WATER DEMAND AND THE URBAN POOR:

A STUDY OF THE FACTORS INFLUENCING WATER CONSUMPTION AMONG HOUSHOLDS IN CAPE TOWN, SOUTH AFRICA

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Ada Jansen og
Carl-Erik Schulz

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Department of Economics and Management
Norwegian College of Fishery Science
University of Tromsø
Norway

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ADA JANSEN*
CARL-ERIK SCHULZ**

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*Corresponding author, Department of Economics, University of Stellenbosch, ada@sun.ac.za
**Department of Economics and Management, University of Tromsø, Norway, Carl-Erik.Schulz@nfh.uit.no
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ABSTRACT

Water demand management is a key focus area for most water managers and even more so in developing countries. Improved access to water is important to the poor. Water scarcity makes efficient management even more urgent and it creates more conflicts in water distribution. Different policies have been introduced to ensure a water management system that cares for the poor, among them the Increasing Block Tariff (IBT) structure. Studies demonstrate that it is very important to know the shape of the demand curve when deciding on the IBT structure. This is particularly so when it comes to supplying water to the poor. The purpose of this paper is to provide a greater understanding of the factors that influence water consumption. It also aims to provide an estimate for the price elasticity of water demand, using data obtained from households living on the Cape Flats in the Western Cape Province, South Africa. The data covers a period of up to 60 months from July 1998 to June 2003. Water consumption data was obtained from the local government, the City of Cape Town (CCT) and a survey study in five suburbs of the area.

A panel data analysis (correcting for heteroscedasticity and serial correlation) demonstrates how different factors influence water consumption, among them the price of water. We find that consumption is insensitive to price changes among the poor, while the richest group of households react to price changes much more. We also find that using actual prices in the estimation does not address the simultaneity in the data and we therefore apply a 2SLS analysis in our model.

Our results reflect a negative price elasticity of demand for water in the short run. A key finding results from splitting the data into different income groups. We find a price elasticity for water demand of only –0.23 for the lowest-income group, whereas the high-income group has a price elasticity of -0.99. The results may add to the knowledge needed to improve an IBT structure to achieve greater equity.

JEL: Q25, Q21, D12

Keywords: Water demand, Income groups, Water pricing

1. Introduction

Water has become increasingly scarce due to factors like population growth, economic growth, increased urbanization and changing climatic patterns. Managing water resources more efficiently has become a priority, especially in developing countries. Water is important for development and poor people usually cannot afford the cost of water. In rural areas water is supplied in different ways, not always tapped and is often not metered. Even in urban areas poor people will often collect unmetered water, but tapped water is more dominant than in the rural areas. Improving the management of water distribution is therefore an important development issue.

Water is metered for many residential consumers in urban areas and pricing policy can be used to manage water distribution among these users. In informal settlements many households pay for their water and low-income groups have metered connections. This allows the pricing of water to be part of a management system to distribute water in an efficient and just way. Payment for water is part of the funding of the water service but it is also a possible way of regulating the consumption of water. However, pricing can only regulate consumption if the households react to price changes.

Three important issues are linked to the pricing of water: the handling of water scarcity, management of water provision and ensuring basic needs. There are different options for handling the scarcity problem. Increased supply, including exploring the building of new dams and other infrastructure, is one possibility. Winpenny (1994) states that projects to increase water supply face hydrological limits, rising costs in terms of pumping and transferring water over long distances and also increasing environmental costs, to which society is more sensitive. For economic efficiency reasons they must be traded off against the willingness to pay for water in some way or another. More recently, the attention has turned to water demand management. Stephenson (1999) argues that water consumption can be curtailed using physical, sociological and economic instruments. In the case of economic instruments, it makes sense to organise water tariffs in a way that combines low price basic supply with a marginal price to curtail total consumption. Demand management can use a combination of quantitative restrictions and a tariff policy. If increased prices reduce water consumption this may be an efficient way of managing water. However, if large groups of consumers do not restrict their consumption of water when the prices increase the price mechanism is working poorly as a management measure. If so, other ways of managing water must be explored. For these reasons, water demand studies are needed to explore the effect of price changes on the consumption of water.

Tapped and metered water is more accessible, but still expensive for the poor.[1] One way of handling this situation is to supply water to the poor at a lower price than to the more well-off households, by using an IBT, where the marginal price for water increases with consumption. Most urban areas in South Africa apply an IBT. Moilanen and Schulz (2002) show how an IBT can be used to support income redistribution. They also show, in a theoretical paper, that differences in the demand structure between rich and poor consumers are important when modelling the IBT structure. If the rich segment of the market is more sensitive to price changes, this information can be used to streamline the IBT structure for equity purposes. Hence, there are various reasons why water managers need information on how price changes impact on the demand for water. This study will try to add to the knowledge of how different groups react to water pricing, based on data from South Africa. It will concentrate on urban residential water supply.

In the next section a literature review provides the background to the empirical study in this paper. It specifically highlights the factors that need to be considered in estimating residential water demand and also elaborates on the estimation techniques that are most common in recent water demand studies done internationally. Section 3 provides an overview of the water resource situation in the Cape Metropolitan Area (CMA). Section 4 discusses the factors that influence water demand, while Section 5 focuses on the data collection process as well as the methodology applied in this particular study. This is followed by Section 6, which discusses the results. Section 7 concludes with some findings and recommendations for water management policy.

2. Water demand studies

Water demand studies give mixed results on the empirical side, but the main result is that water consumption is inelastic. A general overview, a meta-analysis, can be found in Dalhuisen *et. al.* (2003). Here, an analysis of variation is applied to the different price and income elasticities, as found in various studies.

One of the key outcomes in most water demand studies is estimates on how the households react to a price change, i.e. estimates related to the price elasticity for water. According to Martínez-Espiñeira and Nauges (2004), one should view the demand curve for water as consisting of both elastic and inelastic parts. They base their empirical analysis on a demand curve where the theoretical foundation is the Stone-Geary utility function. In this framework, the consumption of a commodity is divided into a fixed quantity that is unresponsive to price changes immediately and a residual component that can adjust to price changes. The results of this study provide water managers with important information about the threshold of the quantity of water below which consumption will not respond to price changes, assuming that the household environment remains the same. However, we do not know if the demand differs systematically between income groups.

