.000	0.005	0.029			
Panel technique	0.040	0.051	0.453			
Other estimator	0.000	0.008	0.041			
Tariff structure						
Flat	-0.083	0.107	0.424			
Increasing	-0.068	0.078	0.512	-0.095	0.041	0.024
Decreasing	-0.009	0.038	0.078			
Countries examined						
Europe	0.004	0.019	0.075			
Other location	0.052	0.066	0.456			
Developed	-0.012	0.039	0.163			
Publication characteristics						
Publication year	0.000	0.000	0.222			
Citations	0.000	0.000	0.026			
Impact	-0.048	0.106	0.217			
Published	0.000	0.006	0.028			
Studies	62			62		
Observations	307			307		

Notes: PIP = posterior inclusion probability. Only variables providing at least weak evidence for an effect are included in the frequentist check. Standard errors are clustered at the study level. All variables are described in Table 5.1. Additional details on the BMA exercise can be found in Table A.2 of Appendix A.
Source: Author's computations.

Figure 5.3: Model Inclusion in Bayesian Model Averaging: Precision-Weighted Specification



Notes: The figure depicts the results of BMA applied on Equation 5.1 weighted by the inverse of a standard error of an estimate. Vertical axis: the explanatory variables ranked according to their PIPs from the highest at the top to the lowest at the bottom. Horizontal axis: values of cumulative PMP. Blue color (darker in greyscale) = the corresponding explanatory variable is included in the model and its effect on the response variable is positive. Red color (lighter in greyscale) = the corresponding explanatory variable is included in the model and its effect on the response variable is negative. No color = the corresponding explanatory variable is not included in the model. Numerical results are reported in Table 5.4. All variables are described in Table 5.1.
Source: Author's computations.

Table 5.4 reports the results of an OLS regression while using variables with PIP higher than 0.5 as explanatory variables and the inverse of a standard error of an estimate as weights. This frequentist check assigns all variables the same sign of corresponding regression coefficients as in the BMA exercise. The weighting, however, brings higher differences in the size of the regression coefficients between BMA and OLS when compared to the unweighted specification. Furthermore, a majority of variables are insignificant at the 5% significance level. The use of annual data leads *ceteris paribus* to higher income elasticity estimates on average than the use of quarterly data at the 10% significance level. Dalhuisen *et al.* (2003) reaches the same conclusion, but in comparison of annual data and daily data. Sebri (2014) finds that monthly data produce significantly lower elasticities than daily data. Hence, we cannot draw a general conclusion about the relationship between the frequency of data and values of the income elasticity estimates.

To sum up, in this section, we performed three BMA estimations for different model specifications. First, we used the unweighted model. Second, we weighted the model by the inverse of the number of estimates per study which assigns each study the same importance. Third, the model was weighted by the inverse of the standard error of an estimate, which assigns the most precise estimates the highest importance. For each BMA estimation we provided a frequentist check with the use of the method of OLS while including only variables with at least weak evidence for an effect from the corresponding BMA exercise; that is, variables with PIP > 0.5. The unweighted specification produced six variables with such evidence: *standard error*, *other price*, *difference variable*, *impact*, *other location*, and *temperature*. The study-weighted specification highlighted the importance of eight variables having PIP higher than 0.5: *standard error*, *evaporation*, *other price*, *temperature*, *daily*, *lagged*, *household size*, and *increasing*. Finally, the precision-weighted specification yielded the lowest number of variables having at least weak evidence for an effect, but the highest number of variables having decisive evidence for an effect: *annual*, *other price*, *discrete continuous*, *other estimator*, and *cross section*. Almost all corresponding regression coefficients have a sign robust both to different models within the BMA method and to its corresponding frequentist check. The size of a BMA regression coefficient, however, coincides with its OLS size only in the unweighted specification. In the line with the results of FAT from the previous chapter, an estimate of the income elasticity of water demand showed to be dependent on its standard error implying that publication selection bias contaminates the literature on the

Table 5.4: Explaining Heterogeneity in the Estimates of the Income Elasticity of Water Demand: Precision-Weighted Specification