Bachrach and Vaughan (1994) provided an overview on water demand estimation, where they addressed statistical methods employed to address estimation problems. Two aspects that are also pertinent to this paper were the simultaneity issue when estimation with increasing block tariffs and the specification of the correct price variables. Olmstead, Haneman and Stavins (2003) used household data to estimate residential water demand, using a piecewise-linear budget constraint model to address block prices. They found a relatively low price elasticity of demand, as well as the fact that the impact of the price structure on demand seemed to be greater than the marginal price. Chicoine and Ramamurthy (1986) focused on testing which price consumers responded to, under a declining block tariff structure. They used household data and found that consumers react to two price variables, not only the marginal price.[2]

Terza and Welch (1982) also looked at statistical methods to employ when dealing with biased and inconsistent results emanating from ordinar least square (OLS) estimation, due to simultaneity. They used a two-stage estimation theoretical model that found consistent results when a "household rule for selection of the block is estimated" (Terza and Welch, 1982: 188).

Höglund (1999) estimated the Swedish household water demand using an aggregated panel data set of 282 communities. Estimation involved two types of models, static and dynamic, where the latter specifically accounts for the fact that adjustments to changes in consumption take time, especially when the cost of water is a small proportion of household expenditure. Höglund (1999) found that the parameter estimates for the dynamic models were quite close to those of the static models and consumers reacted to marginal and average prices. However, these two prices were closely interrelated.

Billings (1982) estimated the price elasticity of water demand, following on from work done by Billings and Agthe (1980), where they reduced the bias from measurement error by removing problem observations. This was in response to concerns raised by Griffin and Martin (1981), where they pointed out the bias in the method used to determine price and quantity.[3] To address these concerns, Billings (1982) estimated an alternative model, where he estimated total revenue as a function of the quantity consumed. His findings were that elasticities ranged from -0.556 (for the log-log model) to -0.66 (for the linear model).

Henson (1984) conducted a study estimating the demand for electricity, based on household data, given multi-block pricing structures. He also found the OLS estimation technique to be biased and inconsistent. His results for an IBT structure ranges between -0.268 and -0.308. Ayadi *et. al.* (2003), a study of African data from Tunisia, split the data in regional and consumption blocks, using average income from budget surveys. They found the average consumption sensitive to price changes (elasticity of -0.4) in the upper bracket of consumption and in dynamic economic regions.

There is a noticeable lack of household studies in the existing literature and there is also a very strong bias to study water demand among relatively rich households. Very few studies have used household data and even less from developing countries. In South Africa, Veck and Bill (2000) applied a contingent valuation method to estimate the price elasticity of demand. Vuuren *et. al.* (2004) extended this analysis and they estimate the response to price shifts based on questions to the households about how they will react to a hypothetical price change. As long as metered water is paid for, it is more appropriate to study the response to real changes in prices and quantities and there is no need to use a contingent valuation study. This makes the estimates better and more reliable since the analysis is based on observed consumption and not hypothetical scenarios.

One particular study conducted at the micro level in developing countries is on household demand for water estimated in Sri Lanka. Gunatilake et. al. (2001) estimated the demand for water using household data. They found the demand for water was price inelastic and income inelastic. They concluded that price increases may not help to conserve water. Further studies using household data are one by Strand and Walker (2003), who study water consumption in different Central American urban areas, and one by Rietveld *et. al.* (1997) who study urban water demand in Indonesia. Strand and Walker (2003) use cross-sectional data, exploring the differences between households with and without access to non-tap resources. They focus on both average and marginal prices but do not allow for different slopes according to income level. They find a price elasticity of about –0.3 for households without access to non-tap water and –0.1 for those with access to non-tap water.

3. A short overview of the water resource situation in the Cape Town Metropolitan Area (CMA)

The Western Cape Province is a region of water scarcity: the mean annual rainfall is only 348 mm, with the highest variability in its mean annual precipitation (Department of Environmental Affairs and Tourism, South Africa, 2005). Most rainfall occurs during winter, while the period October–March is the dry (and hot) season. For each dry season the municipality, the CCT, may also implement water restrictions, aiming for up to 30% reduction in consumption. Since 1997 the CCT used an IBT structure for water pricing. More recently, it implemented the national policy of the free provision of basic services, allowing for 6 kilolitres of free water per metered household. The IBT structure reflects the CCT's efforts to reduce water consumption by using quite steep tariff steps in the upper end (see table in appendix, which provides the pricing structure applied by the CCT). Besides the volumetric water pricing, other fees are also charged for access to tapped water, both for sewage and fixed charges.[4]

4. Factors influencing water demand

Water demand is based on the behaviour of consumers and for this study we concentrate on households. Water is part of the bundle of goods that adds to human well-being. Hence we can use the mainstream approach of demand studies to understand the factors influencing water demand. Water constitutes only a small part of total consumption and we can simplify by doing a partial consumption study. We want to study the variables that influence the demand and the importance of each, with a specific focus on price influences.

4.1 Climate

It is reasonable to assume that weather patterns will influence the consumption of water: more water will be consumed in hot weather and less during rainy periods. Howe and Linaweaver (1967) estimated a sprinkling demand model where they specifically took into account summer precipitation and maximum day evapo-transpiration. Renwick and Green (1999) also included seasons and climate.

4.2 Household demographics and other characteristics

Individual differences between households influence their water demand. Household size is important, (Nieswiadomy and Molina, 1989), as is the age structure of the household. Other variables, like the house size and access to appliances (showers, bathrooms, washing machines, etc.) are also relevant (Barkatullah (2002), Renzetti (2002)). Public information campaigns, the supply of water saving technology, etc., may also influence household water consumption. In modelling water consumption, a distinction is also made between indoor and outdoor use. This specification can also accommodate the distinction between basic use and additional use of water (for pools, lawns, washing cars, etc.).

We include as explanatory variables different household characteristics, as well as an age variable for the household. We also include variables to cover potential effects of the water restrictions applied in Cape Town for the years 2000 and 2001. This is done by using dummy variables.

4.3 Income

Income is a main determinant of consumption. Renwick and Green (1999) use median household income for each of the water agencies included in their study based on aggregated water data. Barkatullah (2002) uses income and property values as indicators of the budget available for households. Höglund (1999) includes the average gross household income in her study. Gunatilake *et. al.* (2001) use household income data from a survey.

Renzetti (2002) reports on a 1998 study by Hanemann which lists price and income elasticities and reflects that most income elasticities are positive but income inelastic. Generally it is difficult to obtain income data that are reliable. Respondents tend to be wary of providing information on their incomes.

4.4 Pricing

Usually economic theory suggests that the consumers react to the marginal price of the product. This is not obvious for a situation with different fixed fees and an IBT. For instance, Arbues *et. al.* (2003) argue that most consumers may not be sufficiently informed about the rate structure to react to marginal prices, but state that this will be determined by empirical investigation.

If the marginal price differs from the average price there exists an implicit lump sum transfer linked to the purchase of water. To include this in the analysis many studies use the Taylor-Nordin difference variable, named the Rate Structure Premium (RSP).[5] According to Barkatullah (2002), the RSP is the second 'price' variable, introduced by Taylor (1975) and further developed by Nordin (1976). We define the RSP as a non-negative subsidy, the difference between what the bill would have been had consumers paid for all units of consumption at the marginal prices and the actual water bill paid. Jones and Morris (1984) refer to this as the inframarginal rate. In our case, where an IBT structure is used, the RSP can be seen as an implicit income subsidy. We distinguish this from income because the subsidy is linked to the actual water consumption, i.e. a transfer in kind. Chicoine and Ramamurthy (1986) state that the RSP represents the income effect entrenched in the IBT. They argue that if there is perfect information, then utility-maximizing households will respond to the marginal price and the RSP. We use the marginal price and the RSP in this study.[6]

When estimating water demand with an IBT structure, it is necessary to take account of the implicit subsidy associated with it. In most instances, researchers opt to model the demand function, including both marginal price and a variable to capture the effects of changes in the RSP. Nieswiadomy and Molina (1989) argue that, in the case of block pricing, the marginal price determines (and is also determined by) consumption. Using OLS as an estimation technique will produce biased and inconsistent results. Due to the IBT structure, high consumption is always observed to be linked to a high marginal price of water. To correct for this other statistical techniques must be used, as demonstrated by Nieswiadomy and Molina (1989), Barkatullah (2002), and others. Barkatullah (2002) used a panel data set, at the household level, to estimate a mixed-effects residential demand model for Sydney, Australia. This study addressed the problem of simultaneity by using instrumental variables. The marginal price of water, income, climate and household specific variables were used to explain water consumption. It also included a 'difference' variable, trying to reflect the difference between the marginal and the average price for water.

Barkatullah (2002) estimated a marginal price elasticity coefficient of -0.21, indicating inelastic water demand. Her estimates reflected high sensitivity to her estimation methods.

5. Data collection and methodology

5.1 Data collection

We want to estimate the influence of different factors on residential water demand. However, we do not aim to estimate the water consumption of some specific area (like the Cape Town Metropolitan Area). We sample accordingly, trying to ensure a diverse group of households. First, we need diversity among the households being studied. The informal settlements and the ultra poor constitute one part of the market. However, they get their water supply from communal standpipes or other unmetered sources. Measuring their consumption can only be done by on spot observation and measurement inside each household.[7] Our study does not include those without metered water. To include possible differences in water consumption between different cultures and income groups we select observations from two historically black suburbs, two historically coloured suburbs and one historically white suburb, all in the CMA. All of them fell under the jurisdiction of the same municipality (the CCT) during the period of our study. Households were selected at random in each suburb.[8] Our sample is therefore not representative for the aggregate water consumption of Cape Town. However, this is not a problem as long as we want to estimate the consumption patterns of households and not of the area as such. Since each household had to give their signed permission to obtain monthly readings of their water consumption from CCT, this makes the date more reliable. Data collectors must definitely have visited all the households included in the study. This procedure could have contributed to less reliable income data. However, the use of categorical income variables may have assisted in a more realistic response.

All household information was collected by use of a questionnaire and later matched with monthly readings from CCT for the period 1998–2003. We employed students, mainly of economics at the University of the Western Cape, to collect the household data. The advantage of this was that the data collectors knew the area, the language and the culture of each suburb. As students of economics they also knew the intention of the study. For Gugulethu we employed assistants from the suburb itself to bridge the gap to the residents. In Pinelands, the richest suburb, we had a problem of access, since we usually needed appointments beforehand. The data collectors randomly selected households to call in order to set up appointments.

Data

The water consumption data covers the period from July 1998 to June 2003, up to 60 observations per household. However, for some households we have shorter time series as meters were installed only later during the specified period. We had to exclude some households due to mismatching or incomplete records with the CCT, leaving 275 households in our final sample. Table 1 gives an overview of the households in the data set.

Table 1. Distribution of household size and household age by suburb

Suburb	Number of		Average number of household members				
	households	Total	Babies (0–3 yrs)	Children (4–11yrs)	Teenagers (12–18yrs)	Adults (19–60yrs)	Elderly (61yrs+)
Gugulethu	64	5.84	0.2	0.82	0.67	3.27	1.03
Langa	49	5.16	0.33	0.63	0.86	2.84	0.51
Mitchell's Plain	73	5.38	0.26	0.75	0.86	3.12	0.38
Kensington	53	4.94	0.13	0.32	0.55	3.19	0.75
Pinelands	36	3.36	0.03	0.19	0.42	2.16	0.55
Total	275	5.14	0.2	0.59	0.70	3	0.65

Source: Own calculations (2005)

The cross-section data was collected from July–August 2003. To make a panel data set, the survey data is combined with the water consumption data from the CCT[9] as well as the average monthly rainfall and average monthly maximum temperatures for the CMA.[10]

Almost all (99%) of the households reside in a house[11] and 97% own their dwelling. Only 1% of the sample can add water from a borehole to their consumption. 7% of the households indicated an increase of the household size during the last two years, while 6.6% indicated a decrease. Out of all households 39% have a bath only, 37% have both a shower and a bath, while 22% have neither. Less than 10% own a dishwasher but 70% own a washing machine. Forty-five per cent of the households have a car, indicating that the real poor are less represented. More than 60% of the households have a geyser, but just 9.5% have a pool. Forty-nine per cent of the households have a garden. The access to car and household appliances indicate that the very poor and destitute groups are not included in our study.