Response variable:	Bayesian model averaging			Frequentist check (OLS)		
Income elasticity	Post. mean	Post. st. dev.	PIP	Coef.	Std. er.	p-value
Constant	1.244	NA	1.000	0.141	0.024	0.000
Precision $\left(\frac{1}{SE}\right)$	0.018	0.662	0.242			
Water demand specification						
Household size	0.006	0.016	0.192			
Population density	-0.002	0.019	0.038			
Temperature	0.003	0.011	0.118			
Rainfall	0.000	0.004	0.038			
Evaporation	-0.002	0.015	0.059			
Difference variable	-0.004	0.013	0.126			
Lagged	0.001	0.008	0.082			
Discrete-continuous	0.213	0.044	0.999	0.152	0.059	0.013
Price specification						
Marginal	0.001	0.007	0.079			
Other price	-0.081	0.019	1.000	-0.024	0.056	0.674
Data characteristics						
Mid-year	0.001	0.002	0.429			
Long-term	0.002	0.012	0.079			
Household data	0.013	0.029	0.204			
Annual	0.246	0.038	1.000	0.118	0.062	0.060
Monthly	0.026	0.032	0.571			
Daily	0.000	0.011	0.101			
Time series	-0.008	0.035	0.076			
Cross section	-0.060	0.031	0.872	-0.003	0.046	0.940
Estimation technique						
OLS	0.000	0.002	0.039			
Panel technique	0.001	0.005	0.073			
Other estimator	-0.196	0.039	0.997	-0.088	0.048	0.073
Tariff structure						
Flat	-0.005	0.023	0.080			
Increasing	-0.013	0.027	0.275			
Decreasing	-0.005	0.045	0.039			
Countries examined						
Europe	0.004	0.020	0.076			
Other location	-0.005	0.016	0.134			
Developed	0.002	0.012	0.086			
Publication characteristics						
Publication year	-0.001	0.002	0.403			
Citations	0.000	0.000	0.046			
Impact	0.001	0.013	0.044			
Published	0.002	0.010	0.113			
Studies	62			62		
Observations	307			307		

Notes: PIP = posterior inclusion probability. Only variables providing at least weak evidence for an effect are included in the frequentist check. Standard errors are clustered at the study level. All variables are described in Table 5.1. Additional details on the BMA exercise can be found in Table A.3 of Appendix A.
Source: Author's computations.

income elasticity of water demand. On the one hand, confirming the results of PET from Chapter 4, there is no significant difference between income elasticity estimates for developing and developed countries. On the other hand, opposing the PET results, different estimation techniques do not lead to different values of the estimates of the income elasticity of water demand as suggested by two from three BMA results.

Chapter 6

Conclusion

The thesis quantitatively examines the topic of the income elasticity of water demand while concentrating on three main issues. First, it takes a closer look on the issue of publication selection bias stemming from the preference of researchers or publishers for statistically significant results or for results of a certain sign. The possibility for its presence can be justified by the expectations about the values of the income elasticity of water demand: they should be positive since water cannot be considered as an inferior good given the lack of adequate substitutes. Consequently, negative estimates of the income elasticity of water demand are less likely to be published, which biases the mean estimate upwards.

Second, it investigates whether the estimates of the income elasticity of water demand are different for areas with different levels of development. The hypothesis is that inhabitants in developing countries are forced to consume lower amount of water since they do not have sufficient income. And, similarly, we assume water consumption of individuals living in developed countries to be sufficient, hence, a change in income should not trigger a significant change in consumption of water. Altogether, individuals from developed countries are expected to dedicate a relatively lower proportion of their additional income to expenditures on water than individuals from developing countries. Third, it tests whether different estimation techniques systematically produce different income elasticity estimates. It is expected that the choice between the method of OLS, the method of IV, a panel technique, and any other estimator has consequences for final results.

The collected dataset of 307 estimates is described and then analyzed by comparing sample means for different subsets of data. The histogram of all estimates seems to be skewed to the right; the median value of the income elasticity of water demand is 0.157, the mean value of the income elasticity of water demand is 0.261. For the case of the level of development of countries, studies of developing countries report lower estimates than those of developed countries. This pattern does not disappear even if we weight the estimates by the inverse of the number of estimates per study, which gives each study the same importance, and contradicts one of the hypothesis of this thesis. If income of an individual from a developing country increases by 1%, it triggers an increase in demand for water roughly by 0.2%. The increase of demand resulting from the same change in income for an individual from a developed country is higher by 0.1 percentage point compared to an individual from a developing country. A possible explanation consists in an analysis of expenditure structures of both groups. The income elasticity of consumers from developed countries may be higher since they are more likely to, for example, fill up swimming pools, wash cars, and irrigate lawns. In such cases, water can be considered as a luxury good. Similarly, the income elasticity of consumers from developing countries may be lower since they tend to assign a higher proportion of their income to other necessities such as food and health.

Mean values of income elasticity estimates for different estimators suggest heterogeneity. Namely, the use of the method of IV leads on average to higher estimates than the use of the method of OLS, by approximately 0.05. Similarly, the OLS estimates are on average by 0.07 higher than estimates yielded by a panel technique. The differences are robust to weighting the estimates. Estimators other than already mentioned produce similar values as the method of OLS in the unweighted specification, but are the only estimators whose estimates decrease in the weighted specifications. Hence, estimated elasticities tend to depend on the choice of an estimation technique.

The analysis of sample means is, however, sensitive to publication selection bias. In order to address this issue, the thesis tests for its presence with the use of graphical and regression analysis. Funnel and Galbraith plots confirm the contamination of the literature on the income elasticity of water demand among all estimates. The regression tests are based on the assumption that if publication selection bias is present, then an estimate of the income elasticity of water demand depends on its standard error. Their relationship is examined with the use of the method of OLS and fixed effects. Moreover, two weighted specifications are performed as robustness checks. We weight the estimates by the inverse of the number of estimates per study and by the inverse of the standard error of an estimate. The latter assigns the most precise estimates the highest importance. The regression tests provide not only an objective evaluation of the publication selection bias with the use of the funnel asymmetry test, but also estimate the true effect beyond the bias with the use of the precision effect test. The regression results are in accordance with the visual evaluation. Publication selection bias is detected among all estimates. PET estimates the genuine income elasticity of water demand corrected for the bias approximately between 0.18 and 0.21. The regression tests reveal that there is no effect of a development level after controlling for publication selection bias, the estimates fluctuate from 0.19 to 0.21.