As for the water-related attitudes, 78% of the households indicated that they are aware of water restrictions, 94% are checking indoor taps for water savings and 45 % prefer paving as a way to save outdoor water use. Only 29% indicated that they know the tariff. Most of the households (64%) stated they do not change their consumption when the tariffs change and the main reason mentioned (70%) is difficulties in doing so. Most (77%) find it reasonable to pay for water and more than 60% said it is not reasonable to cut off water for non-payment of water bills. Out of all households, 25% indicated an income change over the last two years, (18% indicated a decrease and 7% indicated an increase). Given the information of only small changes in income and household size during the last years, we assume the household size and the income are constant over the study period. The income distribution is indicated in Table 2.

Table 2. Distribution of households by income category (Rand per month), percentage of suburb total

Suburb	**< 1000**	**1001–5000**	**5001–10000**	**10001–20000**	**>20000**	**Total No. of households**
Gugulethu	61%	38%	1%	0%	0%	64
Langa	41%	53%	6%	0%	0%	49
Mitchell's Plain	25%	53%	16%	5%	0%	73
Kensington	8%	32%	42%	13%	6%	53
Pinelands	0%	3%	31%	22%	44%	36
Total	29%	39%	18%	7%	7%	275

Source: Water Survey data (2003)

Table 2 shows that most households in Gugulethu (99%), Langa (94%), and Mitchell's Plain (78%) fall within the lowest two income categories. This is a much higher proportion than in Kensington (39%) and Pinelands (2.7%). At the other extreme, only Pinelands and Kensington have households recorded in the highest income category, 44% and 5.6% respectively.

5.2 Methodology

Panel data analysis

Our approach in the econometrics is to use a panel data analysis, using both the information selected from specific households and the time series in the analysis. The reason for this is that the data is a mix of cross-sectional data and time records. Essential information from 275 households is mixed with household records for up to 60 months of water consumption and tariffs, as well as climate information and demographic change. This constitutes an unbalanced panel. We start off with a basic model as follows (see Greene, 2003):

$$Y_{it} = X_{it}'\beta + Z_i'\alpha + \varepsilon_{it} \qquad i = 1.....275,\ t = 1.....60 \tag{1}$$

Y_{it} = household water consumption

X_{it} = vector of independent variables

Z_i = contains a constant term and a set of household specific variables

We select our method of estimation based on the specifics of the data. In the case of a pooled regression, Z_i contains only a constant term. This does not fit our situation. We know that most of the differences in consumption must be between different households, while the changes in water consumption for each household are minor during a period of five years. This makes the traditional 'fixed effect model' less useful, because in this approach we include all household differences in the constant term and we analyse differences *within each household* over the time period. In the fixed model we assume that $Zi'\alpha = \alpha_i$, thus a household-specific *constant* term is added into the regression model. This is given by the following equation:

$$Y_{it} = X_{it}'\beta + \alpha_i + \varepsilon_{it} \qquad (2)$$

In the fixed effects approach all the time-invariant variables drop out of the regression. We miss crucial information in the quantity/price variation by using this technique. The nearby alternative is a 'random effects model' that will use this information, modelling the difference between the households as a random variable. In the panel study the random effects model assumes that we include a household-specific random term $Zi'\ \alpha = \alpha + u_{i,}$, which means that we assume that the unobserved individual heterogeneity is random, but not correlated to the explanatory variables. The model can then be specified as follows:

$$Y_{it} = X_{it}'\ \beta + \alpha + u_i + \varepsilon_{it} \qquad (3)$$

denoting u_i for a group specific random element that, for each group, is identical in each period. However, using the Hausman test (see later) we find that the necessary assumptions for a random effects model fail, due to heteroscedasticity in the data. We also find serial correlation in the data to be a serious problem, which we must correct. Two appropriate models are the 'generalised least square' (GLS), the and the 'panel-corrected standard error' (PCSE). Both allow for corrections of heteroscedasticity. In our case, the GLS model also fails, since our data do not adhere to the necessary assumptions of the model (see Stata Press, 2003). The unbalanced panel structure and the number of households exceeding the time periods make this model's results dubious. This leaves us with the PCSE model as our best choice for the analysis and we use the *Stata* version of this model, XTPCSE, as our benchmark for the demand study. We include a correction for serial correlation and for heteroscedasticity, both within panels and across panels in the same period, using pairwise comparison. We use a Prais Winston regression model that also adjusts for serial correlation (Stata Press, 2003). We will, however, compare our benchmark model estimates with other possible approaches and different model specifications.

The IBT structure

We know that due to the IBT structure, high levels of water consumption will always be observed for a high marginal price. Furthermore, the random element will, due to the rising steps, tend to be skewed; higher prices interact with higher random elements. Hence, OLS estimation will probably yield wrong estimates and we correct for this by using a 2SLS model. This problem is well known from the literature and different ways to solve it have been used. We use the standard approach of Taylor (1975) and Nordin (1976), like Barkatullah (2002), Billings (1982), Nieswiadomy and Molina (1989) and Terza and Welch (2001). In the first step, we estimate the relationship between water consumption and a set of marginal prices for *predetermined* quantities, each reflecting one step on the IBT. Additionally we select a set of other exogenous variables [12] for this estimation. We use the estimated parameters[13] to predict water consumption, Con^*_{it} for each observation.

$$Con^*_{it} = f(MP_{it}, Z_{it}) \quad (4)$$

Where:

Con^*_{it} = predicted water consumption

MP_{it} = vector of prices corresponding to the predetermined quantities

Z_{it} = other exogenous variables selected

Now the predicted water consumption, Con^*_{it} is used to calculate the instruments needed. The instrument for the marginal price (MP), MPIV, is the price in the actual IBT that correspond to the predicted consumption, Con^*_{it}. We know (see Section 4) that an IBT structure will imply an implicit subsidy (a rate subsidy premium, RSP) to the consumer. The instrument for this premium, RSPIV, is calculated likewise as the RSP corresponding to the predicted consumption Con^*_{it} for each observation, using the actual tariff structure. The equations relevant here are as follows:

$$RSP = (\text{marginal price} - \text{average price}) * \text{quantity}$$

$$MPIV = g(Con^*_{it}), \quad \text{where } g(.) \text{ reflects the IBT structure}$$

$$RSPIV = h(Con^*_{it}), \quad \text{where } h(.) \text{ reflects the RSP structure}$$

These instruments are used in the second step to estimate water consumption. A log-linear demand model is adopted, which implies that the coefficients of the explanatory variables are expressed as elasticities. However, the RSP is included in real value to avoid unstable estimators.[14] To allow for different demand curves for each income group we use interaction dummies. The variables used in the econometric analyses are listed in Table 3 below. Real values are indexed to 2003 CPIX(Consumer price index excluding interest costs).

Table 3. List of Variables

Variable Name	Description	Variable Name	Description
lcon	Natural log of Water Consumption	y1	Dummy: monthly income (R 1001–5000)
lrmp	Natural log of Real Marginal Price	y2	Dummy: monthly income (R 5001–10000)
lrmpiv	Natural log of real instrumented	y3	Dummy: monthly income (R 10001–20000)
	marginal price	y4	Dummy: monthly income (R > 20000)
rrspiv	Instrumented real RSP	bath	Dummy: household has bath/shower
realrsp	Actual Real RSP	garden	Dummy: household has a garden
lplot	Natural log of plot size	wmachine	Dummy: Household has a washing machine
ltemp	Natural Log of Average Maximum	d2000	Dummy: water restriction year 2000
	Monthly Temperature	d2001	Dummy: Water restriction year 2001
lrain	Natural Log of Average Maximum	lage	Natural log of average age of household
	Monthly Rainfall[15]	inti	yi*lrmiv, interaction dummy to allow for
lhh	Natural Log of Household Size		different slopes for each income group, i=1-4

The water demand model is estimated based on the following equation:[16]

$$(5) \quad lcon = \beta_0 + \beta_1\, lrmpiv + \beta_2\, y1 + \beta_3 y2 + \beta_4 y3 + \beta_5 y4 + \beta_6 rrspiv + \beta_7 ltemp + \beta_8 lhh + \beta_9 lplot + \beta_{10} lrain + \beta_{11} d2000 + \beta_{12} d2001 + \beta_{13} lage + \beta_{14}\, int1 + \beta_{15} int2 + \beta_{16}\, int3 + \beta_{17} int4 + \beta_{18} bath + \beta_{19} garden + \beta_{20} wmachine$$

To ensure unbiased estimates we also keep open to adjust for heteroscedasticity and serial correlation in the error term.

6. Data analysis and results

6.1 Panel data analysis[17]

The results for the benchmark model, PCSE, and two alternatives are given in Tables 4 and 5. We argue that PCSE is the best way to estimate the coefficients. Due to tests supporting a serial-correlated error term, we apply a first-order autoregrresive process (AR (1)) adjustment with an estimated rho of 0.88. We find a price elasticity coefficient of -0.23 for the poorest group, varying – but close to zero – for all low income segments. However, for the richest group of consumers the consumption of water is more elastic, with a price elasticity of -0.99. This supports the assumptions of the theoretical analysis of Moilanen and Schulz (2002), and it also supports the empirical findings of the contingent valuation study of Veck and Bill (2000). The overall goodness of fit for the PCSE model, R^2, is 0.32. Tables 4 and 5 also report the results from two alternative methods – estimations using a 'random effects model'(REM) with AR(1), and alternatively a 'generalized least square' (GLS) in the second step, still applying an instrumental variable approach. For the latter we include an adjustment for heteroscedasticity as well, but we are not able to correct for serial correlation. Table 5 shows that the estimated parameters for the price elasticity do not change much, which support our random effect estimate as a stable one. The estimation demonstrates serious serial correlation in the data.

Table 4. Estimation results for three different model specifications

Variable	**PCSE Model AR(1) Coefficients** Corrected for heteroscedasticity	**Random Effects Model Coefficients REM AR(1)**	**GLS Model Coefficients** Corrected for heteroscedasticity
lrmpiv	-0.228***	-0.222***	-0.136***
	(-2.55)	(-6.96)	(-5.82)
rrspiv	0.004***	0.004***	0.003***
	(3.49)	(11.73)	(10.69)
int1	-0.016	-0.012	0.003
	(-0.41)	(-0.38)	(0.14)
int2	-0.096***	-0.082***	-0.084***
	(-2.19)	(-2.43)	(-3.46)

int3	-0.178***	-0.152***	-0.072***
	(-3.02)	(-3.52)	(-2.32)
int4	-0.762***	-0.710***	-0.518***
	(-4.64)	(-10.89)	(-9.87)
ltemp	0.318***	0.323***	0.209***
	(2.87)	(15.15)	(14.94)
lrain	0.002	0.003*	0.001
	(0.32)	(1.80)	(1.33)
lhh	0.565***	0.634***	0.620***
	(8.56)	(10.34)	(26.20)
lage	0.181***	0.313***	0.304***
	(2.19)	(3.94)	(9.28)
lplot	0.220***	0.195***	0.175***
	(3.54)	(3.04)	(8.52)
y1	-0.097	-0.108	-0.019
	(-1.64)	(-1.45)	(-0.55)
y2	0.082	0.066	0.109***
	(1.14)	(0.66)	(2.66)
y3	0.168*	0.149	0.086*
	(1.78)	(1.14)	(1.66)
y4	1.338***	1.283***	1.044***
	(5.41)	(7.76)	(12.02)
d2000	0.012	0.017	0.014*
	(0.22)	(1.46)	(1.88)
d2001	-0.004	0.001	-0.002
	(-0.07)	(0.10)	(-0.26)
bath	0.252***	0.233***	0.223***
	(3.97)	(3.42)	(7.41)
garden	0.062	0.086	0.082***
	(1.47)	(1.37)	(3.92)
wmachine	0.191***	0.194***	0.190***
	(7.09)	(3.11)	(9.74)
constant	-1.026***	-1.449***	-1.028***
	(-2.04)	(-3.31)	(-5.83)
Rho AR(1)	0.882	0.846	0.882
Adjusted R^2	0.324	0.289	---

Source: Own Calculations (2005)

Note: 1) All models use instrumental variables, and are correcting for serial correlation
2) z-values in parentheses for PCSE and GLS, t-values for REM AR(1). Level of significance: *** - significant at the 1% level, ** - significant at the 5% level, * - significant at the 10% level.
3) The standard errors reported in the table are not adjusted, given the use of the 2SLS technique. Calculations show that the corrected standard errors are not very different.