The results of precision effect test show a notable variation among estimates produced by different estimation techniques. If the water demand equation is estimated by the method of OLS, the true effect is roughly 0.23. If the method of IV is employed for estimation, the estimates are approximately between 0.16 and 0.21. The application of a panel technique or of any other estimator not already mentioned produces the lowest estimates, from 0.13 to 0.14 and with one exception from 0.08 to 0.12, respectively.

The results of FAT and PET may, however, lead to incorrect conclusions if the omitted variable bias is a problem. Unfortunately, we face an enormous model uncertainty since the set of potential explanatory variables is large and we do not know which variables should be included in the regression equation and which should not. To address this issue, this thesis employs Bayesian model averaging, which estimates many regressions with different subsets of all collected explanatory variables. Each model is assigned with the posterior model probability, which reflects the degree to which the model fits the data. Then, each variable is assigned with the posterior inclusion probability, which reflects the probability of inclusion of the variable in the model. Again, three different model specifications are analyzed: unweighted, study-weighted, and precision-weighted. From each of the Bayesian model averaging exercises, we collect variables with the posterior inclusion probability higher than 0.5 and use them as a set of explanatory variables for a frequentist check via the method of OLS. Even after controlling for omitted variable bias, the literature on the income elasticity of water demand seems to be contaminated by publication selection bias. Moreover, the development level does not play any role in any of the specifications, which confirms the PET results. On the other hand, the choice of a particular estimation technique tends to affect the income elasticity estimates, but only in the model in which the most precise estimates are given the highest importance. According to two of three BMA exercises, different estimation techniques do not systematically affect estimates of the income elasticity of water demand.

Unlike Dalhuisen *et al.* (2003) and Sebri (2014), we address both publication selection bias and omitted variable bias by employing proper econometric methods, hence, we can draw adequate policy recommendations and conclusions. First, the genuine income elasticity of water demand is approximately equal to 0.2, thus, policymakers can define an appropriate corridor for expected change in water demand and prevent wasting water when meeting demand. Second, the choice of a certain tariff structure does not seem to be a suitable policy tool for affecting the elasticity of consumers. Consequently, the options of policymakers to steer water demand are relatively limited. Third, a developing country with similar structural parameters as a developed country can conduct similar water demand policy. This finding is similar to the concept of technology adoption and supports the theory of conditional convergence. It should not, however, be applied unconditionally, but rather within a continent since we find some evidence for spatial dynamics in one of our models. Finally, policymakers may decrease the expenditures on new scientific research of the income elasticity of water demand using alternative estimators since its outcomes are expected to be the same as in the prevailing state and its contribution to the knowledge expansion to be limited.

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Appendix A

Diagnostics of BMA

Table A.1: Summary of BMA Estimation: Unweighted Specification

Mean no. regressors	Draws	Burn-ins	Time
9.1356	$3 \cdot 10^5$	$1 \cdot 10^5$	3.890768 mins
No. models visited	Modelspace	Visited	Topmodels
101204	$4.3 \cdot 10^9$	0.0024%	100%
Corr PMP	No. Obs.	Model Prior	g-Prior
0.9334	307	uniform / 16	UIP
Shrinkage-Stats			
Av = 0.9968			

Notes: PMP = posterior model probability. UIP = unit information prior.
Source: Author's computations.

Table A.2: Summary of BMA Estimation: Study-Weighted Specification

Mean no. regressors	Draws	Burn-ins	Time
10.8983	$3 \cdot 10^5$	$1 \cdot 10^5$	3.060463 mins
No. models visited	Modelspace	Visited	Topmodels
92015	$4.3 \cdot 10^9$	0.0021%	100%
Corr PMP	No. Obs.	Model Prior	g-Prior
0.9399	307	uniform / 16	UIP
Shrinkage-Stats			
Av = 0.9968			

Notes: PMP = posterior model probability. UIP = unit information prior.
Source: Author's computations.

Table A.3: Summary of BMA Estimation: Precision-Weighted Specification

Mean no. regressors	Draws	Burn-ins	Time
9.3632	$3 \cdot 10^5$	$1 \cdot 10^5$	2.62265 mins
No. models visited	Modelspace	Visited	Topmodels
77659	$4.3 \cdot 10^9$	0.0018%	100%
Corr PMP	No. Obs.	Model Prior	g-Prior
0.9736	307	uniform / 16	UIP
Shrinkage-Stats			
Av = 0.9968			

Notes: PMP = posterior model probability. UIP = unit information prior.
Source: Author's computations.

Appendix B

Studies Included in the Meta-Analysis

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