Table 5. Estimated Price Elasticities for Different Income Groups

Income Group	**PCSE Model**	**Random Effects Model**	**GLS model**
Monthly Income	**Price Elasticity**	**Price Elasticity**	**Price Elasticity**
R0-1000	- 0.228	- 0.222	- 0.136
R1001-5000	- 0.244	- 0.235	- 0.133
R5001-10000	- 0.324	- 0.305	- 0.220
R10001-20000	-0.406	-.0.375	- 0.208
R20001 –	- 0.990	- 0.932	- 0.654

Source: Own Calculations (2005)

Looking at the PCSE model, all price elasticities are negative and most of the interaction dummies are significant. This demonstrates a quite strong difference between the upper-income segment and all other households: We find that a 10 % price increase for the highest-income group will reduce the water consumption of each household by 9.90%, while for the poorest group the same price increase will only reduce their (already small) water use by 2.28%. This means that only the highest-income group react considerably to price changes.

The dummies for bath, garden, plot size and washing machine all have the expected sign. They are also statistically significant, except for garden.[18] As for the climate, water consumption increases with temperature and rainfall, however the latter effect is not significant. Household size, the average age of the household as well as the plot size, all contribute positively to water consumption. The dummies for years with water restrictions (2000 and 2001) have positive coefficients, but they are not significantly different from zero. The restriction periods do not significantly influence the residential consumption. This is opposite to the observed long-run effect of the restrictions on total water demand trends for the CMA. Households with access to baths, a garden or with a washing machine all seem to increase their water consumption and the effects are significant. This is no surprise. Lastly, we find that high income seems to increase demand substantially, while for lower segments income does not have a major influence.

From the other approaches of estimation, we find the consumption pattern differs the same way as it does with income, although the price elasticities are slightly different. We find good economic reasons to use the PCSE as our best method. It takes account of the panel structure and it uses the information from all the data for the estimation, also including the specific household structure of the time series. The method includes a correction for heteroscedasticity. The two other (and very different) approaches yield estimates close to the PCSE model. The correction for serial correlation is of crucial importance, with the AR (1) estimated rho close to 1. The GLS model cannot include this correction in our case: the time series (60 periods) are too short compared with the number of households (275) and the panel is unbalanced. This also precludes us from adjusting for correlation across panels in the GLS model – a problem we face in the data. Therefore, the results obtained for the GLS model are dubious.

6.2 Other model specifications

Fixed effects, random effects and pooled data models

We now want to compare our basic results with other model specifications, using the PCSE as the benchmark model. Our main intention here is to check the stability of our results for different model specifications. Hence, we concentrate on reporting the price elasticity estimates, the fitting of the data and, where needed, the serial correlation correction.

First we compare the PCSE model results with a fixed effects model, a random effects model and pooled data, still including the correction for serial correlation. Table 7 presents the main results. In the fixed effects approach all the time-invariant variables drop out of the regression and so do several others due to the unbalanced panel mixed with the use of AR (1). However, the main estimates remain and they do not change a lot from the PCSE results. The problem with the fixed model is a very low goodness of fit, R^2 down to 0.075, which indicates that the fixed effects model may not be appropriate to use. The reason for this is obvious: each household usually only faces minor price changes – they stick to one or two steps of the IBT only. The main improvement using other models is really to add observations from other households to obtain price variations, while controlling for the important differences in background. With the fixed effects model little is left to allow for studies of price shifts. This information is cared for in the PCSE and the 'random effects model', REM AR (1). The price elasticities for the different income groups are reported in Table 6.

Table 6. Estimated price elasticities for different income groups – Panel models: PCSE, REM AR(1), Fixed Effects Model AR(1) and, alternatively, all data pooled

Income Group **Monthly income**	**Reference:** **PCSE**	**Random Effects Model AR(1)**	**Fixed Effect Model AR(1)**	**Pooled data**
R0-1000	-0.228	- 0.222	- 0.231	- 0.244
R1001-5000	-0.244	- 0.235	- 0.256	- 0.149
R5001-10000	-0.324	- 0.305	- 0.348	- 0.138
R10001-20000	-0.406	-.0.375	-0.419	- 0.087
R20001 –	-0.990	- 0.932	- 1.049	- 0.537
Rho AR(1)	0.882	0.846	0.846	---
Adjusted R^2	0.324	0.289	0.075	---

Source: Own Calculations (2005)

Using panel data we have to test if the strong assumptions of the random model can be applied to our sample. The Hausman specification test can test for orthogonality of the random effects and the regressors (Greene, 2003: 301). In our case we test the random effect model without correction for serial correlation.[19] The test gives a chi2(10) = 72.61, which means that we must reject the hypothesis of equal standard errors, Prob>chi2 = 0.0000. Equal standard errors are required for using the random effects model and this result rules out the REM AR(1) as a possible option for our estimation. We therefore use PCSE as the most appropriate model specification.

Table 6 also reports the estimates obtained if we do the calculations for all data pooled, i.e. ignoring the panel and time sequencing of our data. We find that the price elasticities for the different income groups are relatively smaller than in the case of the benchmark model. In this case, all interaction dummies are significant. What remains significant is the result that, once again, there is a marked difference between the elasticities of the highest income group and that of the other groups.

Different number of income groups

We have split the households into 5 income groups, and our results indicated that it is the high income segment that differs most from the rest. We now split our sample differently, to see if the estimates differ for other income groupings. Table 7 reflects these results.

Table 7. Estimated price elasticities for different income group specifications: PCSE model. Income: R per month

Row	**Income Group** / **Monthly Income R**	**Reference: Adjusted R^2**	**Base Group 0-1000**	**Income 1001-5000**	**Income 5001-10000**	**Income 10001-20000**	**Income >20000**
1	Full sample	0.316	- 0.251				
2	0-20000 and > 20000	0.323	-0.274				- 0.981
3	0-10000, 10001-20000 and > 20000	0.324	-0.261			- 0.404	- 0.989
4	All income groups	0.324	- 0.228	- 0.243	- 0.332	- 0.405	- 0.989

Source: Own Calculations (2005)

Note: The underlined groups in the rows indicate that the elasticity figure represents all those groups. For example, in row 1, the full sample is used and therefore -0.251 is the price elasticity for the whole sample (no specification of interaction dummies for different income groups).

The results reflect that, even after splitting the sample into different income groupings, there is still a significant difference between the elasticities of the lowest-income groups and the highest-income group.

Instrumented versus actual real prices

Now we compare our benchmark model with an PCSE model using actual real prices. We have argued that the use of actual prices and the RSP will yield biased estimators since the error term must be correlated with the quantity consumed due to the IBT structure. Table 8 compares our benchmark model results with those obtained from using the actual real prices.

Table 8. Estimated price elasticities for different income groups Comparing PCSE: instrumented versus actual real prices

Income Group Monthly Income	Reference: PCSE (instrumented prices)	PCSE (actual prices)
R 0-1000	- 0.228	0.130
R 1001-5000	- 0.244	0.097
R5001-10000	- 0.324	0.081
R 10001-20000	-.0.406	0.074
R 20001 –	- 0.990	0.052
Rho AR(1)	0.882	0.763
Adjusted R^2	0.324	0.586

Source: Own Calculations (2005)

We find that OLS yields quite different estimates than our reference model. We find, as expected, a positive price elasticity for the poor. This result is like Nieswiadomy and Molina (1989) and Barkatullah (2002). The big difference in the elasticity estimates between OLS and IV regressions support our conclusions that an IV approach is needed.

Semi-log and linear models

We compare our modelling of demand in the benchmark model, where constant price elasticity is assumed, with other shapes of the demand curve. We redefine the model as either a linear one or a semi-log one (setting the log of consumption as a linear function of price). For both we apply IV-analysis and a random effects panel model. In this case it has no meaning to compare the elasticities, since they will vary with consumption for the two new models introduced. However, we refer to the slopes and the R^2.

Table 9. Estimated price elasticities for different model specifications. REM AR(1), semi-log and linear model, all using IV and corrected for serial correlation

Income Group Monthly Income	Reference: PCSE Log-linear Price Elasticity	Semilog Slope	Linear Slope
R 0-1000	- 0.228	- 0.126	- 3.066
R 1001-5000	- 0.244	- 0.139	- 3.255
R5001-10000	- 0.324	- 0.182	- 4.085
R 10001-20000	-.0.406	- 0.203	- 4.288
R 20001 –	- 0.990	- 0.336	- 9.733
Rho AR(1)	-0.882	0.884	0.887
R-squared	0.324	0.322	0.094

Source: Own Calculations (2005)

7. Conclusions and some policy implications

Given the recurring droughts experienced in almost all provinces of South Africa, there should be an emphasis on using all possible policies to change the consumption patterns of consumers, given the presumption that they consume too much. To do so, water managers must know the shape of their demand curves. With this knowledge, they will better be able to design policies that take into account the multiple objectives of different policies.

In the case of pricing policy, it is evident from most studies that demand is price inelastic, at least in the short run. However, our study also concludes that while low-income groups hardly change their consumption due to price shifts, the higher-income groups are relatively more price sensitive. We find that the price elasticity differs significantly between the high-income segment (-0.990) and the rest of the households (low-income segment 0.228). A 10% price increase facing the marginal consumption of the high-income group will trigger a 9.90% reduction in their water consumption.

This finding has policy implications. First, an overall policy to manage water and restrict consumption can build on the price mechanism only for the upper segment of the market. Since the high-income consumers also have the largest consumption of water, an adjustment of the higher steps of an IBT may work very well. This policy was successfully used by Durban Water in the late 1990s.[20] For the low-income groups other measures must be used: pricing cannot be used as an efficient management tool for their consumption of water. If needed, such other measures can include quantitative restrictions, low pressure, other physical restrictions, campaigns etc. Price increases may have implications for equity, especially in circumstances where many people cannot afford to even pay for the basic consumption of water. Our results show that price increases for the low-income groups only work like a tax.

Second, our estimates can be useful to streamline the IBT structure. Moilanen and Schulz (2002) show how an IBT will vary according to the welfare goals of the municipality and also according to the demand structure for the rich and the poor. A more elastic demand for the rich group is a crucial factor to understand how to use an IBT for equity purposes. Our study indicates that it is possible to set the IBT structure in a way that can improve the living conditions for the poor while also caring for overall welfare and the budget restrictions faced by the water services.

The research supports a model specification using constant price elasticity for all levels of consumption, while it differs according to the income level of the household. It seems that the main split in the consumption patterns arise between the high-income groups and the rest of the population. This is so even if we control for the differences in water-demanding appliances and household characteristics. This is important for water policy. Our study demonstrates that water policy will be wrong if all households are pooled and no differences between the income groups are allowed. We find a price elasticity coefficient for the full sample data of -0.25 and this splits into -0.23 for the lowest-income group, and -0.99 for the highest-income group. Ignoring this information will base a water policy on a small reaction to price (2.5% drop in consumption for an overall price increase of 10%). However, including this information means that increasing the water price for the highest blocks (mainly consumed by the rich households) will restrict their water use by 9.9% for a 10% price increase.

The model results for the price elasticities are robust to the model specification. However, there are good reasons to give careful attention to the model specification to ensure all over stable results. As with many other studies, most of the variation in water consumption seems to be explained by factors outside the model.

There are only few water demand studies for low-income areas of the world. Our study gives optimistic management options for using water pricing among the poor. This is not a question of privatisation, but of efficient and fair management of a scarce resource. Metered water opens the way for management that cares for ensuring sufficient water to meet basic needs while restricting water wastage.

Our results seem to compare well with other studies. However, the consumption patterns in Cape Town may not reflect the overall patterns in the developing world. Our study does not include the very poor and destitute groups, who only have unmetered water. We also focus on urban, residential consumption and rural areas probably face different management problems. This opens the way for other, interesting and relevant water demand research. However, for all consumers without metered water demand, management by use of volumetric pricing is irrelevant. A proper and fair management of a scarce resource needs other measures in these cases.

Our main conclusion is that a social manager of water must have a lot of knowledge of the water demand structure to impose a socially efficient water pricing structure. Financial reasoning alone cannot account for this and it may lead to pricing policies that are bad for water distribution.

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APPENDIX:

Table 1: Domestic water consumption tariffs:[21] City of Cape Town

Tariff change date		01 July 1998		01 July 1999		01 July 2000		01 November 2000	
Consumer category	Step	kl	2000/2001	kl	1999/2000	kl	2000/2001	kl	2000/2001
Domestic full	Step 1	0-30	R 1.05	0-5	R 0.50	0-6	R 1.09	0-6	R 1.09
	Step 2	31-150	R 2.22	6-15	R 1.60	7-15	R 1.86	7-15	R 1.95
	Step 3	150+	R 3.65	16-30	R 2.70	16-30	R 2.91	16-30	R 3.06
	Step 4			31-50	R 3.80	31-50	R 4.40	31-60	R 4.62
	Step 5			50+	R 5.00	50+	R 6.00	60+	R 6.30
	Step 6								
Tariff change date		01-May-01		01-Jul-01		01-Jul-02		01-Jul-03	
Consumer category	Step	kl	2000/2001	kl	2001/2002	kl	2002/2003	kl	2002/2003
Domestic full	Step 1	0-6	R 0.00	0-6	R 0.00	0-6	R 0.00	0-6	R 0.00
	Step 2	7-15	R 1.95	7-20	R 2.60	7-20	R 2.73	7-12	R 2.00
	Step 3	16-30	R 3.06	21-40	R 4.10	21-40	R 4.30	13-20	R 4.00
	Step 4	31-60	R 4.62	41-60	R 5.20	41-60	R 5.40	21-40	R 5.10
	Step 5	60+	R 6.30	61+	R 7.00	61+	R 7.35	41-60	R 6.20
	Step 6							61+	R 8.00

Source: Water Services Department, CCT, 2004.

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1 There are other options available, such as communal taps, ground tanks etc. In those management systems water consumption must be regulated by use of volume or pressure restrictions. The volumetric tariff can only be used for metered consumption.
2 "The second price variable is equivalent to average price less marginal price." (Chicoine and Maramurthy, 1986: 27.)
3 Griffin and Martin (1981) commented on Billings and Agthe's study (1980), stating that the relationship between price and quantity, indicated by Billings and Agthe's regression, is the result of the form of the rate schedule.
4 Due to data constraints, we have not included these fees in our analysis. However, the fixed fees will work opposite to the rate structure premium discussed in the text later, like a tax on the access of tapped water.
5 According to Barkatullah (2002), the difference variable (RSP) is the second 'price' variable introduced by Taylor in 1975 and further developed by Nordin in 1976. We define the RSP as a non-negative subsidy, the difference between what the bill would have been had consumers paid for full consumption at the marginal price and the actual water bill paid. This implies that in our case of an IBT, the RSP can be seen as an implicit income subsidy. We distinguish this from income because both we and the consumers will see this as a subsidy linked to the actual water consumption, i.e. a transfer in kind.
6 There is a relationship between 'average price' (AP), 'marginal price' (MP) and the RSP, denoting Q for the quantity consumed: $AP = MP – RSP/Q$.
7 These households do not pay for water and so their consumption cannot be influenced by price changes. Poor households inside the zero-price segment of the metered water supply can not fully represent their consumption since these households have potable water

inside their house. Their consumption is not comparable to households that must bring water from a standpipe. Households without potable water consume only a very small part of the urban water consumption.

[8] Certain areas of some suburbs were not easily accessible. The data collection process also had to maintain safety for the data collectors.

[9] The data set includes *time series* for water consumption, water tariffs, climate and household structure, as well as *cross-sectional data* on the household, such as household size, income, plot size and other demographic variables and appliances etc. The descriptive statistics support our assumption that income and household size did not change significantly during the period under investigation.

[10] The weather variables were obtained from the South African Weather Services.

[11] Households living in flats usually share one water meter for each block.

[12] The variables used in the first step of the analysis include: marginal prices for the predetermined quantities, p1–p11, temperature, rainfall, plot size, household size, income categories and access to borehole dummy, knowledge of water restrictions dummy and knowledge of water tariffs dummy.

[13] The first step regression yields an adjusted $R^2 = 0.20$ between the instruments and the exogenous variables.

[14] Alternative model specifications were tested and the findings of this process indicated that including the log of RSP will easily lead to significant impacts on the results. Since the RSP is of no major interest in this study, we use the real instrument instead of its log value and this produces stable results.

[15] To secure the inclusion of observation months with no rain, these values have been adjusted to 1 mm rainfall.

[16] The study includes only selected explanatory variables, based on the analysis of previous studies.

[17] All regressions are calculated using STATA8.

[18] Garden and plot size will probably measure the same effect.

[19] The test applied for the models with corrections for serial correlations gives mixed results. Some of the variables are randomly not included by STATA (which indicates an unreliable test), while the test variable indicates problems in using the random model. All in all we argue that the random specification adds so much more information to our study (not included by the other specifications) that it justifies its use.

[20] Information from Durban Water, http://www.durban.gov.za/eThekwini/Services/water_and_sanitation.

[21] The tariffs are in nominal prices. For our econometric analysis, these tariffs are converted to 2003 prices.